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ANALYSIS OF THE WORLD EXPERIENCE OF ECONOMIC AND MATHEMATICAL MODELING OF SMART ENTERPRISES

The paper shows the inevitability of technological mode shift driven by the Industry 4.0, which implies the ubiquitous implementation of information technology, total automation of various processes and creation of cyber-physical systems with artificial intelligence. This requires a complete restructuring of manufacturing systems and production relations, especially in the economies of those countries that want to take a decent place in the new international division of labour of the digital future.

An analysis of the world experience of such changes connected with smart industrialization, digital transformations of the economy, the emergence of the industrial Internet of Things and big data processing made it possible to draw the conclusion that it is necessary to apply economic and mathematical methods to justify the expediency of such transformations: economic validity, as well as physical viability of newly created systems. The use of the apparatus of economic and mathematical modeling allows studying properties of the smart system that is being designed, evaluating its effectiveness and risks, anticipating the emergence of problems and errors – without the risk of incurring significant losses which is inevitable when making direct changes in the object of research.

Therefore, the purpose of this paper is to study the world experience in the economic and mathematical modeling of smart enterprises and to substantiate its use in the conditions of Ukraine.

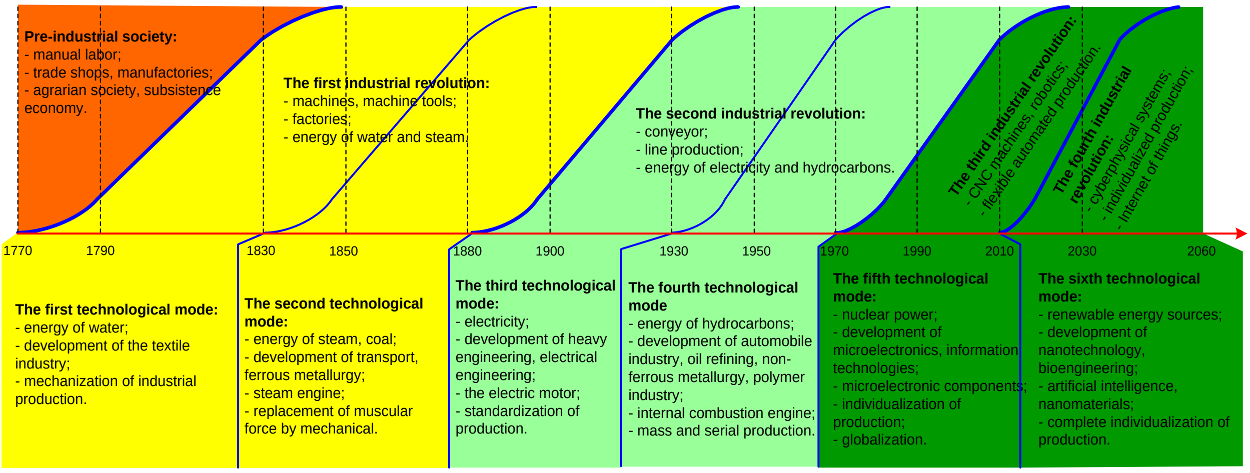
The review of publications, reflecting the aspects of economic and mathematical modeling in these areas, allowed to conclude that the methodical and methodological apparatus for modeling these processes is unsystematic and inefficient, as well as to formulate recommendations on the economic and mathematical modeling of smart enterprises in Ukraine. In order to take into account the specific features of Ukraine's technological and institutional development, a number of economic and mathematical modeling tools based on the use of production functions, models of inter-branch balance, network optimization models and simulation models based on stochastic dependencies were offered to support the creation of smart enterprises.

Keywords: Industry 4.0, digital technologies, smart enterprises, big data, economic and mathematical modeling.

JEL codes: C00; C60; C67; C69; O12; O14.

In 2011, at the Hanover Fair, a group of German researchers, businessmen and public figures from the Industry-Science Research Alliance for the development of strategic principles of high-tech production, offered the term "Industry 4.0" and its principles [23].That event marked the comprehension and the beginning of the transition to a new industrial revolution, based on the ubiquitous application of "smart" technologies that can completely exclude humans from the process of making routine decisions in the area of manufacturing. For several years, these ideas have spread so much in the scientific and business environment that the Fourth Industrial Revolution became the main and dominant topic at the 46th World Economic Forum in Davos [6].

Fig. 1 shows the evolution of world industry development and its relationship with the change of technological modes. The Third and the Fourth Industrial Revolutions are considered by many researchers as two different ones: the Third revolution is the digital revolution associated with the digitization of all processes and the Fourth one is a revolution of cyber-physical systems, associated with the emergence of machines with artificial intelligence. At the same time, there are publications, in which these revolutions are not separated [19], and introduction of technologies of the 5th and 6th technological modes is considered to be the Third industrial revolution, and the key factor in that revolution is the significant change in the role of information and informatization of production processes.



Source: compiled from [5, 22].

Fig. 1. Evolution of the world industry development and its relationship with the change of technological modes

There's certain logic behind that as, firstly, the term the "Third industrial revolution" appeared just 5 years before the "Fourth" one and the principles of manufacturing organization, associated with it, are only beginning to spread across the Western countries (and are still in their infancy in Ukraine). Secondly, it's obvious that the emergence of cyber-physical systems is an evolutionary development of the digitalization process. Therefore, we believe that the concepts of the Third and Fourth revolutions most probably will eventually be combined into a single one, "digital revolution".

In any case, the spread of information technology, comprehensive automation of a wide variety of processes, the discovery of fundamentally new materials and non-waste ways of using them, success in the creation of cyber-physical systems that have artificial intelligence – all that has revolutionized the opportunities in the organization of industrial manufacturing. Ukraine, whose industry uses technologies of the 3rd and 4th technological modes [3], is far behind the Western countries in its development, and the chances of catching up with them in an evolutionary manner seem doubtful. Nevertheless, while being on the periphery of the world economic processes, Ukraine has no right to remain aloof from these major transformations. The creation of new enterprises, operating the technology of the 6^{th} mode, might allow Ukraine to occupy a worthy niche in the new international division of labour of the digital future.

However, any project, even a local one, requires careful justification of its suitability. First of all, from the point of view of the physical viability of the designed system in the environment in which it will exist. The creation of the most modern smart enterprise in the conditions of a corrupt system, undeveloped institutions, contractors working according to old principles, undeveloped culture of using information technologies, might actually lead to non-viability of such an enterprise. Another aspect is the economic feasibility: the costs of creating such enterprises should be justified, and the efficiency of their operation has to exceed the efficiency of the current ones. However, in the above mentioned conditions, such efficiency is not always achieved. Therefore, the transition to a new smart production system and measures to transform production relations should be carefully justified, and economic and mathematical modeling is the most effective tool for describing the systems and processes being designed. The use of the apparatus of economic and mathematical modeling makes it possible to conduct any experiments with the system being designed, study its properties, evaluate efficiency and anticipate the occurrence of problems and errors without the risk of incurring colossal losses that are unavoidable in the case of direct experiments.

The apparatus of economic and mathematical modeling is currently developed enough to describe any, even the most complex processes and systems, however, the novelty of the tasks to be solved when creating smart enterprises does not allow making an unequivocal choice in favor of using certain specific tools. In order to choose the most effective and expedient tools of economic and mathematical modeling, it makes sense to study the foreign experience of applying these methods in the creation of smart enterprises, since the developed countries are way ahead of Ukrainian reformers and already have certain empirical knowledge in this field.

Therefore, the *purpose of this article* is to study the foreign experience of economic and mathematical modeling of smart enterprises and the rationale for its use in Ukrainian conditions.

The following concepts, associated with the digital revolution can be distinguished, which have a certain synonymous character:

– «*the Fourth industrial revolution*» [35], practical manifestations of which are the intensification of information exchange in production, the Internet of Things, cyber-physical systems and cloud computing [38];

– «*Industry 4.0*» (German"Industrie 4.0"), which is used in Germany to describe the Fourth industrial revolution [33];

– «*smart factory*» or «*smart enterprise*» – modular, structured factories, in which cyber-physical systems control physical processes, create a virtual copy of the physical world, and make decentralized decisions [34];

– *«cyber-physical systems»* (CPS) – hardware and software systems, being a close interlacing of the physical and virtual world. Such systems are formed by network of embedded systems that are connected to the outside world using sensors and drives, receiving data streams from the physical world and creating and constantly updating the virtual copy of the physical world [29; 44];

– «*Internet of Things*» [24] (IoT) – information networks of physical objects (objects, goods, machines, cars, buildings and other objects) that ensure the interaction and cooperation of these objects for achieving common goals;

– «*Industrial Internet of Things*» [36] (IIoT) – an information network that, among other things, connects transport and industrial production (digital product views, cyber-physical systems of smart factories, etc.).

Before analyzing the economic and mathematical models of smart enterprises, it is necessary to classify all the variety of publications, concentrated on the problems of their implementation and functioning, and to highlight the areas that make sense studying within the scope of the scientific research on identifying the smart industry development directions in Ukraine.

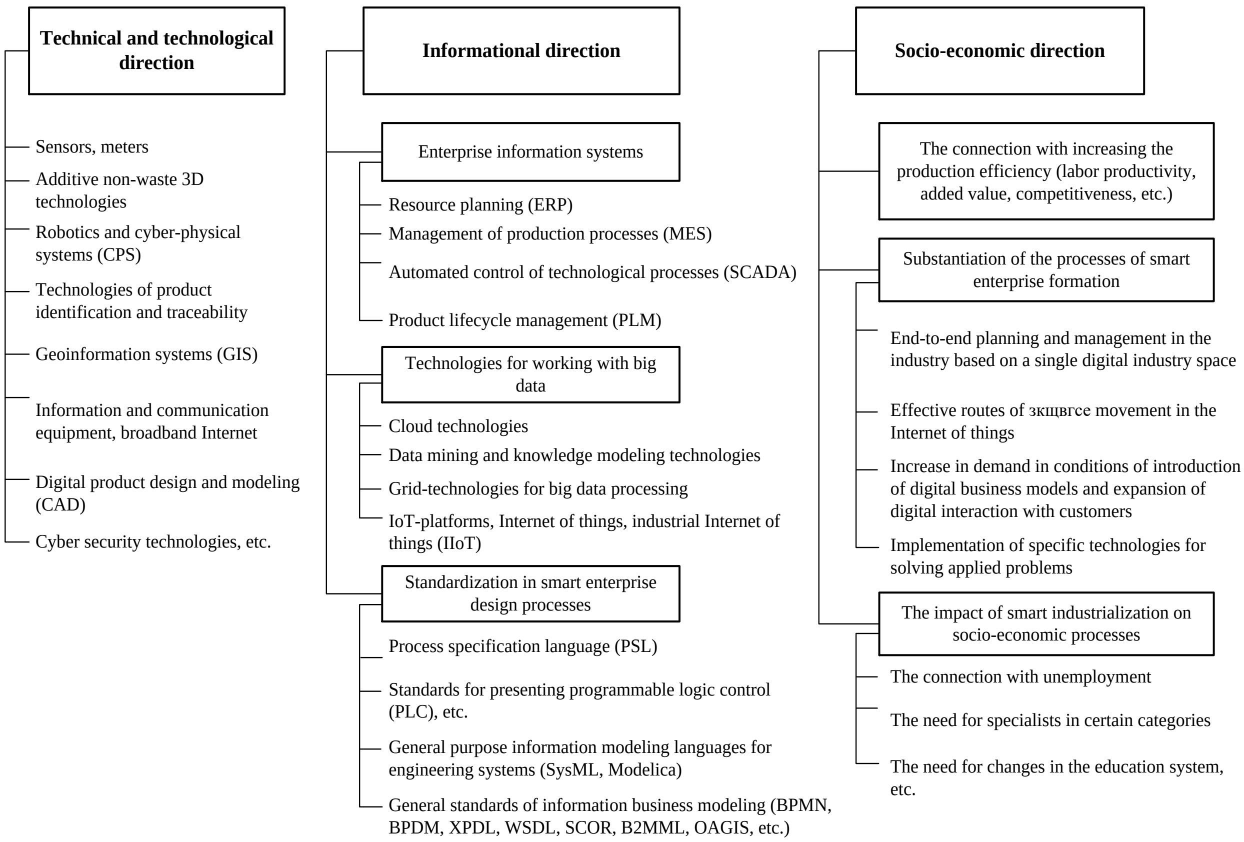
According to the ***objects of research***, the following directions of such publications can be highlighted:

1) technical and technological direction, associated with the design and implementation of high-tech physical systems;

2) information direction, associated with the accumulation, processing and transmission of information;

3) economic direction, associated with changes in the provision of benefits and economic interests of individuals and social groups.

In a closer look, the following objects of study can be identified in these areas (fig. 2).



Source: compiled by the authors

Fig. 2. The main focus objects in the publications on smart industry

Also, all the variety of publications, concerned smart enterprises, depending on the goals that are pursued in a publication, can be divided into following ***tasks to be solved***:

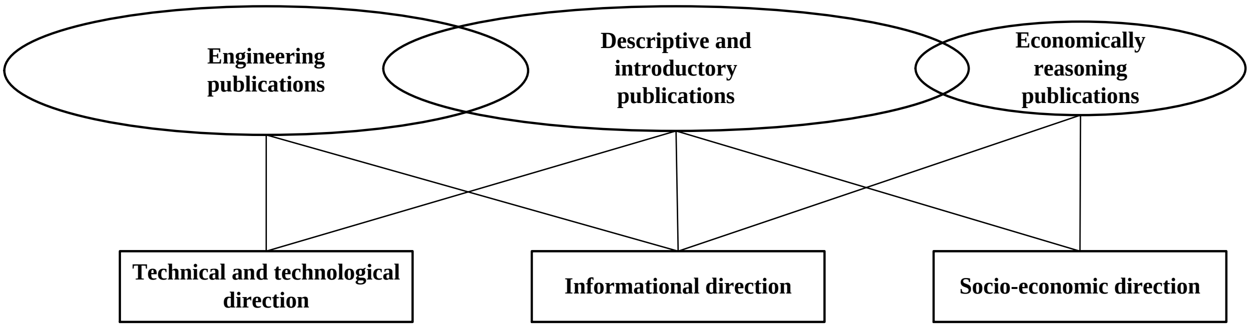
1. *Descriptive and introductory* – the purpose of which is to familiarize the reader with certain objects or phenomena in the smart industrialization. Such publications are not relevant to economic and mathematical modeling, but their subject enables identifying problems that can be solved using such methodological tools.

2. *Engineering* – the purpose of which is to describe the processes. Such publications present numerous descriptions of various models, including mathematical ones, but these models are of engineering nature and solve no economic problems. However, as in the previous case, their analysis enables identifying the occurrence of accompanying economic problems.

3. *Economically reasoning* publications, which confirm the economic feasibility of implementing certain processes, associated with smart industrialization, or substantiate the emergence of new tasks, representing economic and social problems. Such publications directly relate to the subject of this study, but are scarce in number, often inconsistent and are unable to adequately solve the problems.

The publications of the second and third groups usually also include a descriptive-introductory part and thus may overlap with the publications of the first group. However, we were unable to find publications that would represent an intersection of the first and the third group, which would have considered the problem of the engineering design of smart enterprises through the prism of solving economic problems.

Fig. 3 shows the relationship of the nature of publications according to the tasks they solve with their directions according to the objects of research.



Source: compiled by the authors

Fig. 3. Relationship of the nature of publications according to the tasks they solve with their directions according to the objects of research

Let's begin the overview of publications on smart enterprises with *descriptive and introductory studies* related to the identification of objects and their functioning, since these publications form a basic representation of the way such enterprises function.

According to [31], 4 principles of "Industry 4.0" design are distinguished:

– *interaction*: the ability of machines, devices, sensors and humans to connect and interact with each other via the Internet of Things or the Internet of People;

– *information transparency*: the ability of information systems to create a virtual copy of the physical world by filling digital models of enterprises with sensor data. This requires aggregation of raw sensor data into context information with a higher level of usefulness;

– *technical assistance*: firstly, the ability of support systems to help humans by aggregating and visualizing information to make informed decisions and quickly solve urgent problems in a short time; secondly, the ability of cyber-physical systems to physically support humans by performing a number of tasks that are unpleasant, physically exhausting or dangerous to humans;

– *decentralized decision-making*: the ability of cyber-physical systems to independently make decisions and perform their tasks as autonomously as possible. These tasks are transferred to a higher level only in case of abnormal situations, interference or conflicting goals.

Authors of [34] mention three areas of "smart enterprises" that distinguish them from traditional ones:

1. *Monitoring and control*– monitoring and control systems implemented at smart enterprises in real time collect and transmit a wide range of data on the status of enterprise facilities, their operation, the use of resources, and the state of their environment, which allows them to react quickly to changes.

2. *Information exchange and interaction*– the modern information infrastructure allows exchanging large volumes of information between humans and humans, humans and physical objects, as well as between physical objects without human intervention. Often the components of information exchange and cooperation are combined with monitoring and management components, initiating the exchange of information or certain actions in the event of a certain situation detected by sensors. Such capabilities allow production management automation, when human intervention will be necessary only in cases of certain events' occurrence, and rest of the time the exchange of information is limited to physical objects.

3. *Big data and data analysis*– collecting large amounts of data on the status of objects, processes and the environment, and increasing the capacity of data processing systems make it possible to expand the use of analytical tools to improve business processes at all stages, including the development, production and sales.

Given this, the following criteria can be used to classify an enterprise as a smart enterprise: the use of intelligent sensors for monitoring and processes control; automation of information exchange processes and interaction of workers with each other, workers with physical objects (mainly with machines and computer systems), as well as physical objects with each other; use of big data for continuous analysis and process improvement.

Thus, the key factor in the modeling of smart enterprises is the work with big data, the research of which is the topic of a large number of publications, related to smart industrialization.

The use of big data, which, along with the software of cyber-physical systems, forms the basis of information support for the smart industry, is associated with significant difficulties in their processing using traditional methods. Such a complexity is explained not only by the large amount of data, but also by their unstructured nature (the collected data is not generated initially in accordance with the rules for database design), the lack of centralization of collection and processing (data from a variety of different sources can be used), and the weak relationship within the data itself (data from different fields of activity). In [40], big data is defined as data sets with sizes beyond the capabilities of typical database management software to collect, store, manage and analyze data.

In a review article [32], the lifecycle of big data consisting of four stages (generation, collection, storage and analysis) was analyzed, and the main approaches and tools that can be used at each stage are considered. Similar to other publications on this topic, the main problem of analyzing big data is defined as their initial absence of pattern (which not only makes it difficult to collect and store such data, but also makes it impossible to use traditional structured databases), and modeling, visualization, optimization and forecasting are mentioned as the main areas of using big data in practice.

Analysis of big data to obtain practical conclusions is directly related to data mining technologies. Data mining is a collective name, served to denote a set of methods used for detecting previously unknown, nontrivial, practically useful and accessible interpretations of knowledge that is required for decision-making in various areas of human activity [15].

In [48], the following main areas of development of big data and the scope of big data use in the industry are offered:

– new and improved methods for analyzing big data and data mining;

– cloud solutions, related to the storage and transmission of big data;

– use of big data in control and monitoring;

– data-driven optimization and forecasting within manufacturing systems;

– data-driven solutions for supply chain development and risk management;

– the use of the theory of big data in modern industrial applications;

– big data-based solutions for intelligent power transmission networks and clean energy systems.

As a part of implementing data mining in manufacturing management, the authors of [30] propose a platform for advanced manufacturing analytics to eliminate such shortcomings in existing approaches, as isolated consideration of individual data sets, limited tools, insufficiency of reporting and visualization tools, the lack of mechanisms for obtaining specific recommendations, based on results of analysis. Such platform includes three levels:

1. *Process optimization* – involves the use of analytical findings, obtained at level 2 to improve manufacturing processes.

2. *Process analysis* – includes various ways of processing data, collected at level 3, including data mining. The results are stored in the manufacturing analytics repository.

3. *Data integration* – includes a manufacturing data warehouse, which reflects all the data, obtained during the manufacturing process (all aspects of the manufacturing process).

The authors offer two approaches to improving manufacturing processes using big data: optimization of manufacturing processes based on indicators (involves changing the parameters of processes, taking into account the conclusions derived from the analysis) and the optimization of manufacturing processes on the basis of templates (represents the development of the approach to the optimization of manufacturing processes on the basis of indicators by using templates that include sets of indicators for a particular application in the context of time and elements of the manufacturing process).

As a tool for data analysis, it is proposed to use standard models and methods, such as *neural networks, reference vectors, decision trees, Bayesian classifications* and the creation of *decision making rules*. The main advantage of the abovementioned approach is the accentuation of levels of big data use in the improvement of manufacturing processes and the emphasis on the need to create repositories of manufacturing analytics. The shortcomings include the absence of specific models or authorial ways of decision-making support.

With regard to the processing of big data, the main approach, currently used for the distributed processing of large amounts of data and promoted by such major companies as Google and IBM, is the MapReduce architecture [18]. Within the framework of this architecture, the array of input data is processed using the user-defined "map" function (that assigns a value to each attribute called a "key", for example, the frequency of attribute’s occurrence in a specific document) and "reduce" function (folds the "key-value" pairs by summarizing the key values for each characteristic from an array of intermediate data). The user has to specify the data sources, specify the required attributes (keys), the rules for assigning values to the keys (the map function), and folding rules (the reduce function). In turn, the data processing systems form data packets and distribute the execution of these functions on the data packets among the hardware. This approach allows processing data arrays, which even theoretically cannot fit in the RAM or hard drives of individual computers, creating a basis for distributed processing and analysis of big data.

In [41], the use of big data in manufacturing is analyzed, and the conclusion is made that data has become an important production factor along with tangible assets and human capital, and big data allows companies to create new and improve existing products and services, and invent completely new business models.

This conclusion is backed by empirical studies of the McKinsey Global Institute, which provides the following facts about big data as of 2011 [40]:

– the volume of data created increases by 40% each year, while the IT infrastructure spending increases by only 5%;

– the additional need for advanced data analytics professionals in the US alone is about 200 thousand people, and the need for senior specialists with data processing skills is about 1.5 million people;

– big data allows increasing the profitability of retail enterprises by 60%;

– the potential economic effect of the comprehensive use of big data in the US healthcare system is USD 300 billion.

The same paper distinguishes the following mechanisms, by means of which big data creates economic value [40, *p.* 5]:

– *ensuring transparency* – the very fact of relevant stakeholders being able to access big data in a timely manner makes it possible to obtain a significant economic effect;

– *the ability to conduct experiments* to identify needs, analyze variability and increase productivity – by digitally collecting and storing large amounts of data about their activities, organizations can collect more accurate and detailed data in real or near real time about all areas: from inventory to staff sick leave days, which creates the conditions for modeling and forecasting the relevant aspects;

– *customer segmentation* and individual solutions – big data allows organizations to segment and adapt their products and services with high degree of precision to meet the needs of specific customers;

– *replacement / support of human decision making* using automated algorithms – in-depth analytics can significantly improve the decision-making process, minimize risks and discover valuable ideas that are hidden from the attention of a researcher, who is not armed with big data;

– *development of new business models, products and services*– manufacturers can employ data on the use of existing products to improve and develop the next generation of products and create innovative offers in the field of after-sale services.

The general conclusion is that in the near future the use of big data will be a key factor of competitiveness in all sectors of the economy, including industry.

Analysts of the McKinsey consulting company [25] indicate that industries with the maximum potential for the introduction of analytics, based on big data, are pharmaceutical, chemical and mining. In these industries, in the opinion of the authors, minor changes in the characteristics of the process can significantly affect the result, which creates the conditions for the application of "advanced analytics" – the processing of economic data with the help of statistical and other mathematical tools for evaluating and improving various areas of activity.

A number of publications, which will be discussed below, are of engineering nature and consider the models of the functioning of smart enterprises or certain aspects of their functioning, the mechanisms of transforming regular enterprises into smart ones, and the methods of economic and mathematical modeling associated with these processes. We will omit the analytical part of the publications, which is devoted to purely technical aspects, associated with the introduction of cyber-physical systems (see the technical and technological block in the Fig. 2), and will review the most informative publications of that group.

Traditional approaches to centralized control and rigid management are unable to cope with the vast ecosystem of networked systems that are becoming increasingly widespread in the economy as a whole and in the manufacturing sector in particular, which requires the use of modeling tools to predict the behavior of such systems in certain situations and develop optimal control inputs. However, since simulation and modeling tools are usually created for application in a particular field, it's difficult to develop such models, since both physical and cybernetic aspects of such systems need to be modeled [28]. The modeling of cyber-physical systems uses simulation tools such as *hybrid Petri nets, hybrid automata and hybrid processes, aggregated modeling techniques (including such tools as Dymola and gPROMS)* [44].

It should be emphasized that in this case we are talking about the modeling of cyber-physical systems, and not about modeling the economic aspects of the functioning of enterprises, which use such cyber-physical systems in their manufacturing processes.

One of the main modeling trends in the last few years has been the use of the advantages, provided by the modern programming languages and development tools [4]: object orientation, class libraries and visual design environments. Modelica, which is one of the most popular tools at the moment, is a visual modeling environment that includes the Modelica universal object-oriented language for modeling complex physical systems and such tools as Dymola or MathModelica. The Dymola (Dynamic Modeling Laboratory) package supporting Modelica modeling language is a complex tool for modeling and research of complicated systems in such areas as mechatronics, automatics, aerospace research, etc. [27]. The ability to combine components of a different physical nature in one model makes it possible to build models of complex systems that better mirror the reality and to obtain more accurate and transparent results.

The critical importance of the development of cyber-physical systems was noted in [13] from the point of view of national interests and, first of all, for the creation of new digital products with unprecedented economic efficiency. However, calculations of the consequences of the influence of digital technologies on the economy are carried out on the basis of individual, practical experience of functioning of existing digital manufacturing systems, without using the tools of economic and mathematical modeling. The paper emphasizes that the model, used in the management system, is the key one in cyber-physical systems, the viability and functionality of cyber-physical system depends on how that model relates to reality. The reality of the world is embodied in the form of models and data populated in them, so in order to create systems that can work in the real world, a new discipline is required – *model engineering*. With the purpose to understand the new ideology of product lifecycle management (PLM), it's necessary to combine the building information model (BIM) with the manufacturing information model (PLC), which forms a completely new quality. As we can see, the authors of [13] pay considerable attention to the modeling of cyber-physical systems, but mainly to engineering modeling.

The Chinese authors in [50] argue that the modeling of digital manufacturing (which in the context of the work in question is equal to smart manufacturing or manufacturing at smart enterprises) doesn't require any specific approaches to modeling – it uses standard modeling methods. The lifecycle of the digital manufacturing model includes data collection, data processing, data transmission, monitoring, interaction management and decision support. It consists of an ordered series of models, which typically includes a product development model, a resource model, an information model, a control and management model, an organizational model, a decision-making model, etc. "Ordered" means that these models are built at different stages of the lifecycle of the digital manufacturing system [50, *p.* 24]. Objects of modeling are products, resources, information, organizational aspects, decision making, production process and network environment (interaction models). Thus, the authors suggest using standard modeling tools and models, *including process models, object models, structural models, Petri net models* [49], *optimization models,* etc.

Petri nets are used to model asynchronous systems that function as a set of parallel interacting processes. Analysis of Petri networks allows obtaining information on the structure and dynamic behaviour of the simulated system. However, the prospects for the practical application of Petri nets in the modeling of smart enterprises belong to the technical rather than the economic field, in particular, in the field of modeling manufacturing processes, as well as the processes of data collection and processing.

Optimization modeling [12] has a significant potential for practical application both in substantiating general directions of introducing smart technologies, and in selecting and planning specific measures. Its application enables designing mathematical models for solving a wide range of both technical and economic problems, involving the allocation of limited resources to alternative uses, choosing from a list of alternative options, scheduling certain measures in time, etc. The optimization model consists of an objective function capable of taking values within an area, limited by the task conditions (areas of admissible solutions), and constraints, characterizing these conditions. The objective function consists of three elements: controlled variables, parameters (that can't be controlled, for example, those depending on the external environment), and the shape of the relationship between them (the shape of the function). In general, an optimization model is represented as follows:

$$\begin{cases} U = f\left(x_i, y_j\right) \to max\ \ or\ min\,; \\ \quad x_i = A, x_i > A\ or x_i < A\,. \end{cases}$$

where

U – the objective function, for which a maximum or a minimum is sought, depending on which indicator is chosen as the criterion;

x_i – controlled variables, for which there are optimal values at which the objective function would reach the desired extremum, $x_i \in \{X\}$ – the set of controlled variables;

y_i – parameters, used in calculations in the form of fixed values (constants), $y_i \in \{Y\}$ – the set of constants.

When modeling smart enterprises, optimization models can be used to select technologies for implementation, to determine the optimal parameters of technological processes or investment projects, and to solve other problems related to the choice of available alternatives.

In [1], models of *digital transformation of the industry* at the macro-level are presented in the framework of process, sectoral and technological approaches. The model of the process approach is based on viewing the industry as an industrial chain – from the development of industrial products to their sale and service. The elements of digital transformation of the industry include: digital R&D center, digital factory, digital storage and transportation, electronic commerce and digital services. It's noted, that the creation of the Eurasian technology transfer network and the Eurasian network of industrial cooperation and subcontracting can become effective tools for digital transformation of industry.

The industry-specific approach to digital transformation of industry is based on the industry's connection with other sectors of the economy and includes the following digital industrial markets: food and water production and delivery systems, intelligent resource extraction systems, digital (smart) factories, distributed power systems, unmanned automobile systems, unmanned aerial vehicles, digital railway, telemedicine, personal medicine, smart houses, smart roads, digital financial technologies, safety systems, e-commerce, e-education, digital culture and the media.

The model of the technological approach to the digital transformation of the industry includes a set of technologies that form a digital agenda in the industry: IoT and industrial Internet, digital design and modeling, quantum technologies, big data, element base (processors), robotics, sensors, meters, additive 3D technologies, cloud technologies, supercomputer technologies.

This set of technologies is open and can be expanded. At the heart of virtually all technologies are software and hardware, the core of which is software and microelectronics. Broadband Internet access is of key value for the development of digital transformation of the industry. According to Swedish scientists, doubling the average speed of the broadband Internet access in a country increases its GDP by 0.3%. According to the authors of the study [1], an increase in GDP by 0.3% in OECD countries will lead to an increase in the world economy by USD 126 billion. Historically, this is about 1/7 of the average annual growth rate in OECD countries over the past ten years.

It should be noted, that in paper [1] the models of digital transformation of industry within the framework of process, sectoral and technological approaches are presented only in an object form. It lacks economic-mathematical models of digital transformation of industry, but is devoted to the ways of supporting such initiatives in the field of modeling:

– through the introduction of information modeling in the field of industrial and civil construction (BIM-systems). In such way authors offer to encourage projects, aimed at creating and implementing automated process control systems (ACS) in the industrial sectors, including supervisory control and data collection systems (SCADA);

– through the development of mathematical modeling and design of mathematical models for use in industry and engineering.

As for micro-level models, the so-called "S-Model" of digital manufacturing is proposed in [43], where "S" symbolizes statistical processing and simulation (modeling). Within the framework of this model, a closed cycle digital manufacturing system with an autonomous statistical analysis module and an autonomous modeling module for discrete events is offered to create a flexible and efficient value chain. To interact with personnel in this model, it was suggested to use the forecast panel and an interactive production planning interface. That model is not an economic-mathematical model, but rather the author's vision of the use of econometric models in manufacturing control: for example, based on the analysis of statistical information it's proposed to predict crises (equipment failure), demand, and other factors, and make manufacturing planning interactive and adjust it in real time, using the appropriate interface.

Pharaos Navigator [46] is one of examples of practical implementation of the smart enterprise concept, intended for enterprises of various areas of activity (manufacturing, services, etc.). It allows visualizing the operation of a smart enterprise, displaying in a visual form the results of data collection from smart sensors on all equipment and thus allowing the management to receive real-time information about the operation of the enterprise.

In the paper [14], the main focus is on standardizing the processes of digital transformation of industry, as well as the matters of information modeling of manufacturing systems. And the standards are considered as a link between information models and manufacturing at a factory through design systems. Two sets of international standards, specific for modeling manufacturing systems and data exchange are described: the standards of manufacturing resources and processes and the standards of construction/facility modeling. The paper describes the characteristics of standards and their purpose for information modeling. The analysis of paper [14] showed that the main focus is on *standardization of information and engineering modeling of manufacturing systems* for the purpose of digital transformation, but the matters of standardizing economic and mathematical modeling of smart enterprises and economic problems solved at the stage of their formation are not sufficiently investigated.

The paper [21] investigates the consequences of introducing new technologies and creating of smart enterprises, such as technogenic catastrophes, serious manufacturing problems, caused by stealing of confidential data, as well as complete collapse of manufacturing process. The authors of the paper note that new cyber defense tools can't be tested in real manufacturing conditions, since this may entail a slowdown and even stop manufacturing processes, which is completely unacceptable for business. For this reason, this kind of work includes a stage of applied research, at which engineers use special equipment that simulates real manufacturing processes to the best possible extent. Research [21] deals not only with the issues of ensuring information security, but also assessing the impact of cyber defense tools on the productivity of industrial enterprises, which also needs to be taken into account in the economic and mathematical modeling of smart enterprises.

The most interesting from the point of view of economic and mathematical modeling are the papers, devoted to the economic justification of the efficiency of the introduction of the smart industry and its impact on the economy of the country and socio-economic processes.

Let's begin analyzing this direction with paper [45], in which, based on a survey of a number of Dutch companies operating in various areas, it's concluded that companies are actively engaged in the implementation of elements of the smart industry, and the larger the company, the more actively it works in this area. It focuses on the fact that the introduction of digital technologies affects all aspects of a company's operation: products, manufacturing processes, etc. Nevertheless, the work doesn't provide any calculations or even assessments made by the interviewed companies regarding the qualitative or quantitative indicators of the introduction of smart technologies or the economic effect of their implementation. This work is indicative, as it illustrates a whole layer of works on this topic, in which it is possible to distinguish several elements: a short or a more extensive listing of smart industry definitions, such as digital technologies, big data, etc.; a set of statements declaring that it is very important and promises various advantages; if a model or system is declared, in most cases, it's represented by a rather abstract drawing. At the same time, there are no calculations, economic and mathematical models or analysis of statistical data. Thus, the overwhelming number of works on smart industry, in the same manner as the abovementioned paper [45], are devoted to convincing the reader in the importance of this direction, but lack any scientific or practical novelty.

The following few works are a rare exception to the indicated trend.

For example, in a Korean study on the impact of the smart industry on urban development and the country's economy in general [37], the following approach was

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used: the main industries are picked which are suppliers and consumers of smart products (primarily computer equipment, microcircuits, industrial automation, communication equipment, etc.) and on the basis of input-output tables, the impact of demand for such products on the production volumes in the city, employment, added value, etc. was analyzed. An unconditional advantage of this work is an attempt to give a numerical assessments of smart manufacturing (as opposed to the abstract approach seen in many other works), as well as the fact that a specific list of smart products was compiled. On the example of the implementation of the smart cities development program in Korea, the corresponding economic effect is shown – an investment of USD 10 million in such a program allowed increasing output by USD 19 million due to an increase in demand in related industries. The drawback of this work is that there has been no comparison of investments in the smart industry with investments in other industries, as a result of which there was no answer to the question of whether a USD 1 investment in the smart industry gives a greater or lesser effect than a USD 1 investment in traditional industries.

Based on the statistical data on the US industrial enterprises, paper [26] analyzes the impact of data-driven decision-making on the value-added created by an enterprise and concludes that the introduction of data-driven decision-making increases the value added by 3% on average. Such an estimation is made using *regression analysis on the basis of a production function (similar to the Cobb-Douglas function)* with the added value as the dependent variable and labour productivity, capital, labour resources, energy consumption, IT-capital (in the form of cost of hardware and software), measure of structured management (the degree of autonomy of mid-level staff in decision-making) and data-driven decision-making as factors.

Authors propose the following model:

$$Y_{it} = A_{it} K_{it}^{\propto} L_{it}^{\beta} E_{it}^{\gamma} IT_{it}^{\lambda} e^{\mu SM_{it}} e^{\eta X_{it}} e^{\delta DDT_{it}},$$

where

Y_{it} – actual value added (output – material costs);

A_{it} – productivity;

K_{it} – capital value at the beginning of the period;

L_{it} – labour (number of employees);

E_{it} – consumption of energy resources;

IT_{it} –value of IT assets (hardware and software) at the beginning of the period;

SM_{it} – measure of structured management;

X_{it} – additional factors, such as the industry and the level of education;

DDD_{it} – measure of data-driven decision-making.

Among the advantages of the approach is the attempt to analyze the impact on production efficiency, based not just on investments in the IT infrastructure, but specifically on the use of data analysis results in decision-making. Among the shortcomings of the offered approach is the abstractness of the very concept of "data-driven decision-making", as well the fact of using data-driven decision-making as a factor in the model (for each particular enterprise this parameter can be estimated as 0 or 1) that is established according to the results of the survey carried out at enterprises, therefore the question of the intensity and directions of using such an approach remains unanswered. In addition, one of the disadvantages is the inclusion in the function of such poorly assessable factors as structured management and data-driven decision-making, as well as the use of the number of employees as the indicator of labour resources.

From the point of view of the prospects for the introduction of smart technologies in specific industries, worthy of interest is the vision of such perspectives by management of the metallurgical industry, as reflected in the results of a survey, conducted by the PwC consulting agency among more than 2,000 respondents from the nine main industrial sectors and 26 countries [17]. According to the management of metallurgical enterprises, the introduction of digital technologies increases the maneuverability of supply chains, promotes a deeper understanding of processes and increases the level of capacity utilization. Automation combined with data analysis is used to ensure flexibility and manufacturing efficiency. To improve productivity, algorithms are used to trace the relationship between the physical properties of raw materials, used for manufacturing and manufacturing costs, as well as factors that limit the production activity of enterprises. Then, integration of previously specified processes is performed, which allows reducing heat losses, energy consumption, manufacturing time, stock level, and optimizing prices. In general, the management of metallurgical enterprises expects that in 2016-2021 the introduction of digital technologies would be increasing revenue by an average of 2.7% per year and reducing costs by an average of 3.2% per year. All that confirms that the introduction of digital technologies is in demand in industry in general and in metallurgy – in particular, and the management of enterprises places high hopes in it.

In conclusion, the study proposes the following sequence of steps to turn the enterprise into a smart one:

1. Development of an individual strategy for implementing the concept of "Industry 4.0".

2. Development of the first pilot projects.

3. Assessment of the necessary resources.

4. Implementation of data analysis.

5. Transformation of the company into a digital enterprise (comprehensive implementation of digital technologies).

6. Active planning of the ecosystem approach (cooperation with the market environment – suppliers and consumers).

In paper [7] attention is paid to the impact of digital transformation (digital technologies, the Internet) on the labour market and labour productivity. It is noted that some of the perceived benefits of digital technology are compromised by the risks that arise. Many economically developed countries are facing increasing polarization of labour markets and growing inequality – in part because new technologies complement more skilled work and, at the same time, replace standard labour operations, requiring many workers to compete with each other for low-paid jobs. In the absence of accountable institutions, public investment in the development of digital technologies strengthens the influence of the elites, which can lead to subordination of policy to the interests of the establishment and to increased state control. The digital revolution can generate new, profitable business models for consumers – but not where the established companies control the entry to the market. Technology can increase the productivity of workers – but not where they do not have the skills and knowledge, necessary for its application. Digital technology can help control the presence of tutors in the workplaces and improve academic performance – but not where education system is not accountable.

Despite the fact that a fairly modest number of jobs are created directly in the area of digital technologies, these technologies contribute to the creation of a considerable number of jobs in other areas. This way, in Kenya, the digital payment system M-Pesa provides additional income for more than 80,000 of its agents. And according to the China State Information Center, the recent rapid growth in the e- commerce sector in the country has led to the creation of 10 million jobs in online stores and related services, which is about 1.3% of total jobs in the country.

If digital technologies promote economic growth, how are these benefits allocated on the labour market? Although digital technologies increase productivity and overall well-being, labour market turmoil can turn out to be unhealthy and lead to increased inequality. Thus, another area for the use of economic and mathematical modeling of digital and smart enterprises is to assess the impact of digital technology on the labour market, employment structure and labour productivity.

In general, the nature of publications on the modeling of the smart industry and the processes of its implementation, is unsystematic, fragmented and incomplete. That is a consequence of the fact that this scientific direction is still on the early stages of its development, there are no established concepts for the introduction of the smart industry and its modeling, and existing examples of practical implementation of smart enterprises are based more on heuristic methods, rather than on accurate mathematical justifications. As can be seen from the above analysis, most of the publications, devoted to the development of the smart industry, are either descriptive and introductory, or view this process from the engineering point of view, which mainly covers technical, technological and informational directions (Fig. 2). A few mathematical models, which are mentioned in them (but are not given explicitly) are strictly of applied nature and solve technical problems.

Publications, which consider the economic aspects of Industry 4.0, are generally scarce. At the same time, even if certain mathematical justifications for some conclusions are present, most often they're of empirical descriptive nature, based on existing observations, and the methodological variety of economic and mathematical models used at best covers correlation-regression analysis.

However, it should also be noted that the conditions for smart industrialization in Ukraine are significantly different from those in the countries of the West. This not only includes technological lagging, but also the weakness of state institutions, insecurity of capital and investment, unpredictability of state policy (in such areas as taxes, finance, trade, international relations, etc.), the virtual lacking of financial support from the government, corruption in all areas of potential stakeholders' activity. More details about the peculiarities of technological and institutional development of Ukraine can be found in [2; 8-11; 16; 20; 42; 47].Thus, the peculiarities of the functioning of the Ukrainian economy, the specifics and the level of development of its institutions make it senseless to directly use the Western experience of smart industrialization in Ukraine and requires a more thorough scientific justification for the feasibility and cost-effectiveness of implementing measures for the development of the smart industry in Ukraine.

As noted in the study of the Commonwealth of Independent States (CIS) Executive Committee on the status, problems and prospects for the development of the information society, it's necessary to develop new methods to ensure the efficiency of informatization processes in the Commonwealth states that will allow a person to correctly understand and explore the new highly dynamic information picture of the world that opens before them [20].Undoubtedly, methods of economic and mathematical modeling, which allow obtaining objective and unbiased quantitative justification, should play a prominent role among such methods.

Based on the carried above analysis of the current trends in the study of smart industry development in the West and taking into account the peculiarities of the Ukrainian economy, the following promising areas of economic and mathematical modeling of smart enterprises can be highlighted.

1. First of all, we are interested in the development of the macroeconomic production function in connection with the transition to the neo-industrial smart economy. The use of methods of economic and mathematical modeling makes it possible to theo-

retically substantiate the qualitative changes of this function in connection with the emergence of new technological combinations of classical factors of production, and the possible emergence of a new production factor in the form of informatization or artificial intelligence.

It is possible to propose several specifications of the enterprise production function with the account for the effect of this new factor (denoted by *I* below) using:

– multiplicative function (similar to the Cobb-Douglas function):

$$y=\alpha_0 K^{\alpha 1} L^{\alpha 2} I^{\alpha 3},$$

where production factors are presented in the natural form;

– additive-multiplicative shape:

$$y=a_1K+a_2L+a_3I+a_4KL+a_5KI+a_6LI+a_7KLI,$$

where the factors of production are presented in a standardized form.

The second version might be more informative for static models, since it’s able to reflect the various multiplicative effects, obtained from different combinations of factors. If we consider the development of the production function in the dynamics, the first variant might be more informative, since there are reasons to believe that the parameter $\alpha 3$ is described by a time-dependent S-shaped curve, for example, the Gompertz curve or the logistic curve:

$$\alpha 3=\frac{1}{1+be^{-at}}.$$

The choice of the *S*-shaped curve is due to the avalanche-like character of informatization processes, and, possibly, the development of artificial intelligence, when increments depend on the level reached, and in the beginning they increase with the acceleration of development, and then, upon saturation, they decelerate.

Parametrization of models in the first and in the second cases is possible using the standard methods of regression analysis, namely using the method of least squares (in the first case, the equation must be transformed by logarithm).

Another direction in the use of economic and mathematical models of smart enterprises has a more practical focus. They make it possible to do the following.

2. Different variations of the Leontief input-output model and the inter-branch balance which can be used to solve at least three problems:

- end-to-end planning and management of the industry, based on a common digital industry environment;
- selecting enterprises that require priority digital integration, estimating losses from retaining "unsmartized" participants in the value chains, etc.;
- increasing demand in the context of introducing digital business models and expanding digital interaction with customers by reducing transaction costs.

Both natural and monetary values can be used as the coefficients of the technological matrix of the input-output model. When using monetary terms of the cost factor, it’s possible to distinguish certain cost components, for example labour costs (l_{ij}), transport costs (tr_{ij}), transaction costs, associated with intermediate and final consumption of products (z_{ij}). In the same way, the time factor (t_{ij}) can be considered to be a cost element, associated with the value chain.

That opens a whole block of optimizing tasks that allow identifying the interconnected industries and consumers that are most in need of integration on the basis of a common digital industry environment.

Let’s consider one of the versions of the general mathematical formulation of such problems.

We’ll assume that the costs z_{ij} in the inter-branch balance model can be lowered by virtue of smartization of the manufacturing in branches *I* and *j*:

$$z'_{ij} = z_{ij}\,(1 - S_iS_j),$$

where S_i, S_j – a certain level of enterprise smartization, measured by a value in the range (0; 1).

(Moreover, we'll note that if one of the interacting parties is not a smart enterprise, the effect of reducing costs will not be observed). The level of enterprise smartization is presented using an *S*-curve function of investment spending *K*, connected with the transformation of a traditional enterprise into a smart one:

$$S_i = \frac{1}{1+b_i e^{-m_i K_i}}, \quad S_j = \frac{1}{1+b_j e^{-m_j K_j}}.$$

There's a reason to assume that within one industry the relationship between investment costs and the level of smartization is described by the same function (parameter *b* is the same), and differs only in the production scale parameter (m_i, m_j), since it's obvious that the larger the enterprise, the more smart equipment has to be installed in order to achieve the same level of production smartization.

Thus, the task of reducing production costs through the introduction of smart industrialization within the framework of limited investment resources can be presented in the following way:

$$\sum_i X_i \sum_j z'_{ij} \Rightarrow \min$$

$$X = (E - A)^{-1} Y,$$

$$z'_{ij} = z_{ij} \left(1 - \frac{1}{1+b_i e^{-m_i K_i}} \cdot \frac{1}{1+b_j e^{-m_j K_j}}\right),$$

$$\sum_{\forall i} K_i \le K_{\lim}.$$

Where $A=(a_{ij})_{n \times n}$ – a technological matrix, the elements of which $a_{ij} = x_{ij}/X_j$ show how many units of *i* industry products should be spend for the production of one unit of industry *j* products, $Y_{n \times 1}$–column vector of the final product.

Work on the creation of digital business-to-business (B2B) platforms is already being carried out not only in the countries of the West, but also in Eurasian Economic Union (EAEU) countries [1]. The interaction of smart enterprises within these digital platforms significantly reduces transaction costs, creates conditions for the development of an end-to-end planning and management system in industry, frees resources that increase national income (quadrant 2) and, accordingly, the volume of the final consumption, which can also be estimated by balance models.

3. The third direction of economic and mathematical modeling of smart enterprises is represented by variations of network models, transport tasks, assignment tasks, etc. Building a network graph of interactions between consumers, manufacturers and other counterparties, for example, in a particular industry will help finding solutions to the following problems:

– substantiation of network effects in the creation of smart enterprises in the industry and assessing the minimum necessary level of digitalization of the network, in which the costs from the further introduction of smart technologies will be compensated for by the increase in the efficiency of the network as a whole;

– within the limits of the amount of available investment resources, selecting enterprises that require the digitization of their production the most, so that the path from order placement to order receipt would be associated with minimal possible costs;

– optimization of the movement of products (from their design to consumption by end customers) in the conditions of the IoT and smart infrastructure.

The standard objective function in such problems is aimed at minimizing the costs of moving from the initial to the final vertex:

$$Z = \sum_i \sum_j c_{ij} x_{ij} \to \min,$$

where x_{ij} – the volume of products, moved from vertex *i* to vertex *j*; c_{ij}– cost of moving them (for different arcs can be either constant or dependent on the volume of the products being moved).

Standard constraints: the demand of all consumers must be satisfied, the total production is equal to the total consumption:

$$\sum_j x_{ij} = a_i, \quad \forall i,$$

$$\sum_i x_{ij} = b_j, \quad \forall j,$$

$$\sum_i a_i = \sum_j b_j.$$

An obvious extension of this task is to determine the effective path in the conditions of the possibility of smartization of individual enterprises that form part of this network. The following restrictions will be added:

$$c'_{ij} = c_{ij}\,(1 - \frac{1}{1+b_i e^{-m_i K_i}} \cdot \frac{1}{1+b_j e^{-m_j K_j}}),$$

$$\sum_{\forall i} K_i \le K_{\lim}.$$

Digitalization and the IoT can virtually eliminate the cost of traffic through some intermediate vertexes, associated with transactional and organizational costs. In addition, they expand the number of vertices, available for analysis, by increasing the dimension of the graph, and accordingly, making the choice more valid and effective. The accessibility of some vertices mathematically in this task can be regulated by the restriction on the throughput of the vertex. For some vertices that determine the known trunk path, it will be a constant value, for others – a value, proportional to the degree of integration of the enterprise into the IoT, that is, proportional to the value

$$S_i = \frac{1}{1+be^{-mK_i}} \in (0;1):$$

$$\sum_i x_{ij} \le P_j S_j, \quad \forall j,$$

$$\sum_j x_{ij} \le P_i S_i, \quad \forall i,$$

where P_i – nominal (basic, potential) vertex throughput.

4. Another topical area of economic and mathematical modeling is the evaluation of social effects, associated with the impact of digitalization of the economy on the employment. The replacement of human labour by cyber-physical systems has the potential risk of massive job losses in manufacturing, which is the area of primary income distribution. In this case, the effects of lowering transaction costs in the conditions of the IoT may turn out to be lower than the negative effects of a decrease in effective demand, associated with a decrease in the primary incomes of the employed in manufacturing population. This problem becomes especially urgent in the conditions of Ukraine, when the potential superprofits from smart manufacturing will not be redistributed into the economy and stimulate domestic demand, but will accumulate in the pockets of oligarchs and then moved to offshore.

Stochastic modeling, in particular correlation-regression models for estimating stochastic dependencies, as well as simulation models for assessing the consequences of various scenarios of smart industrialization consequences for employment, income of the population and the economy as a whole, can be instrumental in assessing such effects.

Here are some dependencies that require evaluation, specification and parametrization within this research area:

1) labour costs (L_i) in industry i, depending on the smartization of that industry(S_i) (assessment of job losses);

2) demand for labour (L) in the region, depending on the degree of smartization of various industries in this region (assessment of the emergence of new vacancies);

3) production volumes (Q) in the region, depending on the degree of smartization of various industries in the region (assessment of changes);

4) taxable incomes of the population, depending on the possible growth of production volumes and changes in labour costs (assessment of changes);

5) deductions from income of the population (assessment of changes in relevant funds j);

6) volumes of consumption of households depending on the income of the population (assessment of changes);

7) burden of social security funds, depending on the number of population (N) and employment level.

These (and, probably, many more) dependencies can be combined into a single simulation model, the analysis of which will allow assessing the balance of the development of the smart economy, at least along two contours: the balance of household incomes and expenditures for expanded consumption; balance of revenues, raised to budgets and social funds, and the need to spend money from them.

The use of the apparatus of economic and mathematical modeling in substantiating the programs of smart industrialization of Ukrainian economy will make it possible to obtain scientific explanations for solving problems of the formation of smart enterprises and to increase the efficiency of these processes.

Conclusions

1. The Fourth Industrial Revolution (which, in the opinion of some scientists, is the stage of development of the Third one, the digital revolution) is based on the achievements of the 6^{th} technological mode, characterized by the massive introduction of additive production technologies, nanotechnology and bioengineering, full digitalization of manufacturing, implementation of cyber-physical systems that have artificial intelligence, creation of a global information network of products, transport, buildings and industries, capable of interacting with each other independently without human intervention. Ukraine, whose industry uses technologies of the 3^{rd} and 4^{th} technological modes, is lagging far behind in its development from Western countries, and chances of catching up with them in an evolutionary manner seem doubtful. At the same time, the creation of new enterprises that operate the technologies of the 6^{th} mode can enable occupying certain niches in the world's digital production.

2. The most effective way of justifying the economic feasibility of creating smart enterprises and their viability in Ukraine is the use of tools of economic and mathematical modeling that allow conducting experiments with the system being designed, studying its properties, evaluating efficiency and anticipating the occurrence of problems and errors. Despite the rather good development of the modern economic and mathematical modeling apparatus, the novelty of the tasks to be solved when creating smart enterprises prevents from making an unequivocal choice in favor of the use of certain specific tools. To justify such a choice, it seems useful to study the foreign experience of applying economic and mathematical methods in the creation of smart enterprises, since certain empirical knowledge has already been accumulated in that area.

3. The objects of research, which are given attention in the publications devoted to the Fourth industrial revolution and the functioning of smart enterprises, can be classified in three directions. The first one, *technical and technological direction* describes the operation of sensors, meters, robotics and cyber-physical systems, technology of product identification, cyber defense, data transmission, etc. The second direction is the *informational* one, describing the operation of information systems of various levels at enterprises, technologies for working with big data, and approaches to standardizing the development processes of smart enterprises and their elements. Finally, the third one– the *economic direction*–is connected with the rationale for the economic expediency of digitization of certain segments of the economy, or with its impact on socio-economic processes.

4. Most of the publications devoted to the development of the smart industry are either descriptive or introductory, or view this process from the engineering point of view, which mainly covers technical, technological and information directions. A few mathematical models mentioned in them (but not shown in explicit form) are of strictly applied nature and solve technical problems. Publications, which affect the economic aspects of Industry 4.0, are generally scarce. At the same time, even if certain mathematical justifications for some conclusions are present, they are, in most cases, empirically descriptive, based on existing observations, and the methodological variety of economic and mathematical models used at best covers correlation-regression analysis.

5. A separate large segment of publications, devoted to smart enterprises, is connected with the big data, which along with the software of cyber-physical systems form the basis of information support for the smart industry.

6. The analysts of the McKinsey consulting company indicate that the industries with the maximum potential for the introduction of analytics, based on big data, are pharmaceutical, chemical and mining. In those industries, in the opinion of the authors, minor changes in the characteristics of the process can significantly affect the result, which creates the conditions for the application of "advanced analytics" – processing of economic and technical data using statistical and other mathematical tools for assessing and improving various fields of activity. PwC consulting agency emphasizes the positive prospects for the introduction of smart technologies in the metallurgical industry: the introduction of digital technologies increases the maneuverability of supply chains, promotes a deeper understanding of processes and increases the level of capacity utilization. All these industries are well developed in Ukraine, and these conclusions would be useful to take into account, when forming smart industry here.

7. A large number of analyzed publications are of engineering nature, and reflect the design features of certain objects of the smart industry and cyber-physical systems. Modeling objects include products, resources, information, organizational aspects, decision making, manufacturing process and network environment (interaction models). In general, they use standard modeling tools including process models, object models, structural models, Petri net models, optimization models, hybrid automata, queuing systems, balance input-output models, aggregated modeling techniques, including tools such as Dymola and gPROMS, etc.

Nevertheless, the actual models, presented in these publications, are usually limited to object representation in the form of diagrams and graphs, which makes it impossible for them to be directly used in practice, which gives a wide range of possible interpretations about how these models can be specified for solving specific problems.

8. The few publications that reason the economic consequences of the introduction of smart enterprises are devoted to the economic feasibility of such measures. In particular, in a Korean example of investing in the development of the smart industry, it has significantly increased output due to increased demand in related industries. At the US enterprises, the use of big data in decision making was accompanied by a 3% average growth in value added. Despite the fact that a fairly modest number of jobs are created in the area of digital technologies, many publications confirm that these technologies help create jobs in related areas, which helps alleviate the reduction of jobs, caused by the automation of manufacturing processes.

9. In general, the nature of publications on the modeling of the smart industry and the processes of its implementation is unsystematic, fragmented and incomplete.

That is a consequence of the fact that this scientific direction is still quite new, there are no established concepts for the introduction of the smart industry and its modeling, and existing examples of practical implementation of smart enterprises are based more on heuristic methods, rather than on accurate mathematical justifications. The overwhelming number of papers on the topic of the smart industry focuses on convincing the reader of the importance of this direction, but lacks any scientific or practical novelty.

10. The peculiarities of the functioning of the Ukrainian economy, the specifics and level of development of its institutions make it senseless to directly apply the Western experience of conducting smart industrialization to Ukraine and require a more thorough scientific justification for the feasibility and cost-effectiveness of implementing measures to develop the smart industry in Ukraine. However, based on a review of foreign experience, the economic and mathematical modeling of smart enterprises in Ukraine does not require creating any fundamentally new types of models. It can be performed through the evolution of well-known models, with additional parametrization of specific conditions, specific to Ukraine's institutional features, the level of development of its industry and the information technologies used.

In particular, among the promising areas of economic and mathematical modeling of smart enterprises in Ukraine are the following:

– the use of modifications of *production functions*– to justify the qualitative changes in the factors of production, the emergence of new factors of production, their new technological combinations;

– the use *of modifications of Leontief input-output models* and *optimization models* for end-to-end planning and management of the industry, justification of enterprises requiring priority digital integration, reduction of transaction costs in the context of introducing digital business models and expansion of digital interaction with customers;

– the use of modifications of *network models* and *optimization models*– to optimize the movement of goods (from their design to consumption by end customers) in the conditions of the IoT and smart infrastructure, and also to justify the primary candidates for digitalization in conditions of restrictions on the amount of available investment resources;

– the design of *correlation-regression models*– for assessing economic stochastic dependencies, as well as *simulation models* for assessing the consequences of certain scenarios of smart industrialization, that allows assessing the consequences of these scenarios for employment, incomes of the population and the economy as a whole.

The concretization of the formulation of these models and approaches to their implementation requires an in-depth study of the specifics of the tasks being solved and the formalization of specific institutional factors. All of that is the subject of further research.

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АНАЛІЗ СВІТОВОГО ДОСВІДУ ЕКОНОМІКО-МАТЕМАТИЧНОГО МОДЕЛЮВАННЯ СМАРТ-ПІДПРИЄМСТВ

Показано неминучість зміни технологічного укладу у зв'язку з промисловою революцією 4.0, що потребує кардинальної перебудови системи виробництва і виробничих відносин. У результаті аналізу зарубіжного досвіду подібних змін, пов'язаних зі смарт-індустріалізацією, цифровими трансформаціями економіки, становленням промислового інтернету речей, обробки великих даних, встановлено необхідність застосування економіко-математичних методів для обґрунтування доцільності подібних трансформацій: як пов'язаної з їх економічною обґрунтованістю, так і з фізичною життєздатністю новостворюваних систем. Огляд публікацій, які відображають аспекти економіко-математичного моделювання в зазначених сферах, дозволив зробити висновок про несистемність і неопрацьованість методичного і методологічного апарату моделювання даних процесів, а також сформулювати рекомендації щодо економіко-математичного моделювання смарт-підприємств в Україні. Для врахування особливостей технологічного та інституційного розвитку України при обґрунтуванні створення смарт-підприємств запропоновано ряд інструментів економіко-математичного моделювання, заснованих на використанні виробничих функцій, моделей міжгалузевого балансу, мережевих оптимізаційних моделей, імітаційних моделей на базі стохастичних залежностей.

Ключові слова: промисловість 4.0, цифрові технології, смарт-підприємства, великі дані, економіко-математичне моделювання.

JEL codes: C00; C60; C67; C69; O12; O14.

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АНАЛИЗ МИРОВОГО ОПЫТА ЭКОНОМИКО-МАТЕМАТИЧЕСКОГО МОДЕЛИРОВАНИЯ СМАРТ-ПРЕДПРИЯТИЙ

Показана неизбежность смены технологического уклада в связи с промышленной революцией 4.0, что требует кардинальной перестройки системы производства и производственных отношений. В результате анализа зарубежного опыта подобных изменений, связанных со смарт-индустриализацией, цифровыми трансформациями экономики, становлением промышленного интернета вещей, обработки больших данных установлена необходимость применения экономико-математических методов для обоснования целесообразности подобных трансформаций: как связанной с их экономической обоснованностью, так и с физической жизнеспособностью вновь создаваемых систем. Обзор публикаций, отражающих аспекты экономико-математического моделирования в перечисленных сферах, позволил сделать вывод о несистемности и непроработанности методического и методологического аппарата моделирования данных процессов, а также сформулировать рекомендации по экономико-математическому моделированию смарт-предприятий в Украине. Для учёта особенностей технологического и институционального развития Украины при обосновании создания смарт-предприятий предложен ряд инструментов экономико-математического моделирования, основанных на использовании производственных функций, моделей межотраслевого баланса, сетевых оптимизационных моделей, имитационных моделей на базе стохастических зависимостей.

Ключевые слова: промышленность 4.0, цифровые технологии, смарт-предприятия, большие данные, экономико-математическое моделирование.

JEL codes: C00; C60; C67; C69; O12; O14.

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