I.J. Information Engineering and Electronic Business, **2025, 2, 79-94**
Published Online on April 8, 2025 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijieeb.2025.02.04

Formation of Innovativeness for the Business Processes of Enterprise Using Data Processing

Zarina Poberezhna
National Aviation University / Department of Economics and Business Technologies, Kyiv, 03058, Ukraine
Email: zarina_www@ukr.net
ORCID iD: https://orcid.org/0000-0001-6245-038X

Maksym Zaliskyi*
National Aviation University / Department of Telecommunication and Radioelectronic Systems, Kyiv, 03058, Ukraine
E-mail: maximus2812@ukr.net
ORCID iD: https://orcid.org/0000-0002-1535-4384
*Corresponding Author

Anton Kniaziev
State University of Infrastructure and Technologies / Department of Management, Public Administration and Administration, Kyiv, 04071, Ukraine
Email: kniazev_asp@gsuite.duit.edu.ua
ORCID iD: https://orcid.org/0009-0001-4158-7819

Received: 01 January, 2025; Revised: 13 February, 2025; Accepted: 10 March, 2025; Published: 08 April, 2025

Abstract: The article discusses the issues of development and analysis of diagnostic procedures for business processes during enterprise management. The digitalization has become a priority at the state level of every country, influencing the daily lives of citizens and the enterprises activity. As a result, the ability to gather, analyze, process, and use the data has taken center place to support effective decision-making and sustain competitive market positions. The article considers the factors influencing the choice of data processing tools, analyses the difficulties faced during the data processing methods implementation, and outlines the essential features of such systems for effective management of enterprise activity. The main attention was paid to the development of a data processing method during the state diagnosis of business processes in case of assessing their compliance. The method involves calculating the probability density function for the costs of restoring the normal functioning of business processes and statistical characteristics of the probability of correct decision-making. Additionally, the article includes numerical examples demonstrating the use of this method to the business processes of an aviation enterprise engaged in providing and performing technological procedures for the operation of aircraft. The proposed data processing model can be used to analyze the efficiency of enterprises' business processes and make decisions on organizational structure optimization to minimize the costs spent by enterprise.

Index Terms: Data Processing, Enterprise Management, Innovativeness, Business Processes, Efficiency

1. Introduction

Effective management of an enterprise and its business processes, making a profit, ensuring and maintaining the achieved level of development stability is now considered impossible without information systems of data processing, which make it possible to ensure operational interaction between different departments and business processes of an enterprise [1, 2]. The main condition for the successful management of complex processes that take place inside the enterprise is the integration of innovative technologies and management processes, which in turn ensures the creation of innovative models of the entire set of business processes of the enterprise and their organic interaction with innovative technologies for data processing.

Innovative technologies and processes, development and implementation of innovative products allow the company to take a leading position in the market. This will provide the product with a high degree of scientific content and novelty, which makes it competitive in the global market [3, 4].

The use of digital technologies allows an enterprise to maintain centralized control at all stages of the life cycle of a manufactured product (or service) [5]. This applies, in particular, to the following components: digital design and modeling [6], digital manufacturing [7], digital supply chain [8], logistics [9], and digital adaptation for the consumer after delivery [10]. Under such conditions, the issues of building a single integrated system of data processing to ensure effective management of each business process of the enterprise become especially relevant.

Enterprises that constantly use innovative technologies and are actively engaged in innovative activities have great advantages in the market compared to competitors. This is manifested in increasing the efficiency of activities, and it helps to withstand all the challenges of the external environment faced by the business object [11].

The development of innovative technologies has led to a broad consideration of the use of data processing technologies [12, 13]. It is worth noting that the focus of scientific research is both general and detailed. The first of them provides a general description of information systems and data processing systems [14]. A detailed description of the operation of data processing technologies, both for a particular software product and for economic sectors as a whole, is defined in paper [15]. The study of the possibility of using innovative data processing technologies for ensuring the efficiency of enterprise management is studied in research [16].

Paper [17] discusses the current state of accounting information. The authors stated that the development of the system at enterprises should be characterized by the transition to a new qualification level, determined by the impact of scientific and technological progress on the specifics of information technology. Data collection and use are further supported by business process automation, which eases the daily workload of accounting management [18].

The main purpose of automating an enterprise's business processes is to interact with suppliers. This process generates data about them and prices for their goods and services, as well as creates a reporting system for receiving invoices for services, automates the process of concluding contracts and optimizing the overall circulation of contractual documents, and creates a single electronic data repository [19, 20]. At the same time, there are several issues related to the use of innovative technologies. For example, the emergence of new approaches to data-driven management (DDM) [21] or the use of cloud services [22] in the management of business processes of an enterprise remains not fully studied. Taking into account the rapid growth in the use of innovative technologies for data processing in practice by Ukrainian enterprises, this issue is of particular practical importance and requires additional research.

The use of innovative technologies for data processing in a modern enterprise can be used to solve the following problems: monitoring the diagnostic parameters of the equipment or production process [23, 24], calculation and evaluation of the efficiency [25, 26], assessment of the level of equipment reliability [27, 28], detection of processes of deterioration in the efficiency of equipment operation or production processes [29, 30], forecasting [31, 32], cost management [33, 34], optimization of the spare parts stocks [35], improvement of the accuracy of equipment functioning [36, 37], improvement of the enterprise's production processes [38] development and analysis of maintenance and repair processes [39, 40], development of decision-making technologies regarding implementation of preventive and corrective actions [41, 42].

The purpose of the study is to investigate the possibilities of using modern advanced technologies for data processing in enterprise management and the peculiarities of their implementation in practice. The research methods used are the methods of general scientific cognition, along with synthesis and analysis, methods of probability theory and mathematical statistics, theory of reliability and mass service, the method of separating the essential from the general, and the method of critical analysis of literature sources, which made it possible to obtain new scientific results. To achieve the mentioned purpose, the following specific tasks are considered in this article:

1. Summarizing the challenges of modern data processing technologies and their role in decision-making for the enterprise.
2. Analysis of factors influencing the choice of data processing tools, the difficulties faced during the data processing methods implementation, and features of these methods for effective management of enterprise activity.
3. Development of the method of data processing during the state diagnosis of business processes in case of assessing their efficiency and to provide innovativeness for the business processes of the enterprise.
4. Presentation of numerical calculations for the developed method.

This paper consists of five sections. Section 2 presents the methodological approach to the use of innovative technology for data processing in enterprise management. Section 3 contains the description of the method for efficiency analysis of business process diagnostics. Section 4 considers a numerical example, illustrating an application of the proposed method. Section 5 is the conclusion, where research results are discussed.

2. Material and Methods

A part of the enterprise management system is the subsystem of making management decisions. This subsystem is based on the possession of certain knowledge, i.e. information resources [43]. An important characteristic of these resources is completeness, accuracy, reliability, and timeliness, which makes this information valuable at the time of management decision-making. If we want that information will meet the above criteria and be useful in the management process, it is necessary to use modern innovative systems for collecting and processing large amounts of information and information flows coming to the enterprise from various sources [44]. Thus, an integral element of the enterprise information system is information that is presented in a specific context and acquires the concept of "data".

Information flows coming to an enterprise or created directly in its environment form an information system that combines a controlling and a managed system in a single circuit, and the use of modern innovative technologies for processing information flows, transforming them into an understandable and arranged array of data contributes to the rapid achievement of the goals and objectives of the enterprise's development.

Let us consider the constituent elements of an enterprise information system [45]:

– analytical – data processing to obtain management information;
– accounting – recording data for analysis;
– organizational – combines management functions and subordination structure.

The efficiency of an information system is ensured by: technical means, methods, models, pre-designed algorithms for processing information (data), programs and documentation for interaction with technical means, legal norms for the operation of information systems, and others [46]. Data analysis, which is carried out with the help of special algorithms, presents the management with a procedure for action and decision alternatives, depending on the situation being analyzed [47].

Implementation of modern systems of data processing is a top priority for every enterprise today, as it involves systematizing a large amount of information in a unified manner, based on the same source and regulatory and reference data for different tasks. This means that all data processing procedures are viewed as interdependent elements of an inseparable management process. Therefore, we can talk about the digital maturity of the enterprise. Digital maturity is the ability and capacity of an enterprise to use modern digital technologies, process big data to make management decisions based on predictive analytics, and transition from traditional business models to new ones by deeply restructuring its business processes.

Data processing systems help to

– analyze all actual and planned documents;
– track the movement of working capital;
– control the expenditure of resources on various business processes;
– compare data with results.

Therefore, data management requires mastery of the skills of managing the collection, storage, and processing of data [48]. The main trends in modern data processing are innovative technologies used to increase the efficiency of information management, optimize business processes, and improve decision-making.

The main task of innovative data processing technologies is to receive data from the information system, process it, and present it to the management for analysis and making informed management decisions. Completing this task ensures the management process at all levels, facilitates cooperation with business partners and customers of the enterprise, reduces time and labor costs for some processes related to loss calculations, helps optimize the stock of goods in warehouses to create optimal inventory pairs, reduces the loss of personnel's time to perform certain operations and provides the management system with real objective calculation data [49].

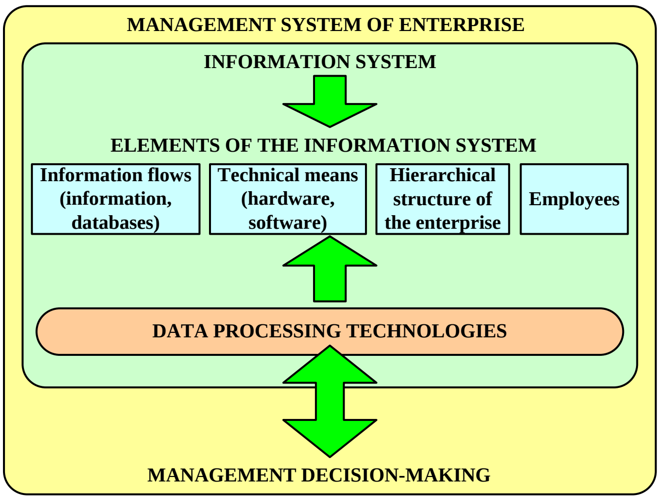

Fig. 1. The place of innovative technologies for data processing in the enterprise management system

Let us consider the place of innovative technologies for data processing in the enterprise management system (Fig. 1). Thus, the information system covers all structural elements involved in managing the enterprise's information flows, which are actively influenced by the data processing technologies used by the enterprise, and based on which management decisions are made. The algorithm for implementing a data processing system at an enterprise consists of the following units.

Unit 1 is the determination of needs and goals. This determination involves analyzing the enterprise's needs for data of a predetermined volume and presented in a certain way; identifying the departments where data processing can bring the maximum effect and those departments that do not require the use of complex data processing systems; identifying data that are critical for making management decisions. The whole process involves defining the specific results that the company wants to achieve with the use of data processing systems (improved sales forecasting, inventory optimization, increased efficiency of operations, and others).

Unit 2 is data collection and preparation. It involves the identification of all data sources: internal (CRM, ERP, accounting systems) and external (market research, social networks). Data collection should provide access to data from various sources by using ETL processes (Extract, Transform, Load) to load data into the warehouse, as well as cleaning and preparing data, which includes removing duplicates, filling in missing values, and standardizing the data format. The efficiency of the entire management process will depend on the quality of the data collected at this stage.

Unit 3 is a selection of data processing system. Based on the analysis of the market environment, the capabilities of available platforms and tools for data processing are assessed, with special attention paid to cloud solutions, local solutions, and open-source solutions. Further, based on the defined parameters of system compliance, such as functionality, scalability, safety, and cost, the one option that meets the needs and goals of the enterprise is selected.

Unit 4 is the implementation of the system. It involves such stages as:

– implementation planning with the development of a detailed implementation plan, including a schedule and responsible persons;

– integration with existing systems (CRM, ERP);

– customization of the system to meet the specific needs of the enterprise (access rights, access levels, dashboards and reports);

– testing of the system to identify errors and confirm its efficiency using test scenarios that simulate real-world conditions.

Unit 5 is a staff training. This unit includes the development of a training plan for different user groups (analysts, managers, technical staff) with the distribution of training materials, training and seminars, and actual training.

Unit 6 is a system operation. This unit combines two components:

– monitoring and management. When monitoring system performance, it is worth using reports and dashboards to analyze key performance indicators (KPIs);

– implementation of software updates to maintain relevance and cyber security and the provision of technical support to resolve emerging issues.

Unit 7 is analysis and optimization. The analysis has a goal of a comparison of actual results with planned indicators. Process optimization includes identifying areas for improvement and optimization of data processing.

Unit 8 is security and compliance. It involves the implementation of security measures to protect data from unauthorized access and cyberattacks through encryption, multi-factor authentication, and security monitoring.

Unit 9 is scaling and development. This unit includes analyzing the scaling needs in response to business growth or changing requirements and drawing up a plan to increase the amount of data processed or add new functionality, which will ultimately ensure the development of the system. System development, in turn, requires investment in new technologies and tools to improve data processing. It is worth noting that the system needs to be constantly improved to ensure its relevance and meet the established needs.

The presented algorithm provides a consistent approach to the implementation and use of data processing systems at an enterprise, which will help to maximize the use of data to make informed management decisions and optimize business processes. The algorithm described above is shown in Fig. 2.

Taking into account the global digitalization of society and the development of information and computer technologies, information systems, including data processing systems, are currently developing in the direction of integrated automation [50]. This makes it possible to carry out an in-depth analysis of the external environment, describe the priorities of product consumers, develop enterprise plans and consider the possibility of restructuring its business processes, and maintain equipment promptly. The result can transfer the enterprise from management as needed to management on demand in the streaming mode (streaming). Streaming, which is the result of the digital interaction of process participants on demand, ensures the synchronization of supply and demand in the market space.

It should be noted that modern enterprises that widely use digital data processing technologies in their activities use the concept of DDM, which is based on digital platforms using Big Data (BD) technology. A feature of BD technology is the speed of processing large amounts of data due to the parallel execution of a large number of calculations, analysis of large volumes of incoming information flows, ensuring the reliability of the data obtained, and others [51].

One of the current trends among Ukrainian enterprises is the use of cloud services, which in turn makes it possible to free up resources and reduce the cost of information protection. Cloud Computing involves the use of software resources of a server located in a company that provides such services [52]. Implementation of the relevant information systems requires the purchase of CPU time, disk space, and a network of the required bandwidth, which in turn makes it possible to reduce costs and free up a significant part of resources to ensure the efficient operation of the main business processes of the enterprise. In general, today a large number of information systems offer their solutions for enterprise management using cloud technologies.

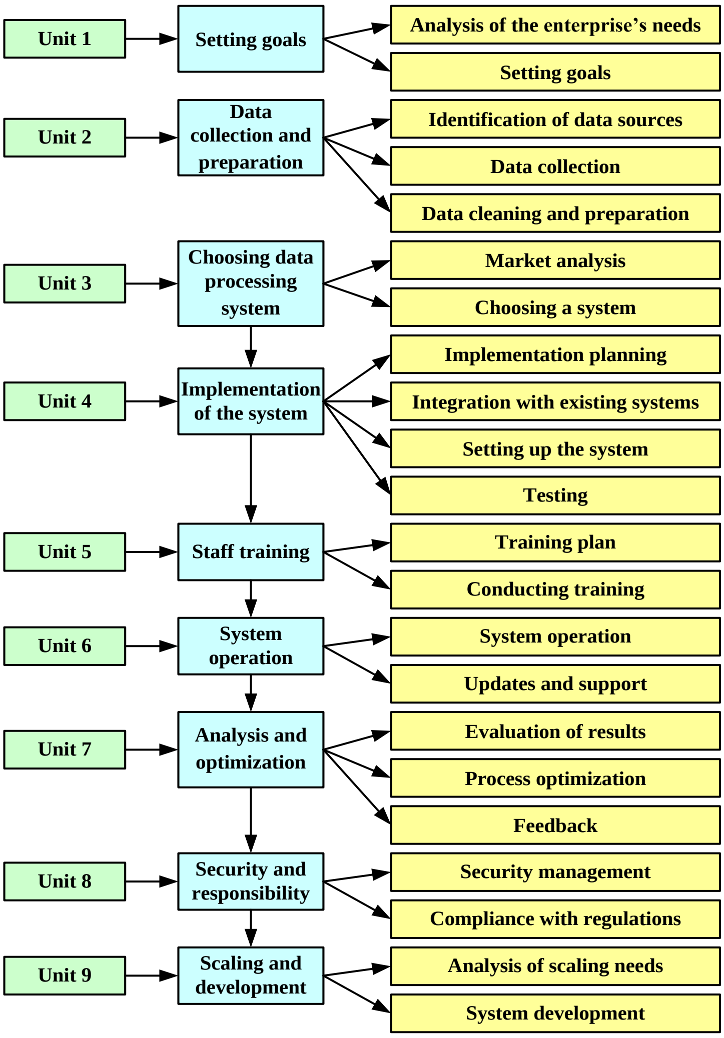

Fig. 2. The place of innovative technologies for data processing in the enterprise management system

The information system of data processing that was selected for use by the enterprise should provide the following capabilities for organizing data for enterprise management purposes [53]:

- input, storage, and processing of analytical data for all business processes of the enterprise;
- search, selection, and sorting of analytical data according to the required features;
- use of analytical data to generate reports and tables according to predefined parameters;
- determining the scope and quality of analytical information for reporting and generating conclusions;
- determining the list of information that will detail the research, depending on the needs of the consumer and his role in the management decision-making process;
- the level of detail of summarized data in various sections of analytical information and their combinations;
- the ability to customize the types of analytics offered by the developers of the information system, with the possibility of making their own adjustments;
- the ability to generate reports in pre-selected formats, for example, the ability to receive and upload documents in special formats (*.dbf, *.xml) that can be processed by electronic document management systems, electronic services of fiscal authorities, systems of financial and credit institutions, and others.

It should be noted that the selection of innovative technologies to be used by an enterprise is a responsible task, as they are usually installed for a long time and must be cost-effective and fully meet the needs of the enterprise. When choosing innovative technologies for data processing, an enterprise needs to:

- assess the enterprise's readiness to implement this system;
- determine the cost of the purchase and its subsequent maintenance and operation, as well as the possibility of its modernization;
- analyze the functionality of this information system;
- to calculate the cost-effectiveness and feasibility of its implementation, it may be worth considering alternative options;
- determine the level of reliability and data security of the selected information system and others.

At the same time, along with the desire to introduce innovative technologies for data processing and use their results in management, enterprises face several difficulties that need to be overcome, among which are worth highlighting:

- inability to use the software;
- inability to interpret the results to make effective decisions;
- inability to be combined with information processing systems available at the enterprise;
- resistance to learning how to use the software.

3. Theory and Calculation

Let's consider the theoretical foundations regarding the peculiarities of applying innovative technologies for data processing in the activities of an enterprise. Typically, data processing tasks include two components: synthesis and analysis [54]. Synthesis is performed based on available a priori information about the characteristics of the processed datasets. In the case of a priori certainty, optimal decision rules can be built that can be used to solve problems of classification, estimation, forecasting, and others [55]. In cases of a priori uncertainty, the distribution-free methods are used. Such methods have less accuracy but can be used for arbitrary data distribution. The technologies of distribution-free methods include not only the nonparametric approach of statistical theory but also the modern tools of neural networks [56]. The analysis is performed to determine the efficiency of the developed data processing method. Analysis tasks can be solved using analytical calculations and statistical modeling [57].

As mentioned earlier, data processing can be applied to different activities and different processes of an enterprise. In general, considering a comprehensive approach to processing is a sophisticated and multi-criteria task. To simplify it, this section will consider the theoretical features of applying data processing methods to the process of diagnostics and restoration of operability. Diagnostics and restoration of operability are integral elements of the technical systems repair process. Diagnostic methods are widely considered in the theory of reliability but insufficient attention has been paid to the comparative analysis of its various variants.

In the process of diagnostics and restoration of operability, attention is usually paid to performance indicators in the form of the expected duration and cost of diagnosis. However, this approach is rather limited in terms of information completeness. Since the duration and cost are usually random variables, it is necessary to use the probability density function (PDF) to characterize them most completely. In this case, the probability density function will contain information not only about the expected value, but also about the variance, standard deviation, skewness, and kurtosis.

In addition, in the process of diagnostics and restoration of operability, erroneous decisions are possible, caused by both the available control and measuring equipment and the human factor. These errors are characterized by the probabilities of the first and second type errors. The first type of error occurs when a serviceable object is diagnosed as faulty. The second type of error occurs when a faulty object is diagnosed as being in good condition.

The presence of errors in diagnosis motivated us to focus on a new performance indicator in the form of the probability of correct decision-making (CDM). This probability is also a random variable distributed in the interval from 0 to 1. Therefore, to describe it completely, it is necessary to find the corresponding PDF.

The diagnostic process can be applied not only to equipment but also to production processes. In the course of an enterprise's activities, it is usually tried to build a model of business processes that are implemented in the enterprise. The efficiency of the enterprise depends on the quality of the main business processes. Therefore, this study was the first to apply the concepts of diagnostics to determine the state of the enterprise's business processes.

The diagnostics process is performed in case of low efficiency of the enterprise's activities to adjust and optimize business processes. According to the process and system approaches, each business process can be evaluated by monitoring certain diagnostic parameters and comparing them with the set values.

Let's assume that if a business process meets all the requirements for its operation, a logical one signal is generated at its output. Otherwise, a logical zero signal is generated at the output of the business process. Let's introduce a restriction on the presence in the scheme of only one business process with inconsistencies (or low efficiency).

During the synthesis of the data processing algorithm, the following restrictions were adopted:

1. A model of business processes interconnection is known.
2. During observation period only one component of business processes can have low efficiency.
3. The monitoring equipment can give erroneous decisions with known probabilities.
4. The process of inconsistencies occurrence is stochastic and can be described by predetermined probabilistic law.
5. The statistical report on inconsistencies occurrence in different components of business process is available for data collecting.
6. Duration and cost of the inspection procedures can be described by normal probability density function with known expected value and standard deviation.
7. In case of low efficiency, additional costs are spent during implementation of corresponding business process.

Let's consider a step-by-step procedure for calculating the efficiency of diagnosing and restoring the required level of efficiency of business processes.

Step 1. Analyze the enterprise's business model and build the model of business process interconnection. While doing so, it is necessary to identify all business processes and define their inputs, outputs, controlling influences, and resources. For each process, it is necessary to establish measurement values that will characterize its performance.

Step 2. Building a diagnostic model. The diagnostic model may not be a repetition of the business process model. Some business processes can be grouped in such a way as to get rid of feedback and simplify the connection scheme of elements as much as possible.

Step 3. Building a diagnostic program. The diagnostic program establishes a chain of checks to identify the business process that does not meet the requirements. Building a diagnostic program can be based on one of the well-known approaches, including engineering, half-split, information parameter, probability-time, and others. In the event of errors of the first and second types, additional programs for restoring the efficiency of the enterprise supplement the diagnostic program. These programs establish a procedure for action in cases of erroneous decisions. The number of such programs is equal to the number of elements in the diagnostic model.

Step 4. Accumulation and analysis of primary datasets. Primary datasets include the following information:

- statistical data on inconsistencies for each business process of the model;
- probabilities of the first and second type errors for diagnosing each process α_i and β_i, respectively, where $i=[1;N]$, N is the number of elements of the diagnostic model;
- the duration and cost of the inspection procedures for each business process;
- the duration and cost of restoring the efficiency of the enterprise.

Based on the collected datasets, preliminary processing is performed. The result of the preprocessing is:

- the probability of inconsistencies in each business process q_i;
- estimates of the PDFs for the duration and cost of the inspection procedures for each business process;
- estimates of the PDFs for the duration and cost of restoring the efficiency of the enterprise for each business process in the event of erroneous decisions.

Step 5. Calculation of the conditional probability matrix of decision-making on the presence of the inconsistencies in the business process under study provided that there is an objective presence of the inconsistencies in the given business process. This matrix is calculated based on the graphical view of the diagnostic program. The matrix has a square shape and dimensions equal to the total number of elements of the diagnostic model. The elements of the main diagonal of the matrix contain the probabilities of correct decisions. In general, under the conditions $\alpha_i=\alpha=\text{const}$ and $\beta_i=\beta=\text{const}$ the elements of the main diagonal of the matrix are equal:

$$p_{i,i}=(1-\alpha)^m(1-\beta)^n, \tag{1}$$

where m is the number of correct decisions on the state of business processes without inconsistencies during an objective inconsistency in the i-th business process; n is the number of correct decisions on the state of business processes with inconsistencies during an objective discrepancy in the i-th business process.

Other elements of the matrix when $i\neq j$ are determined by the formula:

$$p_{i,j}=(1-\alpha)^m(1-\beta)^n\alpha^u\beta^v, \tag{2}$$

where u and v are the number of erroneous decisions about the state of business processes without and with inconsistencies during an objective inconsistency in the i-th business process.

Step 6. Building a probability mass function and finding statistical characteristics for the conditional probabilities of making the correct decisions. Based on the data on the values $p_{i,i}$ and q_i the probability mass function is built.

Next, the expected value and standard deviation are estimated. In this case, the unconditional probability of correct decision-making $p(\mathrm{CDM})$ during the business process inspection:

$$p(\mathrm{CDM}) = \sum_{i=1}^{N} p(\mathrm{CDM}|i) q_i \, , \tag{3}$$

where $p(\mathrm{CDM}|i)$ is the conditional probability of correct decision-making in case of the inconsistencies in the i-th business process. In this case, we have $p(\mathrm{CDM}|i) = p_{i,i}$.

Step 7. Building a matrix F of the conditional PDFs for the duration and cost of restoring the efficiency of the enterprise. These matrices have a square shape and dimensions equal to the total number of elements of the diagnostic model.

Each element of the matrix contains the conditional PDF of the duration and cost of restoration procedures in the event of a decision on an inconsistency in the *j*-th business process and in the event of an objective inconsistency in the *i*-th business process.

Step 8. Calculation of the PDF for the cost and duration of diagnostics and restoration of the enterprise's efficiency.

The formula for the PDF of costs is:

$$f(C) = \sum_{j=1}^{N} q_i \left(F^{T<j>} \right)^T P^{<j>} \, , \tag{4}$$

where T is the matrix transpose operation; $\cdot^{<j>}$ is the operation of selecting *j*-th column from the matrix.

Similarly to equation (4), the formula for the PDF of the duration of diagnosis and recovery can be written.

For the specific implementation of the proposed data processing methods in the activities of the enterprise, it is necessary to:

1. Analyze the existing model of the enterprise's business processes.
2. Determine key monitoring data (costs of performing technological operations, duration of these operations, errors of measuring equipment, and others).
3. Establish the relationship between the efficiency indicator and monitoring data.
4. Implement the data processing algorithm.
5. Make decisions on optimizing the organizational structure, implementing corrective and preventive actions aimed at improving the efficiency.

Data processing can allow aviation enterprises to improve the efficiency of performing business processes related to optimizing aircraft routes, improving maintenance processes, reducing costs, training personnel, etc.

The introduction of data processing methods into the business processes of the enterprise contributes to the efficiency of management decision-making. In general, for the widespread use of data processing methods, it is necessary to:

- organize a system of data collection and storage through the use of CRM systems, Internet of Things sensors, built-in monitoring tools for operating equipment;
- synthesize data processing procedures based on mathematical statistics, machine learning, artificial intelligence, and other technologies;
- develop and implement tools for automating the execution of individual procedures during the implementation of business processes, including during data processing;
- develop a system for forming decisions to improve the efficiency of the enterprise's activities based on the use of processed data;
- organize a system for protecting data and the results of their processing from third-party interference;
- inform staff and consumers about the advantages of using a data-driven decision-making approach and constantly search for improvements.

4. Numerical Example and Discussion

In this section, we will consider an example of implementing data processing methods in the activities of an aviation enterprise. Before moving on to the numerical example, we will analyze the main challenges that aviation enterprises face when implementing data processing technologies.

Today, the aviation industry is saturated with thousands of sensors that generate large amounts of data in various areas of enterprise activity. This data may include trends of changes in equipment parameters, resource provision for the maintenance and repair system, aircraft flight trajectory data, customer behavior analysis, environmental parameters, and others. In addition, data comes from various locally dispersed points, which complicates the formation of common datasets and their subsequent storage in data warehouses.

During the operation of aviation equipment, there is also a problem of integrating data collection and processing technologies with equipment that involves manual monitoring and inspections. Therefore, there is a need to update the equipment fleet, which in turn will require significant material costs.

At the same time, the main unresolved tasks of aviation enterprises remain the detection of equipment with a deteriorated technical condition and minimizing operating costs for maintenance and repair. This is due, on the one hand, to the need to ensure the safety and regularity of aircraft flights, and on the other hand, to the need for an aviation enterprise to make a profit.

Thus, let's build a model of the business processes of an aviation enterprise engaged in providing and performing technological procedures for the operation of aircraft.

For simplicity, we will outline eight main business processes:

1. The process of logistics support.
2. The process of forming a stock of spare parts.
3. The process of accepting requests for maintenance and repair.
4. The process of analyzing resource provision and requirements of regulatory and administrative documentation.
5. The process of personnel training.
6. Maintenance and repair process.
7. The process of collecting and processing information.
8. Decision-making and performance evaluation.

A flowchart of the processes' interconnection is shown in Fig. 3.

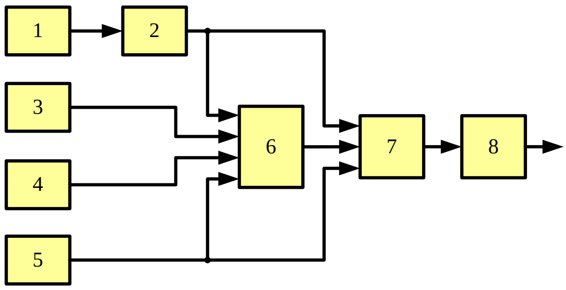

Fig. 3. The flowchart of the processes' interconnection

To identify business processes that have a negative impact on the enterprise's efficiency, we will develop a diagnostic model. In our case, the diagnostic model will coincide with the scheme of the interconnection of business processes (Fig. 3). To find a business process with inconsistencies, we will build a diagnostic program that determines the procedure for performing control and verification operations.

Fig. 4 shows a diagnostic program built using the half-split method. In this case, the second process divides the diagram of the business process relationship approximately in half. Fig. 4 establishes a chain of checks to determine the number of business processes with inconsistency. Therefore, to determine that the first business process does not meet the requirements, we need to check the second and first processes.

For simplicity, let's assume that errors of the first and second types are characterized by the same probabilities for all business processes and are equal to α and β, respectively. In addition, we will assume that probabilistic laws describe the nature of inconsistencies. That is, there are probabilities q_i of an inconsistency occurring in the i-th business process in the case of low efficiency of the aviation company.

We will analyze the efficiency of the diagnostic program. To do this, we calculate the probability of correct decisions $p(\mathrm{CDM})$ when checking business processes. The total probability will be calculated using the formula (3). Conditional probabilities for the diagnostic program in Fig. 4 are determined according to the formulas:

$$p(\mathrm{CDM}|i=1)=(1-\beta)^2; \tag{5}$$

$$p(\mathrm{CDM}|i=2)=(1-\beta)(1-\alpha)^2; \tag{6}$$

$$p(\mathrm{CDM}|i=3)=(1-\beta)^2(1-\alpha); \tag{7}$$

$$p(\mathrm{CDM}|i=4)=(1-\beta)^2(1-\alpha)^2\,; \tag{8}$$

$$p(\mathrm{CDM}|i=5)=(1-\beta)^2(1-\alpha)^3\,; \tag{9}$$

$$p(\mathrm{CDM}|i=6)=(1-\beta)(1-\alpha)^4\,; \tag{10}$$

$$p(\mathrm{CDM}|i=7)=(1-\beta)(1-\alpha)^2\,; \tag{11}$$

$$p(\mathrm{CDM}|i=8)=(1-\alpha)^3\,. \tag{12}$$

Equations (5) – (12) were obtained as follows. The probability of correct decisions is equal to the product of probabilities of errors absence during each inspection in the process of diagnostics. The probabilities of errors absence are complimentary to the probabilities of errors of the first and second types. Therefore, they are equal to $1-\alpha$ and $1-\beta$. Sign "0" in Fig. 4 corresponds to the absence of the second type error. Sign "1" in Fig. 4 corresponds to the absence of the first type error. For example, to make correct decision on inconsistencies occurrence for the first business process we need to inspect the first and second business processes without errors of the second type. Therefore, the probability of correct decision will be equal to squared probability of the second type errors absence, and we will equation (5). Similar considerations can be made to prove correctness of equations (6) – (12).

The conditional probabilities and the probabilities of inconsistencies form probability mass function. Such a function can be evaluated using point characteristics of expected value and variance. In this case, physically, the expected value will coincide with the probability of correct decisions $p(\mathrm{CDM})$.

A graphical illustration of the probability mass function is shown in Fig. 5. This function was obtained for the following initial data: $\alpha=0.035$, $\beta=0.012$, $q_1=0.1$, $q_2=0.05$, $q_3=0.08$, $q_4=0.2$, $q_5=0.07$, $q_6=0.3$, $q_7=0.14$, $q_8=0.06$.

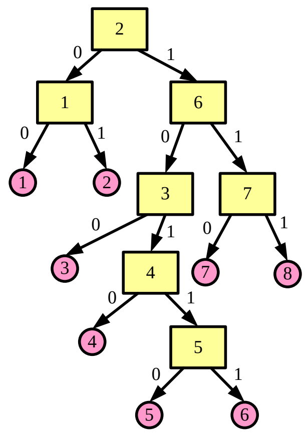

Fig. 4. The diagnostic program for business processes

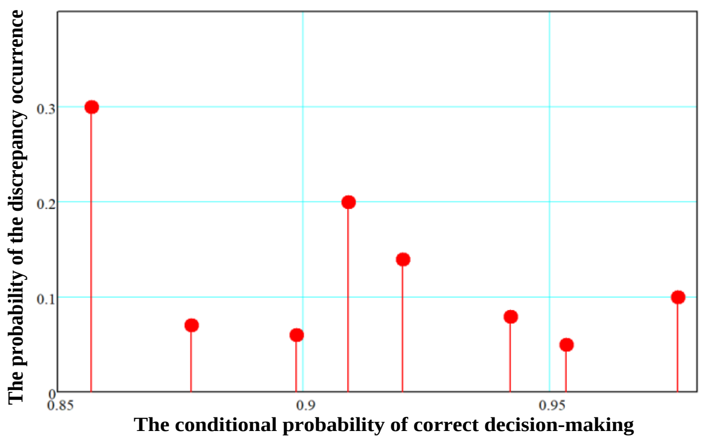

Fig. 5. The graphical illustration of the probability mass function

Fig. 6 and Fig. 7 show the graphical dependence of the expected value and variance on the probability of the first type error for constant values of the probability of the second type error.

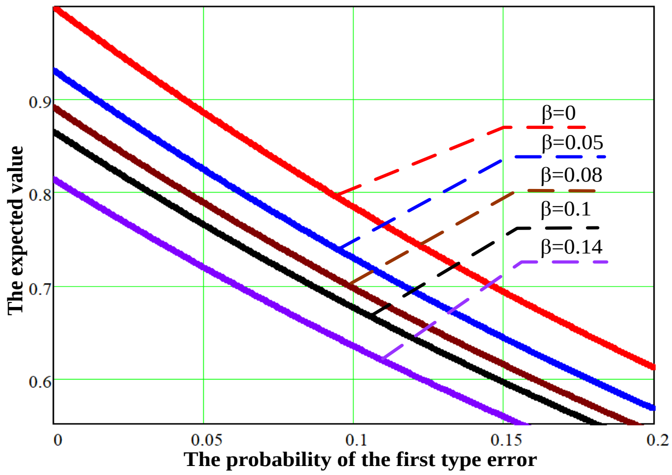

Fig. 6. The dependence of the expected value on the probability of the first type error for constant values of the probability of the second type error

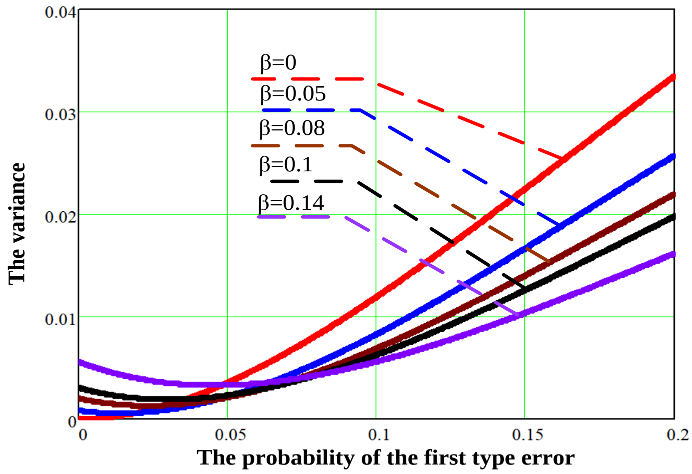

Fig. 7. The dependence of the variance on the probability of the first type error for constant values of the probability of the second type error

The analysis of the above graphs allows us to draw logical conclusions that by increasing the probability of the first and second type errors, the probability of making the correct decision decreases.

Let's analyze the second performance indicator in the form of the costs of an aviation enterprise for diagnostics and restoration of the normal functioning of business processes. This indicator is a random variable, so for its most complete characterization, it is necessary to determine the probability density function.

According to our proposed approach, the primary information for the calculation is the graphical view of the diagnostic program (Fig. 4), the costs of inspection and recovery operations. We will also assume that in this case, errors of the first and second types are possible. In this case, we have 8 business processes, that is, the matrix of conditional probabilities of making decisions about the presence of an inconsistency in the studied business process will have dimensions 8·8. As a result of the calculations, we get a matrix of the form

$$P = \begin{pmatrix} P_1 & P_2 \\ P_3 & P_4 \end{pmatrix}; \tag{13}$$

$$P_1 = \begin{pmatrix} (1-\beta)^2 & \alpha(1-\beta) & \alpha^2 & \alpha^2 \\ \beta(1-\beta) & (1-\alpha)(1-\beta) & \alpha(1-\alpha) & \alpha(1-\alpha) \\ \alpha\beta(1-\beta) & \alpha\beta(1-\beta) & (1-\alpha)(1-\beta)^2 & \alpha(1-\alpha)(1-\beta) \\ \alpha\beta(1-\alpha)(1-\beta) & \alpha\beta(1-\alpha)(1-\beta) & \alpha\beta(1-\alpha)(1-\beta) & (1-\alpha)^2(1-\beta)^2 \end{pmatrix}; \tag{14}$$

$$P_2 = \begin{pmatrix} \alpha^2 & \alpha^2 & \alpha^2 & \alpha^2 \\ \alpha(1-\alpha) & \alpha(1-\alpha) & \alpha(1-\alpha) & \alpha(1-\alpha) \\ \alpha(1-\alpha)(1-\beta) & \alpha(1-\alpha)(1-\beta) & \alpha^2(1-\alpha) & \alpha^2(1-\alpha) \\ \alpha(1-\alpha)^2(1-\beta) & \alpha(1-\alpha)^2(1-\beta) & \alpha^2(1-\alpha)^2 & \alpha^2(1-\alpha)^2 \end{pmatrix}; \tag{15}$$

$$P_3 = \begin{pmatrix} \alpha\beta(1-\alpha)^2(1-\beta) & \alpha\beta(1-\alpha)^2(1-\beta) & \alpha\beta(1-\alpha)^2(1-\beta) & \alpha\beta(1-\alpha)^2(1-\beta) \\ \beta(1-\beta)(1-\alpha)^3 & \beta(1-\beta)(1-\alpha)^3 & \beta(1-\beta)(1-\alpha)^3 & \beta(1-\beta)(1-\alpha)^3 \\ \beta^2(1-\beta) & \beta^2(1-\beta) & \beta(1-\alpha)(1-\beta) & \beta(1-\alpha)(1-\beta) \\ \beta^3 & \beta^3 & \beta^2(1-\alpha) & \beta^2(1-\alpha) \end{pmatrix}; \tag{16}$$

$$P_4 = \begin{pmatrix} (1-\alpha)^3(1-\beta)^2 & \alpha(1-\alpha)^3(1-\beta) & \alpha^2(1-\alpha)^3 & \alpha^2(1-\alpha)^3 \\ \beta(1-\beta)(1-\alpha)^3 & (1-\alpha)^4(1-\beta) & \alpha(1-\alpha)^4 & \alpha(1-\alpha)^4 \\ \beta(1-\alpha)(1-\beta) & \beta(1-\alpha)(1-\beta) & (1-\alpha)^2(1-\beta) & \alpha(1-\alpha)^2 \\ \beta^2(1-\alpha) & \beta^2(1-\alpha) & \beta(1-\alpha)^2 & (1-\alpha)^3 \end{pmatrix}. \tag{17}$$

Suppose that as a result of the observation, information is available on the conditional probability density function of the costs of diagnosis and recovery. In this case, a matrix F can also be constructed of size $8 \cdot 8$ for the conditional densities. Then, according to equation (4), we have:

$$f(C) = \sum_{j=1}^{8} q_i \left(F^{T<j>}\right)^T P^{<j>} . \tag{18}$$

Let's perform a numerical calculation. Let the costs of control operations is described by a normal distribution law. In this case, the average recovery costs for business processes are: $c_1 = 520$, $c_2 = 620$, $c_3 = 830$, $c_4 = 540$, $c_5 = 650$, $c_6 = 650$, $c_7 = 830$, $c_8 = 530$. The corresponding standard deviations are: $s_1 = 30$, $s_2 = 50$, $s_3 = 100$, $s_4 = 30$, $s_5 = 60$, $s_6 = 50$, $s_7 = 90$, $s_8 = 30$. In the case of a wrong decision, additional costs are spent $\Delta c = 100$. The probabilities of inconsistencies are: $q_1 = 0.1$, $q_2 = 0.07$, $q_3 = 0.2$, $q_4 = 0.08$, $q_5 = 0.05$, $q_6 = 0.3$, $q_7 = 0.14$, $q_8 = 0.06$.

The results of the calculations in the form of a family of probability density functions in the cases of absence and presence of false solutions are shown in Fig. 8. As can be seen, the obtained densities are multimodal in nature, with the number of maxima and their position depending on the probabilities of the first and second type errors.

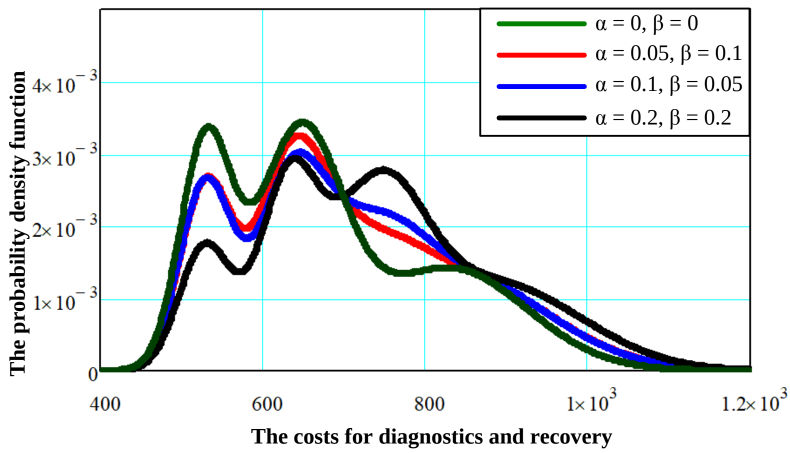

Fig. 8. The family of PDFs in the case of erroneous decisions

A simulation model was developed to verify the reliability of the obtained results. The results of simulation and calculations are shown in Fig. 9. As can be seen, a good convergence was obtained, which confirms the correctness of the calculations. Fig. 10 and Fig. 11 show the graphical dependencies of the expected value and variance of the costs of aviation enterprise for diagnosing and restoring business processes on the probability of the first type error for constant values of the probability of the second type error.

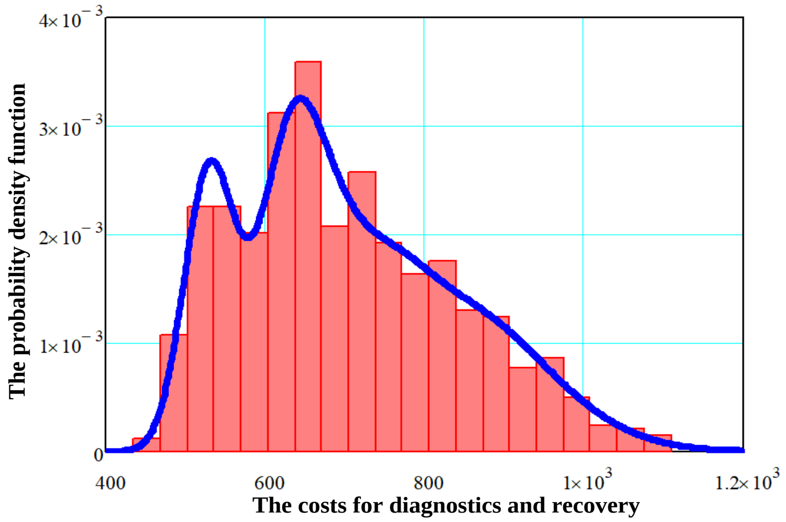

Fig. 9. Comparison of modeling results with analytical calculations

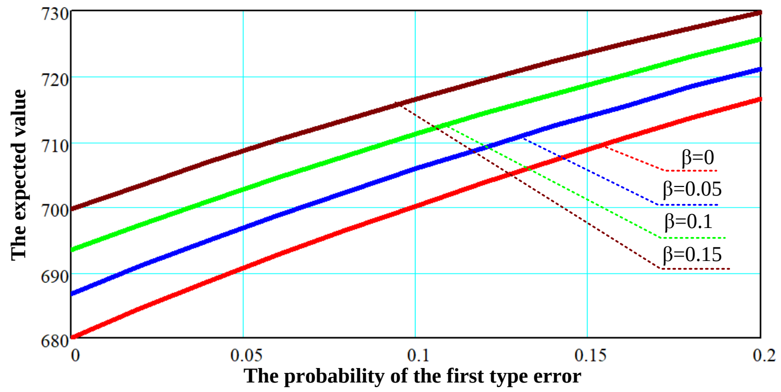

Fig. 10. The dependence of the expected value of the cost of diagnosis and recovery on the probability of a first-order error

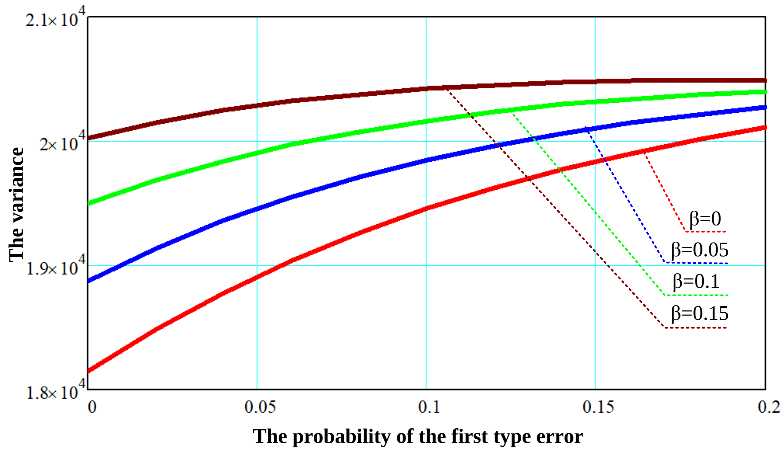

Fig. 11. The dependence of the variance of the cost of diagnosis and recovery on the probability of a first-order error

To validate the obtained results, we conducted statistical simulation. The simulation results showed coincidence with the analytical equations. In particular, to check the correctness of the results presented in Fig. 8 and Fig. 9, the Pearson chi-square consistency criterion was used, which with a probability of 0.99 gave a decision that the simulation results do not contradict the given analytical formulas.

5. Conclusions

Summarizing the study, it is worth noting that every enterprise that wants to succeed must create its information ecosystems and improve business processes according to the new requirements of the external environment. After all, the development of digital technologies gives impetus to the development of the value of data, data flows, and predictive analytics, which can change the decision-making process and the view of management as a DDM system.

There are many offers of various data processing technologies on the market, among which an enterprise should choose those that are suitable for it in terms of functionality, cost, and possibilities of implementation in its information systems. The author determines the place of data processing technologies in the enterprise management system and the algorithm for implementing a data processing system at an enterprise, which once again emphasizes the relevance of the study and determines the need for the digital transformation of modern enterprises.

It is established that the achievement of digital maturity of an enterprise is characterized by the ability to perform work on-demand, which in turn enables it to quickly adapt to changing market conditions using modern digital technology packages such as BD and DDM. At the same time, this transformation requires managers to acquire new knowledge and approaches to management based on digital competencies that go hand in hand with the development of digital technologies. All of this will make it possible to track the costs and financial flows of the enterprise, resulting in an increase in the circulation of funds, which will ultimately lead to an increase in efficiency indicators of management of all structural units of an enterprise.

The possibilities of applying innovative technologies for data processing are considered to assess the productivity of the process of diagnosing and restoring the required level of efficiency of the aviation enterprise business processes. A systematic instruction for the implementation of this process is provided. As an indicator of efficiency, we have chosen the PDFs for the cost, duration, and probability of making the correct decision during the diagnostic process. The choice of the statistical characteristic in the form of the PDF is explained by the completeness of the information and the content of all other characteristics in it.

The process of diagnosing and calculating efficiency was explained using a numerical example for a business process model of an aviation enterprise engaged in the provision and execution of technological procedures for aircraft operations. The results of the calculations based on the above methodology were verified using statistical simulation.

Further research will focus on the introduction of innovative technologies for data processing, including the use of machine and deep learning tools, cloud computing, and others, to improve decision support systems for enterprises in various industries. The main tasks that will be solved by implementing data processing methods will be the following: identifying deterioration in the technical condition of equipment operated in the aviation enterprise; optimizing maintenance and repair processes; minimizing operating costs; assessing reliability indicators for the equipment; increasing the veracity of management decisions; formation of the structure and content of data hubs for collecting, storing, processing, and using statistical data on the aviation enterprise activities.

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Authors’ Profiles

Zarina Poberezhna, Doctor of Sciences (DSc)
Date and place of birth: 1985, Kyiv, Ukraine.
Education: National Aviation University, 2008.
Affiliation and functions: DSc in economic sciences since 2023, professor of Economics and Business Technologies Department at the National Aviation University since 2023.
Research interests: development of business models of enterprises; increasing the efficiency of air transportation; development of a strategy for the functioning of airlines.
Publications: more than 140 papers.

Maksym Zaliskyi, Doctor of Sciences (DSc)
Date and place of birth: 1984, Kyiv, Ukraine.
Education: National Aviation University, 2007.
Affiliation and functions: DSc in technical sciences since 2021, professor of Telecommunications and Radioelectronic Systems Department at the National Aviation University since 2021.
Research interests: signal and data processing, equipment operation and reliability analysis.
Publications: more than 250 papers.

Anton Kniaziev, PhD Student
Date and place of birth: 1994, Lugansk, Ukraine.
Education: Kharkiv National University of Economics named after S. Kuznets, 2017.
Affiliation and functions: Master's degree "Marketing"
Research interests: innovative technologies, business process management.
Publications: more than 20 papers.

How to cite this paper: Zarina Poberezhna, Maksym Zaliskyi, Anton Kniaziev, "Formation of Innovativeness for the Business Processes of Enterprise Using Data Processing ", International Journal of Information Engineering and Electronic Business(IJIEEB), Vol.17, No.2, pp. 79-94, 2025. DOI:10.5815/ijieeb.2025.02.04