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Industrial digital ecosystems: Predictive models and architecture development issues

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ABSTRACT

The concept of digital ecosystem (DES) is widely used in autonomous manufacturing process control and the development of complex, stable, interactive, self-organizing and reliable management systems for various industries. The paper offers a concept of DES control system architecture based on predictive models. For estimating and predicting the state of resources in production processes, an approach is developed using data mining based model generation. The paper also reviews the current state of research in the field of DES and their applications in supply chain management (SCM).

Introduction

The development of information technologies and their widespread dissemination to various sectors of economy resulted in new business models and, eventually, additional benefits (Akram, 2015). In processing and power industries, competitive advantages of enterprises currently rest upon both state-of-the-art production technologies and the advanced production management underpinned by wide capabilities of modern IT. A key role is assigned to fast and efficient processing of digital information, in particular, its exchange between production management systems and levels (plant floor, MES, ERP, etc.). Cluster-network production systems with horizontal linkages are becoming predominant.

The recent years of production management development in industry have seen the evolution of *digital platforms*, in particular, the enhancement of their functionality (Babiolakis, 2020),Companies create their products, which can be used by other companies for creating new products based on their own services. This approach contributed to the quantum growth of Google, Facebook, Apple, Amazon, AirBnB, and other major IT companies. However, the authors note, a new era has arisen: the creation of *digital ecosystems*.

Currently, there are certain discrepancies in the literature about the definition of a digital ecosystem (Chang & West, 2006; Dong, Hussain, & Chang, 2007; Nachira, Dini, & Nicolai, 2007; (Baker and Bowker, 2007), (Saleh and Abel, 2016); Fuller, 2007; (Papaioannou et al., 2009)).

High-growth companies don’t go it alone. Increasingly, they are achieving results by creating and orchestrating digitally connected ecosystems – coordinated networks of enterprises, devices, and customers – that create value for all of their participants (Sebastian, Weill, & Woerner, 2020).

Taking into account the variety of definitions, we will further understand a digital ecosystem (DES) as a distributed sociotechnical system with the properties of self-organization, stability, and adaptability and the elements (automated systems and economic entities) competing against and/or cooperating with each other. DES brings together autonomous participants who share resources and expertise for collaborative development of products with the overall economic value larger than the ones developed outside the DES.

In view of the technological, economic and organizational autonomy of DES participants, its operation on the basis of a computer network infrastructure using intelligent control technologies, in particular, multi-agent ones (Rzevski, 2019) looks quite natural for the following reasons. The increasing information density and complexity of various production problems solved in real time at different levels (process control, production scheduling and logistics, resource management and relationships within suppliers and consumers) make it natural to move from rigid hierarchical verticals of management organization to cluster network patterns. Ensuring the system stability in a dynamically unstable environment (e.g., economic) as well as its sustainable development are the tasks of paramount importance.

DES can not only improve the efficiency of control and make it more transparent for all stakeholders, but also generate new services able to

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evolve as a separate ecosystem and interact with other external ecosystems.

This is especially important for the operation of supply chain (SC) management. Digitalization results in the emergence of DES in SC ensuring the integrity, transparency, monitoring, and controllability of the entire product life cycle from supplier selection to manufacturing to warehousing to distribution to shipment up to the end user (Ivanov, Sethi, Dolgui, & Sokolov, 2018). SC are complex organisms, and effictive organization of their interaction to ensure transparency, flexibility and scalability of their architecture is important. A variety of effective supply chain management (SCM) models and methods are presented in Dolgui, Ivanov, and Rozhkov (2018, 2020), Ivanov (2020), Ivanov and Dolgui (2020), (Dolgui & Ivanov, 2020; Ivanov, Tang, Dolgui, Battini, & Das, 2020); Panetto, Iung, Ivanov, Weichhart, and Wang (2019), Sokolov et al. (2020).

The paper (Ivanov, 2020) proposed a SC ecosystem framework. The paper (Ivanov & Dolgui, 2020) offered a digital framework.

This article offers a new framework combining both concepts. The authors discuss the design concept and development methodology of DES architecture for SCM systems. Despite the wide-ranging discussion of DES design and development in numerous forums and a growing number of publications, the problems of developing the structure and semantics of DES control systems has not been resolved as yet. Against this background, this article addresses the problem of developing the concept and architecture of such systems. It looks promising to create DES control systems based on real-time predictive models, which are developed and adjusted based on big data mining approach. This should require the processing of large data amounts; the acceleration may be attained owing to big data technics such as batch data uploading or in-memory computing.

Based on the survey of 400 companies conducting digital transformation, the analysts from Capgemini Consulting and MIT Sloan School of Management have ascertained (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012) that:

- conservative companies focusing on management improvement increase their profit by 9% but could potentially gain three times more with digital technologies;
- organizations investing heavily in digital technology but paying little attention to management demonstrate financial performance 11% less than possible at the same level of digitalization.

KAMAZ PJSC (Tatarstan, Russia) sets a good example. This major vehicle and truck manufacturer has increased its sales by 21% within a year since the digital transformation began. The company established a specialized “Digital Transformation Center” to underpin the following projects: creation of a logistics department; development of a monitoring and operational production control system (in collaboration with Siemens); transformation of the sales business model into a system of customer interaction based on the SAP Hybris Cloud for Customer platform. Further integration of these and other company’s digital transformation fragments into a balanced integrated management system is a paramount task. Another example is given by Fiat which declares the possibility of creating "smart cars" on its own Uconnect digital platform in collaboration with popular customer service companies: TomTom, Reuters, Facebook, TuneIn. It can be concluded, that for these and many other enterprises that successfully carry out digital transformation of their activities, it is equally important to establish management and control based on the “information benefits” provided by the digitalization.

The digital transformation of industrial enterprises and the creation of digital platforms is not an end in itself. When a system has a wide range of DES operation data and the ability to quickly process and efficiently store large amounts of this data, there appear the possibilities of efficient detailed analysis, forecasting for control, scheduling and planning. This may include also scenario forecasting and situational management. Optimality can be understood both in terms of production and finance.

To optimize DES management we propose the concept of identification analysis that presumes the use of models (including predictive ones) of various DES fragments for real-time control. Real-time identification models are embedded directly into automatic control systems and decision support systems at such levels as process control, planning and resource management, production logistics systems and relationships with feedstock and component suppliers product consumers, product management and services throughout their lifecycle (PLM / SLM).

In fact, we propose to create control systems for DES on the basis on their detailed digital descriptions (digital twins). The article presents the architecture of such control systems; the architecture reflects the possibility of control based on digital predictive models. In general, a DES control system can currently employ: calculation models for various processes and technical characteristics; modern simulation models; identification models based on data mining.

We focus on developing predictive identification models. In terms of DES, these models use various data types (with numerical values and categorical), therefore we propose to use the model data fusion technology and data coding.

The article focuses on two key aspects of DES control system:

- development of models that can be tuned using real-time Big Data Mining,
- creating a system architecture that provides stream processing of big data, data fusion, flexible scalability, and the ability to balanced management of all subsystems and the DES as a whole. The acceleration may be attained owing to in-memory computing.

Intelligent identification predictive models for DES

We propose to develop control systems for DES on the basis of model predictive control (MPC) technology (Qin & Badgwell, 2003a,b). In the recent years, MPC systems have become the most popular class of control systems for complex objects with many interconnections, time lags, nonlinearities, and constraints. MPC rests upon the inclusion of the object model into the control loop. Model structure and/or parameters may be updated from time to time. MPC technology belongs to a more generic control philosophy named Advanced Process Control (APC).

However, the increased requirements for speed, accuracy and control capabilities under uncertainty conditions and various kinds of disturbances in production control systems have demonstrated the drawbacks of traditional MPC approaches (Ratner, 2017). Moreover, conventional MPC algorithms solve an optimization problem at each time step thus consuming significant computing power, especially for control objects of large dimension.

At the same time, real-time identification models of dynamic objects developed on the basis of e-learning with reference to the patterns extracted from historical and current process data have demonstrated their high efficiency. These patterns are called *inductive knowledge* (Vapnik, 1998). Most of the calculations are carried out at the system learning stage thus ensuring high performance of the on-line identification algorithm embedded in the control loop.

For developing on-line predictive models for DES, we propose to use the *associative search algorithm*. It belongs to the type described above and has demonstrated high accuracy over a wide range of objects ((Bakhtadze and Lototsky, 2016), including nonlinear ones. A featured property of this identification algorithm is the development of a *new* linear model at each time step. The algorithm is, in fact, the implementation of a “smart” least squares method. From the whole set of historical data accumulated up to the current moment *t*, only a part is selected which meets a certain criterion. Further on, the solution of the corresponding system of linear equations determines the coefficients of the current linear model. At the next time step, the procedure recurs: a new linear model is built, etc.

For time-varying objects, identification by the associative search method is carried out in the wavelet transform space. The stability conditions were obtained in the form of restrictions imposed on the wavelet spectrum. This approach enables, in particular, effective prediction of various emergency situations thus ensuring the operation stability and safety of production DES.

Predicting the state of the DES resource complex

A paramount task in large-scale DES management is predicting the state of its resource complex (Bakhtadze et al., 2018). The assessment and prediction of the state of production resources increase the flexibility of operational management and allow to anticipate the situations when the execution of the production plan might be problematic or impossible. We will further call these situations abnormal.

However, the key indicators of the production system (industrial enterprise or company) are not always expressed numerically that impedes the application of identification methods, including the intelligent ones. For example, the states of some equipment pieces may take on the values: “working” or “not working”, “normal” or “not normal”, etc. One can characterize similarly the state of human resources which also belong to the DES resource complex. To overcome the challenge, the identification models allowing for such binary indicators should be object-specific.

Moreover, traditional identification algorithms for multidimensional models assume that some indicators are statistically independent of each other. However, in real complex systems, this is seldom the case: abnormal situation precursors (characterized by a certain state of one or several resources) may look like the values of some set of indicators several time steps before the current one.

It therefore seems reasonable that the algorithms predicting the state of a complex of various production resources are based on the well-known data mining technique named *the search for association rules* (Agrawal & Srikant, 1994).

Taking into account that the available DES resources may be described in different ways (their states can be numerical or binary) and abide by different operation standards, it is proposed to develop unified digital models that make it possible to predict production situation as a whole. Such an algorithm would use knowledge bases and search for specially formed association rules for a given production process.

Further discussion will comprise not only processes but also manufacturing execution systems (MES), SCM, etc. Enterprise resource scheduling will be also included.

Binary coding of production resource complex state

To apply the association rules algorithm, all production resources with either numerical or binary state description will be further encoded as binary chains.

The term “production resources” will hereinafter mean the following:

- input flows characterized by formal properties dependent on production specificity
- production equipment

$$d_{ij,}i = 1, \ldots, N; j = 1, \ldots, M,$$

where i is the number of production equipment piece used for performing the jth operation;

- human resources

$$h_{sj,}s = 1, \ldots, S; j = 1, \ldots, M,$$

involved in the j-the operation; s is the number of human resources;

- other factors

$$f_{kj,}k = 1, \ldots, F; j = 1, \ldots, M,$$

affecting the jth operation such as utilities and a variety of formal indices and factors related with the production process.

Production resources may be described in different ways.

- Some have qualitative characteristics which take on specific values that may be checked against standards at any moment.
- The state of others such as certain equipment pieces may be described as either “working” or “not working”. The remaining life time may be known or not for such resources. The process historian may however keep failure statistics for a specific equipment piece; maintenance downtime statistics may be also available.
- One more resource type (including human resources) is not subject to maintenance. In case of outage, such resources should be immediately replaced from the backlog. The replacement process is typically fast; therefore, no values other than 1 (OK) and 0 (not OK) should be assigned to such resource.

Assume a model of a specific manufacturing situation as a dynamic schedule fragment comprises the following components:

$$r_{ij}(t) = \{ < C_1 >< C_2 >< C_3 >< C_4 >< C_5 > \}_{ijt},$$

where:

$< C_1 > \stackrel{\text{def}}{=} < ijt >$ is a *resource identifier* including the resource number, the operation number and the time stamp (the number of characteristics may be increased).

Other components of the resource state vector at the time step t may be represented by a binary code.

$< C_2 >$ is the code of the numerical value of a state variable; for each of the above-listed resource types, this code is different.

$< C_3 >$, $< C_4 >$, and $< C_5 >$ will be discussed further.

First of all, we consider the resources whose state may be described by some quantitative characteristic such as temperature or pressure for chemical processes or average equipment failure.

The solution to the problem described above is based on the possibility of representing numerical values of resource state’s characteristics as a set of nested self-similar structures (Bakhtadze et al., 2018).

For a specific resource, we assume that the characteristic of its state possesses the values on the half-interval [0; 1) (this half-interval was chosen as an example for simplicity, the results can be easily spread to any other one). This half-interval can be represented as the union [0; 0.5)∪[0.5; 1), see Fig. 1.

We will further correspond the symbols {0; 1} to the left and right half-intervals respectively, namely, 0 to the left half-interval, and 1 to the right one. Each of the two subintervals can be further split in the

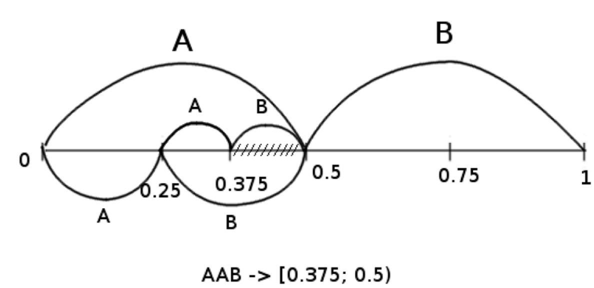

Fig. 1. A code for the numerical value of a quantity on the half-interval [0;1).

same way, and, again, the values 0 and 1 can be assigned to the left and the right parts respectively.

In that way, a finite chain of symbols from {0; 1} has a one-to-one correspondence with a half-interval embedded in [0; 1). For example, the chain 00 corresponds to [0; 0.25), and the chain 100 to [0.5; 0.625) respectively. For a binary partition, the chain of n symbols corresponds to a half-interval with the length $\frac{1}{2^n}$.

Thus, for each value of a numerical characteristic at the current instant we obtain a binary code. The number of digits, as we show further, will determine the prediction accuracy.

For the resources from the categories 2 and 3, the respective codes will have the same value (either 1 or 0) in all digits.

$\langle C_3 \rangle$ in (1) is the code of the time before the maintenance end. If a resource is available and operated, the respective code consists of ones.

$\langle C_4 \rangle$ is the code of the time before the equipment piece fails with the probability close to 1 (remaining life).

In the scheduling practice, this time is not less than the operating time. However, resource replacement during the operation may be sometimes more cost-effective. Moreover, the equipment piece may fail unexpectedly.

For resource types from categories 1 and 3, $\langle C_4 \rangle$ has ones in all positions.

$\langle C_5 \rangle$ is the time before the scheduled end of the operation. In real-life manufacturing situations, the time may be lost (with the need in schedule update) for the reasons neither stipulated in the production model nor caused by equipment failures. Generally, it is hardly possible to formalize all such causes of schedule disruption. Therefore, their consolidation as the "remaining plan execution time" is a way to allow for those hidden factors in the production state model.

Thus, for each resource with reference to a specific production operation, we have defined a binary code with its specific time identifier. By combining resource codes with equal values of this identifier, we obtain a description of the manufacturing situation at the current time step (from the viewpoint of the state of resources). To a great extent (under the assumption of insignificant influence of external factors on the system) this state determines the possibility of plan execution according to the schedule.

Resource state prediction for production processes by means of associative rules

For the developed binary chain, a forecast may be obtained using data mining techniques. It makes sense to apply the methods named association rules search, (not to be confused with associative search technique, (Bakhtadze and Lototsky, 2016), where:

(i) associations of dynamic system states are developed with the help of a database and cluster analysis,
(ii) parameter values are further calculated by means of least square method,
(iii) the system's output is finally predicted.

The association rules search allows to:

- reveal the hidden statistical relationship between the state of various resources at different time steps without any preliminary statistical analysis,
- operate with state variables of various resources differing in their characteristics and the ways of formalization.

The forecast of a state described by a binary chain with an identifier can be obtained by revealing the most probable combination of two binary sets of values at some fixed time step and at the next one (in a one-step forecast). A more distant prediction horizon is also possible.

Thus, the most statistically probable sets of resource state values are identified for future time steps, provided that they took certain values at the previous ones.

Supply chain management digital ecosystem

To ensure sustainable development of the production DES and achieve a competitive advantage, it is not enough to guarantee the optimal management of key production processes at the enterprise and the states of its resources. It is also necessary to examine the entire added value chain, including the meeting points of various production phases. Moreover, taking into account the peculiarities of modern digital infrastructures for production management, the processes of design, planning and implementation of SCM tools are becoming increasingly important because such tools ensure maximum synergy of internal and inter-organizational integration and coordination within the industrial business DES.

Managing production and business DES in terms of SC operation organization poses a serious challenge that cannot be surmounted without developing an effective, scalable, and fault-tolerant decentralized architecture of such systems.

The concept of supply chain DES

The concept of SC DES was formulated in different ways (Seuring, 2012). In (Sidra, Kanhere, & Raja, 2018), the term ecosystem is used as a unit of analysis in the description of supplier groups and distribution chains, which are understood as free groups of organizations involved in the creation and delivery of products and services.

The same term is used by Iansiti and Levien (2004) for describing "strategy as ecology". The concept of value creation is defined in (Porter, 1985) as a vertical chain extending from resource supplier to firms and buyers of goods and services from these firms. In this context, a value chain is a collection of actors, resources, and processes that altogether represent the product processing stages and a set of services. In Markus and Loebbecke (2013), the term "ecosystem" is used as a unit of analysis when describing groups of suppliers and distribution chains, which are understood as free groups of organizations involved in the creation and delivery of products and services.

Basic and auxiliary activity types are discerned. The primary activity is related directly with product or service creation or delivery. The supply chain extends the internal value chain of a company for external cooperation and the exchange of raw materials, products, services, and knowledge with other participants.

The emergence of DES produces the reconfiguration of value creation. In Pagani (2013), three types of "constellations of control points" are described, which "represent three models of the topology of the participants in the chain: a closed vertically integrated model, a loosely coupled coalition model, and a multilateral platform model".

A new topological model emerges around major players striving for the dominance in the global market and overstep industry boundaries. This model is formed by business communities which include large organizations and their DES. In Averian (2017), the author discusses "a global evolutionary trend towards a supply chain driven by digital ecosystems" and describes the general concept of supply chain development and the place of DES in it.

In Walsh and Wellman (1999), a distributed supply chain model based on multi-agent technology is proposed. In Walsh and Wellman (2003), the delivery chain objective was formulated in terms of a network of task dependencies. Equilibrium and convergence issues are studied on the basis of a mathematical model; the results may be applied for developing a delivery chain in the automotive industry. Roto and Heikkilä (2017), focuses on the investigation of value creation in digital supply chains for organizations included in the research program that combines all theoretical research and implements a fully autonomous supply chain from the factory to the client company.

In this article, we propose to build an industrial DES control system for SC that differs from existing solutions. Based on Lambda-Driven architectural concepts (Suleykin & Panfilov, 2019), effective practices of intelligent identification and big data techniques and applications such as Transport Railway industry (Panfilov, et al., 2019), (Suleykin and Panfilov, 2019), telecom (Suleykin, Panfilov, & Bakhtadze, 2019), and power industries (Suleykin et al., 2019a), a set of digital agents and their interconnections is proposed for industrial SCM systems.

The proposed DES comprises of digital infrastructure, i.e., a set of digital agents, which have properties of self-organization, reliability, fault-tolerance, decentralization and demonstrate high SCM data processing capacity due to the nature of the underlying components and technologies. The proposed set of agents and their properties applied to SCM makes a framework for batch and real-time machine learning models development, tuning and implementation, that makes the proposed DES unique and different from existing platforms, models, techniques, which are typically focused on solving a specific SCM task (such as route optimization, selection of suppliers etc.) and the development a custom model.

Commercial digital supply chain platforms

Commercial digital platforms available in the global market are, in fact, supply chain DES.

Oracle Transportation Management (OTM) included in Oracle Logistics suite is just an example of such platform for managing all transportation activities in the supply chain. OTM supports both transportation companies and logistics service providers, it addresses all transportation activities in the global supply chain. The software reduces freight costs, optimizes service levels and automates the processes thus improving the overall logistics efficiency (www.tadviser.ru/Oracle_Transportation_Management_ (OTM)).

Cargo Stream (www.cargostream.net/) gives another example. This independent pan-European platform coordinates the actions of shippers, logistics service providers and multimodal terminals thus optimizing transportation routes. Shippers communicate their regular shipping needs. The optimization tool anonymizes this data and makes it available to approved optimizers. The optimizers analyze, optimize, and launch approved providers to generate proposals that would satisfy all shippers. Once a solution is attained, the providers upload order fulfillment updates to the platform to update the information with the respective shippers.

One more example is PwC Australia, Australian Chamber of Commerce and Industry (ACCI), and the Port of Brisbane have been developing a blockchain-based solution to improve supply chain efficiency. The solution is named the Trade Community System.

All the listed platforms are mostly transaction-oriented and automate business processes. They do not provide such SCM infrastructure for real-time and batch machine learning models development and implementation. Moreover, they are vendor-specific, and the data exchange between the SCM and external DES environment is very complicated.

Blockchain technologies for a supply chain

Blockchain is a distributed database that contains and updates information about transactions of system participants as a chain of blocks (Saberi et al., 2019).

The recent years have seen the growth in the number of blockchain projects such as:

- blockchain technology for the execution of Mercedes-Benz contract documentation (together with Icertis),
- TradeLens, a collaborative Maersk and IBM project,
- a secure supply system for the aerospace and defense industry (Accenture and Thales, UK),
- etc.

Many known IT companies and startups initiate promising pilot projects, such as (Barata et al., 2018):

- Walmart's application for verifying the authenticity of trade transactions as well as the accuracy and efficiency of record keeping;
- Maersk and IBM tool for cross-border transactions between parties that use blockchain technology to improve process efficiency;
- Samsung Electronics blockchain system to manage the company's huge global supply chain, developed by its subsidiary Samsung SDS;
- Blockchain-based food supplies tracking solution developed by Provenance, a British startup.

The following areas demonstrate the clearest efficiency improvement owing to blockchain technology:

- reduction of logistics costs, minimization of its share in the cost of goods, elimination of intermediaries;
- less loss from unfair business practices or invalid shipping contracts;
- automation of basic business processes. Although SCM systems can currently process large and complex datasets, many such processes are still slow, especially at lower levels of supply;
- increased transparency. Growing regulatory and consumer demand for information on product provenance drives change. Moreover, improved transparency also increases product value by reducing excess or unexpected quality-related costs such as recall, damage to reputation, or loss of revenue from counterfeit or grey market goods. Simplifying a complex supply base opens up additional opportunities for value creation;
- formation of confidential SC;
- reduction of legal and transport costs for shippers;
- lower IT transactions cost across the supply chain.

Digital supply chain business model

The supply of a digital supply chain is to produce and deliver the product to the client as quickly as possible, yet in a responsible and reliable way, while using automation to increase efficiency and reduce costs. This goal can only be attained once the supply chain functions as a reliable and efficient network of suppliers, production, logistics, warehousing, and customers (Alicke, Rachor, & Seyfert, 2016).

With modern integration format, the signals that trigger events in supply chains can originate from anywhere in the network and alert to all problems affecting supply or demand, such as shortages of feedstock, materials, components, finished or intermediate products, or spare parts. Such organization of production processes is especially effective in flexible, in particular, custom production, which is rapidly gaining popularity (as well as the increasing customer demands and expectations).

Effective communication is a major key to success for any SC. Traditional supply chains is fraught with complications caused primarily by the lack of complete and timely information. Sudden changes in demand, shortages of raw materials, and other incidents pose high risk of disrupting the supply chain schedule.

That is why the main goal of a digital supply chain is to put the supply network on public display, to make it transparent for all participants. This goal can be attained by developing a drastically new system architecture that ensures horizontal scaling and fast processing of heterogeneous, asynchronously incoming big data.

Architecture of the supply chain DES management system

Architecture for the basic model of information flows interaction in a digital supply chain DES

For interaction and information exchange between the components of the supply chain DES, it is proposed to highlight the architectural components shown in Fig. 2.

The main sources of data for DES are various transactional systems, such as ERP, CRM, SRM, or WMS, which provide data about suppliers, consumers, planned production resources, stock balances, planned delivery times, etc. The data are transmitted through the corporate data bus to the messaging layer in accordance with the pub / sub model (pub / sub means “publisher–subscriber”; it is a message transfer template, in which messages are divided into classes and do not contain information about their subscriber. The templates can then be used to create real-time e-learning models).

At the visualization and decision-making level, the data are available for suppliers, consumers, and everyone else interested in process efficiency and transparency, such as production and warehouse managers, etc. At this level, operational, near-term, and strategic management and decision-making support based on data analysis are carried out. These can be decisions on changing production schedules, the volume of inventory in warehouses, the number of suppliers, customers, etc.

All decisions at this level affect directly the plans and records for customer and supplier orders by changing the corresponding plans and records in source systems.

Model of the extended architecture of DES information flows interaction

An extended DES model in supply chains features the transition to full digitalization in all components of the architecture. Such systems must have the following characteristics:

- The ability to receive data from internal and external sources, including tracking the device transport and social listening placed on a single platform;
- Aggregated and cross-referenced data, such as supply chain events affecting the supply proposal. Relevant information can be extracted from weather monitoring data, traffic and news feeds, as well as social networks;
- This “enriched” information is then “linked” within the platform and placed using additional analytical and simulation algorithms that perform strategic optimization at various levels. This information should go to the control block where control signals are generated on the basis of intelligent predictive models, system state analysis, and predicting techniques, as well as the algorithms for control logistics activities;
- As a result, a “single source of truth” allows companies to optimize their choices in various conditions, using all available information to alert businesses, warehouses, and customers about various risks and to participate in actions that reduce those risks. Monitoring the status of transport units and anticipated external influences during order execution, as well as the ability to change plans in real time, are useful for companies leveraging their supply chains to achieve competitive advantages and to manage tighter the risks associated with their supply chains.

Based on the proposed approach to managerial decision-making support, the corresponding actions will be more effective and justified.

The “visibility” of the chain will increase owing to the creation of a transparent information storage system that will allow participants to determine the status of any parameter of a shipped product at any point of its journey by any transport type.

Transport data and process status information will come from the ERP system as well as from carriers through either direct connections or third-party portals. GPS technology will allow companies to verify precise locations; a variety of sensors will monitor the environment to shape storage conditions and provide remote protection against thefts. As far as the data comes from various sources, such as suppliers, carriers, warehouses, and distributors, its quality and interoperability is critical.

One of the most important achievements and advantages of the proposed extended architectural model is the capability of creating new services, which can develop subsequently as independent DES interacting with other external ones. By forming such “networks of digital ecosystems” DES themselves will act as drivers for the development of new services, and, probably, new promising technological solutions. The extended architecture model of information interaction between DES in supply chains is shown in Fig. 3.

The extended architecture model embodies the principles of distributed computing and the creation of high-load big data systems based on the *Lambda architecture*. These principles underlie the development of a framework for mobile network monitoring (Suleykin et al., 2019). This is a scalable and resilient data processing and storage architecture that addresses the need for a robust and fault-tolerant system with regards to both hardware failures and human errors.

It is able to operate in a wide range of workloads and applications where low latency reads and updates are required. The system designed this way should be linearly scalable and must scale rather horizontally than vertically.

The integration layer of the extended architecture model serves as a single entry point for all incoming information flows and for data exchange between different DES (agents). All data is converted into a

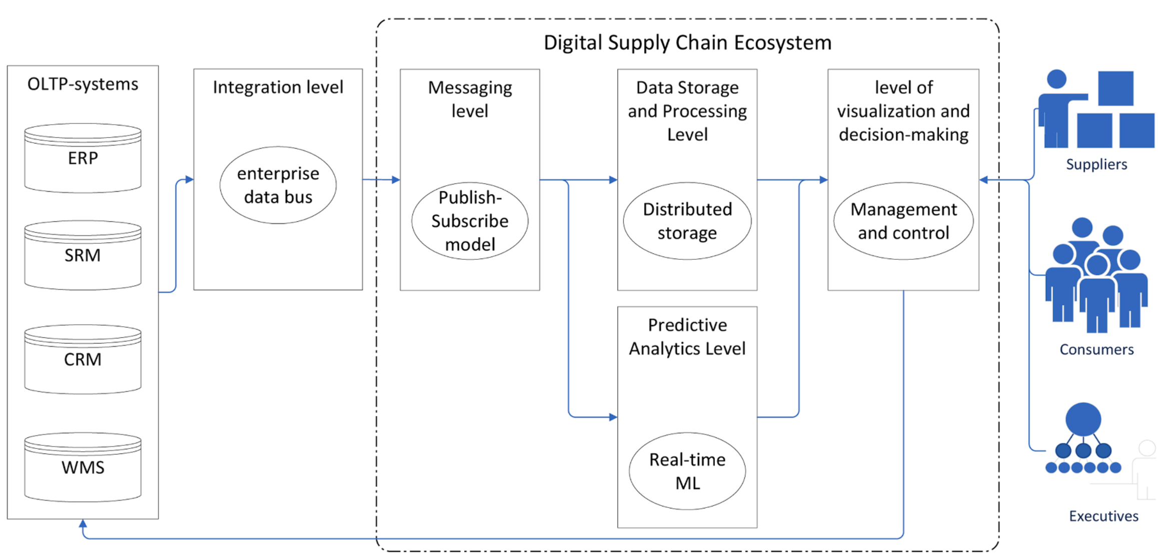

Fig. 2. Basic model of information flows interaction in a DES.

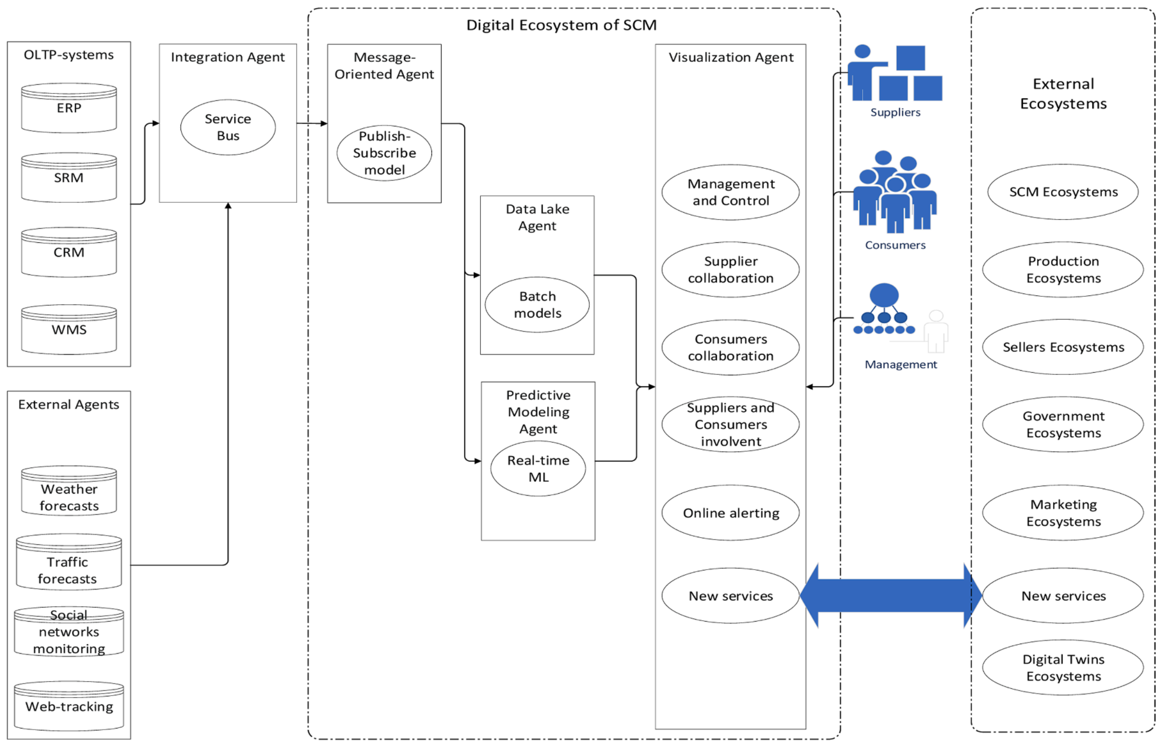

Fig. 3. A model for the extended architecture of supply chain DES interaction.

single format using common data transfer protocols.

The messaging layer is, in turn, required to allow different subscribers to access the same data or data consumers. This enables data usage for developing various control models either for real-time applications, or for subsequent analysis, visualization, and creating other models that do not require permanent online model changes. The models can be developed based on batch data uploading into the storage or Data Lake.

Visualization and decision-making level allows to make on-line and off-line decisions on the basis of different data formats: analysis results, data visualization, or predictive e-learning models. Management and control of a real-life system is carried out on the basis of the obtained results and signal messages of the *alert module* in real time.

Suppliers and consumers are also involved in the decision-making process and form collaborations to attain maximum benefits from joint activities. In that way, new services are formed, which subsequently serve as drivers for further development of new ones. The model becomes autonomous, self-learning and self-organizing.

Example: digital warehouse management agent

The operation of a DES control system may be discussed by examining its fragment: a Digital Agent (DA) of company's warehouse, say, in automotive industry. Major automotive companies practice external procurement of components for assembly, metals, auxiliary products and materials, tools, and spare parts. DA carries out information interaction with other corporate information management systems, as well as support for decision-making on inventory control.

DA is characterized by the presence of some intelligent add-on over WMS, which, along with the coordination of data exchange (within the warehouse, as well as with MES, ERP and other corporate systems), helps to optimize warehouse and other production processes in real time. DA contains a description of business processes and scenarios for interacting with corporate information systems which enable on-line information exchange. DA also stores the structured data on the operation of these business processes.

On the basis of data streaming, the system:

- predicts on-line the deviations of the actual delivery times of components from the scheduled ones,
- forecasts shortages (if, e.g., the delivery time increases due to unforeseen circumstances) and illiquidity,
- determins the inventory size for scarce items, taking into account the forecast demand.

Based on the algorithms for predicting demand dynamics and possible bottlenecks, delivery planning for the next period can be carried out by the ERP system.

Also, by getting information from these models, a manufacturing execution system (MES) may carry out on-line the necessary changes in the current production planning and scheduling, as well as modeling the schemes of component parts transportation from suppliers directly to the workshop without warehousing. This eliminates time delays in order execution with inevitable losses. The scheme of the above mentioned and other on-line operations is generalized in the form of a dynamic mathematical model of the control and prediction system. After a preliminary (at the learning phase) statistical analysis, identification models are developed and tuned on-line using associative search algorithms (Bakhtadze and Lototsky, 2016).

The model for delivery times prediction may look as follows:

$$y_{\widehat{m}}(t) = \sum_{i=1}^{L} a_i y_{\widehat{m}}(t-i) + \sum_{j=1}^{n} \sum_{r=1}^{R} b_{jr} x_{rm}(t-j),$$

where:

$y_{\widehat{m}}(t)$ is the remaining (at the time step t) actual stock of time for the execution of the order for the supply of the m-th component (once the earlier orders for the supply of this item from the same source were completed).

$x_{rm}(t)$, $r = 1, \ldots, R$ are the factors of possible deviation of the lead time from the contractual value. The values of the coefficients a_i and b_j are determined while the predictive model is updated.

If, for a certain time, the item was supplied from several sources, the model becomes more complicated:

$$y_{m}^{\frown}(t) = \sum_{k=1}^{K}\sum_{i=1}^{L} a_{ik} y_{mk}^{\frown}(t-i) + \sum_{k=1}^{K}\sum_{j=1}^{n}\sum_{r=1}^{R} b_{jr} x_{rmk}(t-j),$$

where K is the number of involved suppliers.

The factors of possible deviation of the order execution time from the planned one should include the following variables whose values are received and processed on-line:

- risks of transportation delay,
- possible delays of other orders processing,
- expert forecasts of production risks.

Data processing includes data fusion with asynchronous update of various type data.

The DT also contains updated models for various purposes: forecasting the deviations of deficit and illiquidity values in the warehouse from the planned indicators, forecasting sales and demand, forecasting the dynamics of components need and possible bottlenecks, etc.

Digital processing and storage of the data for these identification models makes it possible to support decision-making on the management of key business processes in cargo handling management based on the address storage system in an automatic digital warehouse.

Conclusion

The article offers an approach to DES control based on model predictive control (MPC) technology. The models developed by means of e-learning algorithms and inductive knowledge about DES dynamics were proposed as predictive identification models. The cases of nonlinear and nonstationary systems were investigated.

An approach was proposed to evaluating the state of a complex of heterogeneous DES resources and predicting emergency situations in real time. The approach is based on binary coding of state values for different types of DES resources with subsequent application of the association rule search algorithm which belongs to data mining techniques.

The development of DES in the field of supply chains was investigated. Key advantages of such DES for companies and enterprises were analyzed. The article offers a business model, as well as the model of general and enhanced architectural interaction of information flows between different classes of systems as well as within the DES itself.

Further investigation of digital identification models for the *situational DES management* looks promising. This may include the modeling of poorly formalized factors such as the effect of ambient conditions. Future work also aims at the enhancement and specification of the development of DES elements and subsystems.

Another research perspective is the implementation of the proposed SCM DES control system framework for certain companies: design of necessary digital agents, integration of incoming SCM data for modelling, development of predictive models (both real-time and batch) for control system and, finally, modeling the data exchange with external environment (external DES). The implementation of DES in SCM is planned on the basis of Open-Source Big Data technologies that have already proved their efficiency in data processing and machine learning models development and implementation.

In the post-pandemic world, the need for external data exchange of SCM DES with other DES (not only SCM) holds much promise. We propose to use DES for SCM as a basic concept for communicating with external DES environment such as governmental, sales, marketing ecosystems, etc. This will be a strong driver for the development of new DES with high effectiveness of regular data utilization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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