Technologia i Automatyzacja Montażu

Volume 127, Issue 1/2025, Pages 22-53
https://doi.org/10.7862/tiam.2025.1.3

Original Research

ANALYSIS AND MODELING OF DESIGN PROBLEMS IN THE CONTEXT OF RANDOM TECHNOLOGICAL CHANGES

ANALIZA I MODELOWANIE PROBLEMÓW PROJEKTOWYCH W KONTEKŚCIE LOSOWYCH ZMIAN TECHNOLOGICZNYCH

Paweł KNAST [1,*]

[1] Department of Mechanics and Mechanical Engineering, Faculty of Polytechnic, Calisia University, Poland

* Corresponding author: p.knast@uniwersytetkaliski.edu.pl; pawel@knast.pl; phone +48 603 97 37 83

Abstract

This article presents a novel approach to analyzing and modeling design challenges, addressing the impact of dynamically changing technologies. Based on extensive research and industrial experience, the author developed hypotheses defining key modeling parameters: time, displacement, mass, and temperature. Through advanced mathematical formulas and numerical calculations, the author demonstrates how each parameter can be effectively integrated to model randomly changing technological processes. Calculations and the structuring of measurement space into virtual cubes enable precise forecasting and adaptability to variable conditions, significantly enhancing the accuracy and responsiveness of industrial processes.

By analyzing historical data and iterative scenario modeling, this methodology facilitates rapid switching between design variants, allowing designers to identify optimization paths and adjust processes in response to unpredictable changes. The author suggests that these foundations may serve as a robust basis for developing intelligent machines with artificial intelligence technology, capable of automatic response and adaptation in dynamically evolving operational environments.

Keywords: stochastic design, artificial intelligence, process modeling, time analysis, system optimization, data integration, adaptive processes

Streszczenie

W niniejszym artykule autor przedstawia nowatorskie podejście do analizy i modelowania problemów projektowych, uwzględniając wpływ dynamicznie zmieniających się technologii. W oparciu o wieloletnie badania i doświadczenie przemysłowe, opracowano hipotezy definiujące kluczowe parametry modelowania: czas, przemieszczenie, masę i temperaturę. Autor, korzystając z zaawansowanych wzorów matematycznych oraz obliczeń numerycznych, ukazuje, jak każdy z tych parametrów można efektywnie integrować w celu modelowania losowo zmiennych procesów technologicznych. Podjęte obliczenia i strukturyzacja przestrzeni pomiarowej na wirtualne sześciany umożliwiają dokładne prognozowanie oraz dostosowywanie się do zmiennych warunków, co znacząco zwiększa precyzję i adaptacyjność procesów przemysłowych. Dzięki analizie danych historycznych i iteracyjnym scenariuszom, metodologia pozwala na szybkie przełączanie wariantów projektowych, umożliwiając projektantom identyfikowanie ścieżek optymalizacyjnych i dostosowywanie procesów do nieprzewidywalnych zmian. Autor sugeruje, że te założenia mogą stanowić solidną podstawę dla rozwoju inteligentnych maszyn z technologią sztucznej inteligencji, zdolnych do automatycznego reagowania i adaptacji w kontekście dynamicznie zmieniających się środowisk operacyjnych.

Słowa kluczowe: projektowanie stochastyczne, sztuczna inteligencja, modelowanie procesów, analiza czasu, optymalizacja systemów, integracja danych, procesy adaptacyjne

1. Introduction – Innovative Technologies as a Driver of Social Development

The purpose of this study is to develop a universal procedure for modeling complex design problems for randomly changing technological processes. This work presents an analysis and proposes solutions that enable more precise design and management of processes subject to dynamic and often unpredictable changes.

The foundation of this research lies in the efforts of scientists and engineers to create solutions that improve the quality of life for people worldwide. The more complex the production process, the greater the demands placed on the designed machines. Increased customer awareness and the variability of geopolitical conditions contribute to the rise in randomly changing production processes, which must meet new requirements.

The level of innovation in an economy is reflected in the number of patents granted. According to data published in the World Intellectual Property Indicators 2021 report, the highest number of patent applications came from China (1,497,159), followed by the United States (597,172) and Japan (288,472) (WIPO, 2021). The percentage share of patent applications by region is as follows:

1) 66.6% Asia
2) 19.3% North America
3) 10.9% Europe
4) 1.6% Latin America and the Caribbean
5) 1.1% Oceania
6) 0.5% Africa

Most projects are currently carried out in Asia, with China playing a leading role. However, translating investments in innovation into products remains a challenge. Global statistics divide economies into four technological groups: low, medium, medium-high, and advanced technology (Galindo-Rueda & Verger, 2021). The more advanced the industry, the higher the demands placed on designers in terms of skills and speed of response to changing conditions.

Every institution operates in the real world and must be prepared for changing economic conditions. The more complex the process, the more resilient it must be to changing conditions. Therefore, 21st-century designers need to analyze far more variables than in the past. Creating innovative designs requires vision, experience, and the courage to face challenges. In the past, less complex technical solutions were developed, and designers did not have access to advanced tools supporting analysis and decision-making, which are available today.

In the following sections of this work, the author presents a set of original methods to support the analysis, evaluation, and optimization of various design processes.

2. Review of Forecasting, Optimization, and Project Management Methods

2.1. Introduction

Modern technological processes are defined by high variability and dynamism, driven by rapid technological advancements, evolving customer demands, and fluctuating market and geopolitical conditions. Managing projects within such unpredictable environments necessitates the use of advanced analytical and modeling methods that can effectively support decision-making and the optimization of technological processes. Developing a methodology that integrates a variety of tools and techniques has become essential, as it enables a more profound understanding of project complexity and facilitates adaptation to dynamic changes.

Since 1993, the author of this study has conducted extensive observational research and actively participated in the design of machines and industrial technologies. These experiences have revealed the necessity of organizing and systematizing tools that are useful for modeling design problems, especially in the context of unpredictable technological changes and the need to manufacture various products on a single production line. Historically, limited access to databases and insufficient data processing capabilities posed significant barriers to comprehensive project analysis. However, the development of Big Data technologies in recent decades has enabled efficient collection, processing, and analysis of vast data sets, creating new opportunities for modeling, project management, and customized production (tailored to the specific requirements of each client within the same production setup).

Today, with advanced tools, it is possible to apply multiple complementary methods within a single project, allowing for comprehensive verification across different contexts–technological, economic, social, legal, and environmental–while meeting the principles of a circular economy.

2.2. Comprehensive Overview of Analysis and Modeling Methods

This section aims to provide an extensive review of analytical and modeling tools that can aid engineers and designers in making informed decisions and optimizing technological processes. As highlighted by Trott et al. (2016), the methodology for managing technological entrepreneurship requires innovative approaches to integrate production processes. Table 1 classifies these methods into three main categories: universal methods, customer-oriented methods, and specialized methods. Each category has unique applications, essential at different stages of technology design and implementation. This classification aligns with the reliability concepts discussed by Saleh and Marais (2006), emphasizing the importance of robustness from the earliest design stages.

2.2.1. Universal Methods

Universal methods, as presented in Table 1, encompass a range of techniques widely employed across various industries and scientific disciplines. This includes 25 tools, such as the *Affinity Diagram*, *PDCA*, *Six Sigma*, and *Gantt Chart*. For instance, the Affinity Diagram facilitates the organization and analysis of complex data, which is particularly beneficial in the context of random technological changes, where there is a need to group unpredictable operations into logical clusters. Six Sigma, on the other hand, is effective in reducing process variability, which is critical when implementing new technologies under unstable conditions.

As depicted in Table 1, the use of universal methods allows for flexible project management and swift adaptation to changing conditions. The Gantt Chart exemplifies this, enabling dynamic project planning, which ensures efficient responses to unpredictable changes in both technological and organizational environments.

2.2.2. Customer-Centric Methods

Adapting technological projects to evolving customer needs requires methodologies that allow for continuous monitoring and response to market expectations. Table 2 outlines seven customer-centric methods, including Customer Satisfaction Score (CSAT), Net Promoter Score (NPS), and Quality Function Deployment (QFD). These methods provide organizations with tools to effectively assess how new technologies impact customer satisfaction and loyalty, which is crucial for maintaining market competitiveness.

As illustrated in Table 2, using methods like QFD facilitates a quicker translation of customer requirements into technical specifications, thereby enhancing the efficiency of product adaptation to evolving market demands. This enables organizations to introduce innovations more effectively, meeting the expectations of consumers and service users.

2.2.3. Advanced Specialized Methods

The design of complex technological systems, influenced by numerous random variables, requires the application of sophisticated, specialized methods. One of the most effective approaches to managing such projects is the combination of sequential optimization and reliability assessment, which facilitates precise planning and control of technological processes (Du & Chen, 2004).

Sequential Minimal Optimization has proven to be a fast and efficient algorithm for training Support Vector Machines (SVMs), significantly enhancing the analysis of large datasets (Platt, 1998). Additionally, the SVM model, developed by Cortes and Vapnik (1995), has become a widely recognized tool in data analysis due to its versatility and precision.

As the modern information society grows increasingly complex-encompassing embedded systems and diverse applications – the requirements for system reliability have also intensified. Addressing these growing concerns has driven the advancement of sophisticated methods for modeling and optimizing technological systems (Pham, 2006).

A summary of specialized techniques is provided in Table 3, featuring 24 selected tools such as the Monte Carlo Method, Markov Model, and Harmonic Analysis. These tools allow for precise simulations and risk assessments, offering insights into how random factors affect projects, thereby enabling early detection of potential issues.

The Monte Carlo Method, as demonstrated, is particularly effective in simulating risk scenarios, providing insights into how different variables influence project stability and technological processes. Similarly, the Markov Model is employed in analyzing stochastic systems, offering predictive capabilities and facilitating the understanding of dynamic technological changes, thus enhancing the efficiency of managing complex design processes.

The breakthroughs in analyzing design problems have been made possible by the evolution of Big Data technologies, which support the efficient collection, searching, and analysis of extensive data sets. In the past, limited access to advanced databases and data processing tools hindered comprehensive project analysis, reducing the ability to integrate various methods effectively. Today, Big Data technologies enable the use of complementary tools, allowing for comprehensive analysis across diverse contexts––technological, organizational, market, economic, and environmental.

Table 4 presents a summary of 40 essential software tools that assist in project management. Integration with cloud-based solutions and real-time collaboration tools enhances flexibility and efficiency, making it easier to adapt projects to rapidly changing conditions.

2.3. Multi-Context Approach for Project Verification

A multi-context approach enables comprehensive project assessment across technological, economic, environmental, social, and legal dimensions, addressing the complexities inherent in modern technological processes. By integrating methods from Tables 1, 2, 3, and 4, this approach enhances adaptability and resilience, supporting the core goal of effective modeling and optimization of design problems in the face of random technological changes.

Universal methods such as Gantt Charts and PDCA (Table 1) aid in dynamic planning and continuous improvement, ensuring that technological solutions are integrated smoothly within projects. Tools like Digital Twins facilitate virtual simulations, allowing organizations to mitigate risks associated with system compatibility and performance before physical implementation. Customer-centric approaches, including Customer Satisfaction Score (CSAT) and Net Promoter Score (NPS) (Table 2), assist in aligning projects with evolving market demands, while economic analysis tools ensure cost-efficiency and optimized resource allocation. Scenario planning and sensitivity analyses help organizations navigate financial viability even under fluctuating conditions.

Specialized methods like Life Cycle Assessment (LCA) and Environmental Impact Analysis (EIA) (Table 3) are essential for evaluating sustainability, enabling projects to minimize ecological impacts and comply with environmental regulations. This is particularly important for projects aiming to meet the principles of a circular economy. Furthermore, projects often face scrutiny regarding their social and ethical implications. Utilizing Social Impact Assessments (SIA) alongside methods like Quality Function Deployment (QFD) (Table 2) ensures that projects respect community welfare, data privacy, and ethical standards, fostering trust and adherence to regulatory frameworks.

Legal compliance is a critical aspect of project verification, especially for projects with global reach. Integrating compliance tools from Table 4 helps maintain adherence to diverse legal requirements, reducing potential liabilities and ensuring that technological solutions meet all necessary standards. Additionally, predictive modeling and real-time analytics, supported by software tools listed in Table 4 such as LIBSVM and Monte Carlo simulations (Table 3), allow organizations to anticipate challenges and adjust strategies dynamically, making project management more resilient to unexpected changes.

The multi-context approach directly supports the effective modeling and optimization of design problems, which is the central theme of this study. By integrating universal, customer-centric, and specialized methods, projects can be holistically evaluated and managed, ensuring flexibility and robustness against random technological changes. This comprehensive verification process leads to more informed decision-making, proactive risk management, and long-term project success, essential for thriving in an environment where technological advancements and market demands evolve rapidly.

Table 1. Universal Methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
1	Affinity Diagram (K-J Method)	Facilitates the organization and synthesis of brainstorming data, enabling identification of critical elements and informed decision-making.	Essential for grouping unpredictable technological variables into logical clusters, aiding in the structured analysis of random changes.
2	APQC (American Productivity & Quality Center)	Provides a framework for process structures and performance metrics, enabling strategic decision-making and process optimization.	Assists in evaluating efficiency and adaptability to changes in the technological landscape, fostering resilience in process adjustments.
3	Brainstorming	Encourages rapid idea generation and creative solutions, enhancing the adaptability and flexibility of decision-making processes.	Vital for fostering organizational adaptability, particularly in environments experiencing sudden technological changes and innovation.
4	BS 5750 Quality Standard	Supports the maintenance of process quality by aligning decision-making with established quality benchmarks.	Quality standardization simplifies management under changing technological conditions, promoting stability and consistency in dynamic environments.

Table 1 (cont.). Universal Methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
5	Five Whys (method for identifying root causes by asking "why" five times)	Facilitates the identification of fundamental issues, enabling more effective, targeted decision-making.	Highly effective for swift problem resolution in response to unexpected technological challenges, driving root-cause analysis of unforeseen changes.
6	Gantt Chart	Enables structured project management through timeline visualization and tracking, supporting clear scheduling and progress oversight.	Allows for dynamic adjustments in project timelines to accommodate random and unforeseen technological shifts, enhancing project flexibility.
7	Ishikawa Diagram	Provides a structured approach to identifying causes of issues, supporting more precise and efficient process improvements.	Aids in understanding the influence of various factors on project quality, especially in dynamic technological environments where causes are varied.
8	Just-In-Time (JIT)	Optimizes production by aligning outputs with real-time demand, reducing waste and enhancing resource allocation efficiency.	Facilitates agile resource management in response to rapid changes in technology, reducing the impact of unexpected shifts in demand and supply.
9	Kaizen	Focuses on continuous, incremental improvements in processes, fostering sustained growth and development in performance.	Supports adaptive, incremental changes necessary for continuous alignment with unpredictable technological advancements.
10	KPI (Key Performance Indicators)	Provides metrics for monitoring progress toward business goals, allowing ongoing optimization of organizational processes.	Enables the evaluation of goal attainment and strategic alignment in the face of fluctuating technological variables.
11	Lean Project Management	Minimizes waste by focusing on value-driven outcomes, enhancing resource efficiency and operational simplicity.	Allows rapid adaptation to evolving technological requirements, supporting lean, resource-efficient project strategies in volatile conditions.
12	Lean Software Development	Streamlines software development processes, fostering efficiency in IT project management and product delivery.	Ideal for managing random technological changes in IT, as its adaptability to varying project conditions supports sustained alignment with changes.
13	Matrix Diagram	Clarifies relationships among project components, facilitating a more integrated understanding of project elements.	Essential for adapting to technological variability by mapping dependencies and interactions, enhancing overall project resilience.
14	PDCA (Plan-Do-Check-Act)	Provides a continuous improvement cycle for process optimization, promoting iterative decision-making and refinements.	Enables responsive adjustments to technological shifts by supporting structured iteration and continuous learning.
15	PMA (Performance Measure Approach)	Enhances operational resource management by linking performance metrics to operational goals.	Reduces risk and fosters rapid response in technological projects by monitoring key performance metrics under changing conditions.
16	PRINCE2 (Projects in Controlled Environments, a structured project management method)	Provides a robust, structured approach to project management, enhancing control and accountability.	Effective in managing unpredictable technological shifts by ensuring consistent project controls and structured methodologies.
17	RBD (Reliability Block Diagram)	Visualizes system reliability, supporting resource allocation and preventive maintenance.	Facilitates reliability assessments, particularly critical in fluctuating technological environments where system dependability must be ensured.

Table 1 (cont.). Universal Methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
18	Six Sigma (6σ)	Reduces process variability and defect rates, leading to enhanced quality and optimized performance outcomes.	Mitigates error rates resulting from sudden technological changes, maintaining consistency and quality standards in unpredictable environments.
19	SMO (Sequential Minimal Optimization)	Optimizes support vector machine models, enabling efficient, rapid decision-making through machine learning.	Useful in optimizing AI algorithms for adaptive responses to technological changes, particularly in data-intensive environments.
20	SORA (Sequential Optimization and Reliability Assessment)	Supports process optimization by incorporating uncertainty into planning, fostering robust project outcomes.	Especially relevant for assessing and modeling risks in technology-intensive projects, enhancing predictive reliability in dynamic contexts.
21	SPC (Statistical Process Control)	Monitors and controls processes statistically, ensuring stability in operational processes.	Allows rapid adaptation of production processes to technological changes by identifying deviations early.
22	SWOT (Strengths, Weaknesses, Opportunities, Threats) Analysis	Aids strategic planning by analyzing strengths, weaknesses, opportunities, and threats.	Essential for assessing risks and opportunities in response to unexpected technological changes, enhancing strategic flexibility.
23	TQM (Total Quality Management)	Engages employees in continuous improvement, boosting overall process quality and efficiency.	Minimizes risk associated with technological change by embedding quality practices at all organizational levels, supporting resilient adaptation.
24	Tree Diagram	Assists in modeling decision pathways, providing a structured approach to complex decision-making.	Useful for probabilistic scenario analysis, particularly in technology-driven contexts where decision complexity is elevated.
25	LIBSVM (Library for Support Vector Machines)	Facilitates machine learning and data processing, enabling advanced analysis and optimization.	Supports optimization problem-solving, multi-class classification, probability estimation, and parameter selection in technology-centric projects.

Table 2. Customer-centric methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
1	CES (Customer Effort Score)	Measures the ease with which customers achieve their goals, supporting customer service process optimization.	Helps companies identify improvements in adaptive processes in response to technological changes, enhancing customer experience and efficiency.
2	CSAT (Customer Satisfaction Score)	Assesses customer satisfaction levels, guiding decisions to optimize product and service offerings.	Enables the evaluation of the impact of technological changes on customer satisfaction, providing insights into areas for further improvement.
3	NPS (Net Promoter Score)	Measures customer loyalty, supporting customer service and retention strategy optimization.	Allows companies to quickly adapt strategies to respond to technological changes, maintaining customer loyalty and engagement in evolving markets.
4	DRS (Dual Response Surface)	Optimizes processes and products through experimental design, improving response precision and adaptability.	Facilitates scenario modeling and prediction of technological changes' impacts on products, enhancing resilience to market shifts.
5	DACE (Design and Analysis of Computer Experiments)	Supports engineering and analytical process optimization by allowing detailed experimental design and analysis.	Enables modeling of complex technological projects with multiple variables, improving adaptability to random process changes.

Table 2 (cont.). Customer-centric methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
6	QFD (Quality Function Deployment)	Translates customer needs into technical specifications, aiding product development and ensuring customer-centric designs.	Helps companies adapt products to evolving technological demands, ensuring relevance and alignment with customer expectations in dynamic markets.
7	MUSA (Multi-Criteria Satisfaction Analysis)	Assesses customer satisfaction across multiple service and product aspects, providing a holistic view of customer experience.	Analyzes the impact of new technologies on customer satisfaction, modeling future customer behaviors and preferences to inform strategic planning.

Table 3. Specialized methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
1	Boolean Algebra	Optimizes processes through logical evaluation of design scenarios, ensuring systematic and efficient analysis.	Facilitates modeling of random technological scenarios, improving precision in scenario-based decision-making.
2	Harmonic Analysis (Fourier Analysis)	Useful for analyzing signals and processes that vary over time, aiding in frequency-based data decomposition.	Enables modeling of dynamic technological changes, capturing time-based fluctuations essential in adaptive processes.
3	Pareto-Lorenz Analysis	Identifies key factors affecting processes based on the 80/20 principle, improving focus on critical issues.	Effectively models technological changes by allocating resources based on priority, optimizing resource management.
4	Rosenbrock Function	Optimizes nonlinear problems, supporting complex engineering processes by minimizing error margins.	Aids in optimization analysis for new technologies, ensuring robust solutions to nonlinear design challenges.
5	RNG (Random Number Generator)	Essential for simulations and optimizing processes requiring random data, adding stochastic elements for realistic modeling.	Enables modeling and simulation of processes involving unpredictable variables, enhancing system flexibility in real-time adjustments.
6	CMMI (Capability Maturity Model Integration)	Improves process quality and supports organizational function integration, facilitating higher standards.	Prepares organizations for dynamic technological shifts by aligning process maturity with adaptability.
7	Kriging	A spatial data prediction tool that aids in precise optimization of resources in design.	Allows analysis of spatial variables in technological projects, particularly beneficial in predictive modeling of environmental conditions.
8	LS (Least Squares Method)	Minimizes discrepancies between predicted and actual values, enhancing predictive accuracy in variable processes.	Useful in modeling design problems with random variables, providing stable and reliable projections.
9	MCMC (Markov Chain Monte Carlo)	Enables scenario simulation and outcome prediction, enhancing decision-making under uncertainty.	Assists in analyzing complex design problems with uncertain variables, refining risk assessment in unpredictable technological environments.
10	Dimensionality Reduction	Reduces the number of variables in complex systems, streamlining process optimization by focusing on critical data.	Enables efficient analysis of projects with numerous technological variables, managing complexity in large-scale simulations.
11	Mission and Vision Statement Methods	Crucial for strategic, long-term decision-making, guiding organizations toward consistent objectives.	Adapts organizational actions to evolving conditions, allowing better process planning to meet future challenges.
12	Gaussian Quadrature Methods	Used for precise integration calculations, supporting process optimization through accurate numerical results.	Enables precise modeling of design problems under variable conditions, reducing calculation errors in complex scenarios.

Table 3 (cont.). Specialized methods

Lp.	Method Name	Usefulness in Decision-Making, Optimization, and Process Improvement	Usefulness in Analyzing and Modeling Design Problems in the Context of Random Technological Changes
13	Markov Model	Analyzes stochastic systems, aiding in the optimization of processes with inherent randomness.	Models systems where changes occur stochastically, useful in anticipating technological fluctuations.
14	Reliability Modeling, Analysis, and Optimization	Minimizes failure risks by analyzing system variables, improving operational dependability.	Models system behavior under dynamic changes, enhancing robustness in unpredictable conditions.
15	MDO (Multidisciplinary Design Optimization)	Enables optimization of various project aspects, promoting efficiency across engineering disciplines.	Assists in modeling projects requiring flexibility in response to technological variability, ensuring comprehensive adaptability.
16	RBMDO (Reliability-Based Multidisciplinary Design Optimization)	Optimizes engineering projects with a focus on reliability under challenging conditions.	Enables risk prediction and adapts projects to variable operational conditions, enhancing reliability in fluctuating environments.
17	BLUP and BLUE (Best Linear Unbiased Predictions and Estimators)	Aid in precise decisions based on predictive models, ensuring reliability in statistical projections.	Enable accurate estimation of effects in technological systems, particularly useful in quality control and variance prediction.
18	Moore's Law	Helps forecast technology development trends, guiding long-term planning in high-tech industries.	Allows modeling of long-term technological projects, offering insights into development pace and innovation potential.
19	Hotelling's T-squared Distribution	A statistical tool for multivariate analysis, aiding in the detection of significant deviations across variables.	Assists in analyzing technological variables and their impact on future outcomes, supporting robust design through statistical validation.
20	Taguchi Method	Optimizes design parameters, minimizing the impact of random variables on process quality.	Enables better modeling and optimization of projects under variable conditions, enhancing resilience against random fluctuations.
21	Monte Carlo Simulation	Widely used to predict outcomes based on random sampling, supporting probabilistic decision-making.	Facilitates modeling and prediction of outcomes in scenarios with multiple random variables, ensuring adaptable planning in uncertain fields.
22	VR (Virtual Reality)	Simulates complex scenarios, valuable for testing design concepts and training personnel in a controlled environment.	Enables modeling and testing of new technological solutions, reducing real-world trial risks and accelerating the innovation cycle.

Table 4. Summary of software supporting design work

Creator/Key Person	Program/Software	Year
Patrick J. Hanratty	PRONTO	1957
Ivan Sutherland	Sketchpad	1960
MAGI	Modele krawędziowe 3D (Synthavision)	1969
Siemens	Siemens NX	1973
Bentley Systems	MicroStation	1980
Graphisoft	ArchiCAD	1982
Autodesk	AutoCAD	1982
Dassault Systèmes	CATIA	1982
Vectorworks, Inc.	Vectorworks	1985
IMSI/Design, LLC	TurboCAD	1986
T-FLEX	T-FLEX CAD	1989
Parametric Technology Corporation (PTC)	Pro/ENGINEER	1989
CAS Berlin	Interactive NURBS modeling program	1993
Siemens Digital Industries	Solid Edge	1995
Dassault Systèmes	SolidWorks	1995

Table 4 (cont.). Summary of software supporting design work

Creator/Key Person	Program/Software	Year
Autodesk	Revit	1997
Visionary Design Systems (VDS)	IRONCAD	1998
Alibre, Inc.	Alibre Design	1999
Autodesk	Autodesk Inventor	1999
IntelliCAD Technology Consortium (ITC)	IntelliCAD	1999
Trimble Inc.	SketchUp	2000
Bricsys nv	BricsCAD	2002
CAD Schroer	MEDUSA	2002
Kubotek3D	KeyCreator	2004
Remograf AB	Remo 3D	2005
SpaceClaim Corporation	SpaceClaim	2007
Encore Software, LLC	PunchCAD	2008
Alludo	CorelCAD	2011
PTC	PTC Creo	2011
Autodesk	Fusion 360	2013
Promine Inc.	Promine	2015
Robert McNeil and Associates	Rhinoceros 3D	2020
AgiliCity d.o.o	Modelur	2021
Bricsys nv	BricsCAD Shape	2022

2.4. The Importance of Historical Data in Analyzing Technological Trends

Historical data play a crucial role in the process of analysis and modeling, particularly in understanding and predicting trends within technological systems. In the 2021 publication, *Theory of Efficient Preparedness and Operation of the Military and Emergency Manufacturing Industry*, I introduced a unique hypothesis known as *4 Steps + What Next?* (4SH+WN) (Knast, 2021), which emphasizes continuous inquiry by asking, “what next?” at every decision point.

Every decision made within a workplace or institution impacts production, safety, and future opportunities, either creating new possibilities or imposing constraints. The *4SH+WN* methodology facilitates the modeling of complex design problems, especially for processes subject to random technological changes, by enabling better scenario planning and future forecasting. The foundation of this approach is the idea that all history is essentially everything that has passed. By this definition, even a fraction of a second ago is already history. Time dictates history, and though it cannot be reversed, it serves as a foundation upon which future predictions can be built. Hence, data gathered from past events can be stored, analyzed, and archived for future use.

In this framework, knowledge, scientific principles, formulas, and computational procedures are regarded as recorded history, expressed through numbers, dates, events, and statistical data. This historical record allows for a comprehensive understanding of machine operation times, human and machine behavior in various random scenarios, and other critical patterns. The collection of historical data, therefore, is boundless, limited only by the creativity of the designer who leverages it to forecast future scenarios based on identified trends and recorded similarities.

Decisions have a direct influence on the future, impacting not only the *time* that is yet to come but also the safety, efficiency, and success of processes. For instance, automated measurement systems in technologically unpredictable environments must be capable of reacting to events and waiting for triggers. Each decision affects safety in its broadest sense, encompassing the prevention of accidents, injuries, equipment damage, environmental risks, logistical and organizational disruptions, financial losses, legal consequences, and adherence to schedules and contractual obligations. Additionally, decisions can either create new opportunities or restrict them––affecting technological development, creativity, financial gains or losses, and overall safety and sustainability.

Moreover, decisions are not always explicit; sometimes, the act of *not making a decision* is itself an unconscious decision with consequences. Thus, understanding the impact of decisions, including those that may seem negligible, is vital. The *4SH+WN* methodology encourages constant reflection on the future implications of every action taken.

The methods and software tools described throughout this work aim to contribute to making the world a better and safer place. In the global macroeconomic context, production companies must be agile and responsive to changes. Figure 1 illustrates how events that occur anywhere in the world can quickly influence other regions through the interconnectedness facilitated by the Internet. For instance, a military conflict in one area can have a significant effect on global commodity prices. Technologies developed in one country are often rapidly disseminated across borders, reaching new enterprises and societies.

Global corporations, when designing a new product and distributing it through their worldwide networks, must adapt it to meet the expectations of customers across diverse regions, not just in a single country or continent. There are industries, of course, where specific products or services have limited applicability due to unique characteristics and purposes. The recent period of pandemics and climate change has highlighted how diminishing borders and increasing global interconnectedness force a reevaluation of production approaches. With modern production systems relying on vast amounts of information, many of which are random variables, the role of historical data becomes ever more essential.

For individual designers, the sheer volume of data to analyze can be overwhelming, underlining the need for robust methodologies to tackle design problems associated with randomly changing technological processes. By systematically organizing and utilizing historical data, designers can develop more adaptable, efficient, and resilient solutions that anticipate future challenges and capitalize on emerging opportunities.

3. Four Key Parameters in Modeling Technological Processes Amidst Random Changes

The evolution of design methodologies over the past 30 years has been remarkable, driven by the need for *stochastic design* and adaptive approaches in modern engineering. In the 1980s, drafting boards remained the standard tool in design offices worldwide, despite the early availability of CAD programs. It was not until the 1990s that the widespread adoption of 2D CAD software began, driven by demands for more efficient and precise design documentation. By the late 1990s and into the 2000s, the industry saw rapid advancements with the development of 3D CAD and engineering software capable of performing complex simulations–such as motion, deformation, and stress analysis–which are essential for assessing the strength and functionality of structural components.

Through my research spanning over three decades, I have developed an *original methodology* that identifies *four key parameters* essential for modeling and understanding random phenomena in technological processes: *time, path of displacement, mass,* and *temperature.* These parameters serve as the foundation for robust methodologies that can adapt to *random technological changes,* integrating principles of *artificial intelligence, process modeling,* and *system optimization.* This approach not only aids in accurate design but also ensures adaptability, essential in the rapidly changing technological landscape of the 21st century. The following sections will provide detailed justification for these parameters, showing how they support adaptive processes and contribute to broader goals in *data integration* and *technological innovation.*

3.1. Methodology for Continuous Analysis: The "What Next?" Approach

The complexity of real-world technological processes arises not only from the physical and chemical phenomena involved but also from various factors such as mathematical simplifications, numerical rounding, data sampling rates, measurement inaccuracies, model precision, and the ability to interpret results. A model that accurately reflects reality allows for more reliable conclusions and better decision-making.

Based on this understanding, I have developed a unique *four-step methodology* enhanced by a continuous inquiry, encapsulated in the principle of *"What Next?"* This method allows for a precise and iterative analysis of each process, ensuring that no aspect is overlooked and that each stage flows seamlessly into the next. This is illustrated in **Fig. 1**, which demonstrates how the structured approach ensures adaptability and forward-thinking, essential for effective management of *random technological changes.*

3.2. The "What Next?" methodology proceeds as follows

To introduce the "What Next?" methodology, it is essential to recognize that effective decision-making in uncertain environments relies on a systematic approach that not only anticipates future developments but also grounds actions in present realities. This methodology proceeds through the following four steps.

a) **Reality — and what next**?

Every process begins by observing and understanding the current state. Establishing this baseline is critical for building accurate models. However, recognizing the present is just the starting point. What next? The method requires anticipating shifts and preparing for adaptation, guiding the direction of further actions.

b) **Data Collection — and what next**?

Collecting data is essential, but it must be treated as a dynamic and ongoing process. What next? Effective data analysis ensures that collected information is transformed into actionable insights. Identifying patterns, anomalies, and trends allows for a deeper understanding of underlying processes, which is crucial for building reliable models.

c) **Building a Model of Reality — and what next**? Models are created to represent reality as accurately as possible. But their true value lies in their ability to predict and adapt. What next? After constructing a model, it is essential to validate and refine it through iterative testing. This step ensures that the model can handle real-world variability and adapt to unexpected changes, making it a robust tool for decision-making.

d) **Interpreting Simulation Results – and what next? Decision-making**.

Interpreting the results of simulations is crucial, but it should always lead to the question: What next? The insights gained must inform strategic decisions, guiding improvements, adjustments, and future planning. This final step ensures that actions are not just reactive but are proactively shaping the course of future developments.

This "**What Next?**" approach has been extensively tested across multiple projects over the years, consistently yielding positive results. Its flexibility and iterative nature make it an ideal framework for integrating artificial intelligence and adaptive technologies into design processes. The methodology's ability to trace back to historical data and combine this with forward-looking forecasting creates a robust system for managing unpredictable technological changes.

3.3. Bridging Historical Data with Future Forecasting

One of the key strengths of this original methodology is its ability to integrate historical data with predictive scenarios. This approach enhances the understanding of technological processes by creating a continuous feedback loop between past data and future projections. Fig. 1 illustrates how each stage, from data collection to decision-making, feeds into a continuous and adaptable loop, allowing for a seamless transition between understanding the past and anticipating the future.

By leveraging historical data, systems can identify patterns and trends that inform current operations. Combining this with multi-scenario forecasting improves the reliability of predictions, offering a higher probability of accuracy. This unique integration allows for strategic planning that is both informed by past events and adaptable to future changes. Current research continues to refine this integration, with the aim of further enhancing the precision and applicability of predictive models, which will be discussed in forthcoming publications.

3.4. Connection to the Core Theme – Managing Random Technological Changes

The seamless integration of the "What Next?" approach with the core theme of this study – Analysis and Modeling of Design Problems in the Context of Random Technological Changes – demonstrates its practical value. Fig. 1 visually captures how this methodology ensures a structured, adaptive response to the complexities of modern engineering environments. As technological changes become more frequent and unpredictable, the ability to adapt quickly and effectively is crucial. This method encourages a forward-thinking mindset, ensuring that systems are not just reactive but are strategically positioned to handle uncertainty.

3.5. Conclusion. Advancing Adaptive Design Through the "What Next?" Methodology

The *"What Next?"* methodology, meticulously developed by the author over decades of research and industrial application, presents a comprehensive framework for addressing complex design problems, particularly in the context of *random technological changes.* This approach has been extensively verified through numerous projects, demonstrating its effectiveness in real-world engineering environments. Unlike conventional methodologies, which often follow linear or static models, the *"What Next?"* approach introduces a dynamic, iterative system that enables continuous analysis, adaptation, and decision-making.

The strength of this methodology lies in its ability to not only address current challenges but also to create a robust connection between *historical data* and future scenarios. This dual capability allows for tracing past events to understand root causes while simultaneously building predictive models that prepare for potential future outcomes. The author posits a *hypothesis* that this ability to explore multiple variant scenarios––continuously asking "what next?" at every step––makes this method particularly suited to the demands of the 21st century. By generating and analyzing a range of possible scenarios, the approach enhances preparedness, adaptability, and strategic foresight.

Fig. 1 illustrates the broader implications of this methodology, showing how decisions made at one point can have ripple effects throughout a system, particularly in a highly interconnected, globalized world. As global integration and digitization increase, every decision influences a network of processes and organizations. The *"What Next?"* methodology ensures that each decision not only addresses the immediate issue but also considers its impact on safety, future possibilities, and constraints. By creating a structured loop of inquiry, this approach fosters a deeper understanding of complex systems and allows organizations to navigate changes more effectively.

Fig. 1. The higher the level of globalization and digitization in the world, the stronger the impact of each decision on other organizations. Every decision creates new opportunities or limits them to varying degrees. The speed of response to change, alongside technological development, is essential for efficient functioning in the 21st century

3.6. Integration of the "What Next?" Hypothesis and Decision-Making Cycle

The *"What Next?"* methodology can be visualized through a structured decision-making cycle, as depicted in Fig. 2. This figure represents the *hypothesis* of a four-step cycle, enriched with the continuous question of *"what next?"* The core concept revolves around analyzing the consequences of decisions and their impact on the environment. Each decision is not an endpoint but a point of reflection, prompting further actions and adjustments based on a comprehensive assessment of the situation.

The diagram in Fig. 2 outlines how the methodology guides decision-making across four key dimensions:

1) **Historical Data** – *and what is next?* By understanding past events, the methodology enables the identification of patterns and trends, which are critical for building accurate models of future scenarios. This backward analysis serves as a foundational step in ensuring that each decision is grounded in historical insight.
2) **Safety** – *and what is next?* Maintaining safety is a core requirement in any technological system. By continuously evaluating the implycations of each decision on safety, the methodology ensures that risks are mitigated effectively.
3) **Future Possibilities** – *and what is next?* The ability to anticipate and model future scenarios allows for strategic planning that can adapt to various outcomes, making the methodology inherently more robust than static approaches.
4) **Creating New Opportunities or Limitations** – *and what is next?* Each decision opens new pathways or imposes constraints, which must be carefully assessed. The *"What Next?"* approach helps organizations maximize potential while minimizing risks, ensuring that future options remain viable.

The structured nature of this method creates a continuous chain of inquiry, leading to an infinite loop of questions and answers. Each step feeds into the next, maintaining a dynamic flow of information and analysis. This iterative process enhances the ability to forecast future scenarios with greater precision, making the system more resilient to change. While traditional approaches may falter under the weight of complexity, the *"What Next?"* methodology thrives, using this complexity as a basis for deeper understanding and more accurate predictions.

To further enrich this section, it is essential to highlight that the proposed "What Next?" methodology facilitates rapid switching between scenarios, enabling the navigation of paths influenced by each key aspect triggered by a single decision. Every decision carries consequences, and thus decision-making presents challenges at every stage of design. Until a machine or process is activated, it remains impossible to be 100% certain of its functionality. Post-completion, with historical data in hand, it may become evident that an error was made. Such errors, however, can typically be attributed to unintentional oversights despite best intentions.

The system proposed herein, grounded in historical data to reveal the effects of each decision, is viewed by the author as a valuable approach. Moreover, past decisions should not be evaluated through a single lens or criterion. Single-criterion evaluations obscure the complexity of the model and leave numerous aspects unexplored.

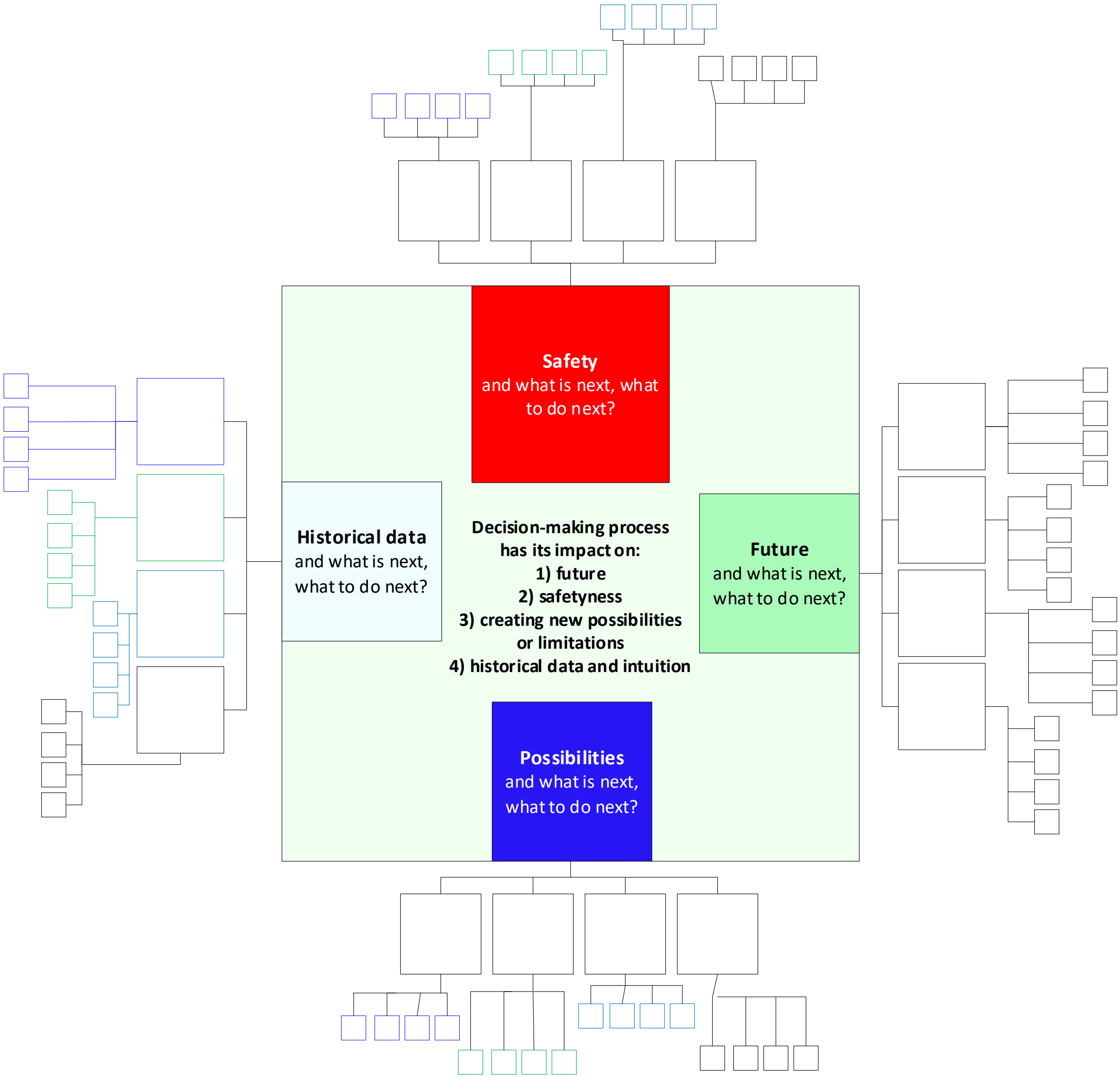


Fig. 2. The *"What Next?"* methodology, an original framework developed by the author, forms a multi-threaded network across four core areas – **Safety**, **Future**, **Possibilities**, and **Historical Data** – which are adaptable to any process or scientific discipline, fostering universal applicability and flexibility

In this methodology, the *"What Next?"* question, enhanced by the supplementary *"and what to do next?"*, serves as a structured approach to understanding complex environments and decision-making processes. As shown in Figure 2, it constructs a multi-threaded network across four primary domains: **Safety**, **Future**, **Possibilities**, and **Historical Data**. These domains provide a comprehensive view, universally applicable to both technological processes and fundamental aspects of human existence. Importantly, these threads are not rigidly defined; they can be modified or expanded to suit specific analytical or strategic needs. This flexibility makes the methodology inherently adaptable and suitable for various scientific disciplines and practical problem-solving scenarios, as it does not constrain the user to a fixed structure. Instead, it encourages a dynamic and responsive approach, ideal for situations requiring adaptive and strategic foresight.

3.7. Universal Application and Future Research Directions

The author asserts that this methodology is not confined to engineering alone. Its principles can be applied across a wide range of fields, including business management, logistics, healthcare, and other areas where the need for adaptive, real-time decision-making is crucial. By creating a flexible system that allows for both *retrospective analysis* (looking back at past events) and *future-oriented planning*, the methodology presents a universal tool for addressing the complexities of modern systems.

A key aspect of this approach is its ability to *integrate historical insights* (combine knowledge from past experiences) with *future forecasting* (predicting future events), effectively bridging the gap between past events and future possibilities. This unique capability allows for a more *holistic understanding* (comprehensive view of the whole system) of processes, facilitating more accurate predictions and better-informed decisions. The author introduces a *hypothesis* that this approach, by fostering the *exploration of multiple variant scenarios* (analyzing different possible outcomes) and continuously asking, *"what next?"* at each stage, is more relevant and adaptable than many conventional methods. This makes it particularly valuable for modern systems, as it aligns with the need for more flexible and adaptive strategies in the 21st century.

Figure 3 highlights the complexity of modeling reality, showing how it consists of interconnected factors that are inherently multifaceted. Reality, in this context, is seen as *multi-threaded* (involving multiple, simultaneous processes), *behavioral* (reflecting actions and reactions), *stochastic* (possessing many scenarios that can occur randomly with different probabilities, much like rolling a die where outcomes range from one to six), and *predictive* (capable of forecasting future events). The figure illustrates how *reality is always complete (100%)*, but the *data collected* about the process often falls short, leading to a model that may not capture every detail. The more data we can gather and the better we can interpret it, the closer the model approximates reality. However, even with substantial data, there will always be scenarios or situations that change unpredictably, requiring rapid analysis and adjustment.

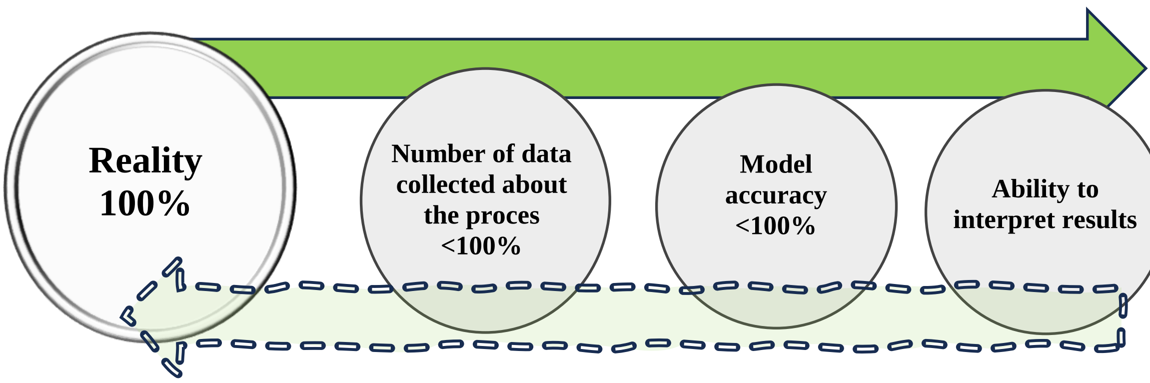


Fig. 3. The *"What Next?"* hypothesis with a supplementary question of *"and what to do next?"* This is an *original methodology* developed by the author, designed to analyze the consequences of decisions and their impact on the environment. The approach is based on the continuous inquiry of *"what next?"* at each stage, fostering a deeper understanding, proactive decision-making, and strategic adaptability

This dynamic aspect makes planning for future production, technological, and everyday events extraordinarily complex, necessitating instant processing of new information. The continuous feedback cycle, as depicted in Figure 3, underscores that the *accuracy of the model depends* on how well we can interpret results and adjust strategies in real-time. Thus, even with robust models, unexpected changes or new scenarios can still emerge, requiring adaptability.

The author's *hypothesis* concerning *model accuracy* (the ability of the model to precisely reflect reality) is especially significant here. While models aim to replicate reality, their effectiveness is inherently tied to the level of knowledge, skills, and experience of those developing them. A well-informed and experienced designer will build models that closely mirror real-world processes, reducing errors and inaccuracies. Conversely, models created with less knowledge or experience are prone to more significant deviations from reality, potentially leading to ineffective or even useless solutions. This awareness of the *imperfections* and simplifications in processes is crucial at the design stage, as it allows for the integration of *adaptive systems* (systems that can change and adjust based on new information) capable of adjusting to new information or unexpected scenarios.

This capability, once technically unattainable, has become feasible due to recent advancements in data processing and algorithmic development. The author is actively engaged in further research to develop sophisticated algorithms that enhance this methodology, aiming to improve its *predictive accuracy* (the ability to foresee and model future outcomes accurately) and applicability. Future publications will explore these developments in greater detail, providing insights into how this system can continue to evolve and adapt to new challenges, thereby offering a robust framework not just for engineering but for a broad spectrum of applications.

By acknowledging that reality is subject to constant change and by preparing for multiple outcomes, this methodology allows organizations to navigate complex, multifaceted realities with greater precision. The continuous loop of inquiry–asking *"what next?"* at every step–ensures that systems are not just *reactive* (responding after something happens) but can *proactively adapt* (adjust in advance) to new challenges. This approach aligns well with the needs of modern, interconnected environments, where quick adaptation is essential for success.

4. Four Key Parameters in Modeling Technological Processes Amidst Random Changes

Reality contains an infinite number of parameters that can not only be represented through mathematical, physical, and chemical dependencies but are also influenced by behavioral factors of living beings, nature, and economics.

An excess of information complicates swift decision-making and requires enormous computational power from computers. Too much collected data can cause a model to deviate further from reality, which, in extreme cases, renders it useless, as it prevents proper interpretation of simulation results. Reality is a set that has more data than we are capable of collecting, and the collected data is useful only as long as the model is sufficiently accurate, and the analyst can interpret the measurement results correctly. These can be recorded in the form of interrelated data sets, according to the following relational expressions (1) and (2):

$$R > D \cap M \cap I \tag{1}$$

$$100\% > (D \cap M \cap I) \cdot 100\% \tag{2}$$

where:
R – the set of phenomena occurring in reality, which can be expressed as a percentage,
D – the set of data recorded based on measurements in reality,
M – the set of elements processed in the model,
I – he set of results from simulations conducted in the model and their interpretation.

4.1. Time as the Key Parameter Describing Random Phenomena in Reality

Every movement can be repeated, and every design can be modified, but one technical parameter remains shrouded in the mystery of today's technological state. It is *time*, which we can measure but cannot reverse (see Figure 4).

Fig. 4. Time is a parameter that determines all processes occurring in the world because, in our current state of knowledge, we cannot turn it back

Time flows in one direction. Every action can be repeated, but it will not take place in the same time frame. This is akin to a process observed in a river. When stepping into the current, each fraction of a second brings a different drop of water into contact with us.

Repeating any action will always involve a different time. Customers demand that suppliers specify the delivery time of a product. To meet these requirements, employers strive to influence employees to complete tasks in accordance with schedules. Goods are expected to arrive at the production facility at a specified time. Any system failure leads to time disruptions and delays, creating a cascade of events with random variables.

Time begins in infinity, and on its axis, a zero point is set, symbolizing the start of the time measurement. From this point, we count and measure its passage. According to the author, it is possible to categorize time into four distinct types:

Absolute time (Figure 5) flows continuously, unidirectional, and beyond our control. It cannot be reversed, halted, or moved into the future; it can only be measured.

$$T_b(t) = \int_{-\infty}^{0} f(t)dt + \int_{0}^{t_1} f(t)dt \tag{3}$$

where:
T_b – absolute time,
$f(t)$ – function of time,
dt – integration variable,
t_1 – considered time interval.

The illustration (Figure 5) represents the concept of absolute time, flowing continuously from negative infinity, through a defined zero point (the start of measurement), and extending into positive infinity. This visual emphasizes the unidirectional nature of time, which progresses steadily and cannot be altered, paused, or manipulated. The years marked, such as "Year 0" and "Year 2024," signify specific points in time, demonstrating how events are anchored on this perpetual timeline.

According to the author of this study, determining the absolute beginning of time is almost impossible with the current state of scientific knowledge. It represents a kind of “**black hole of ignorance**,” a boundary to our present understanding of the universe. This lack of complete knowledge about the absolute origins of time presents a fascinating challenge for scientists, inspiring new research and exploration. Reflections on the beginning of time and its absolute nature impact numerous scientific and philosophical disciplines, offering a perspective for discoveries that could fundamentally broaden our comprehension of reality.

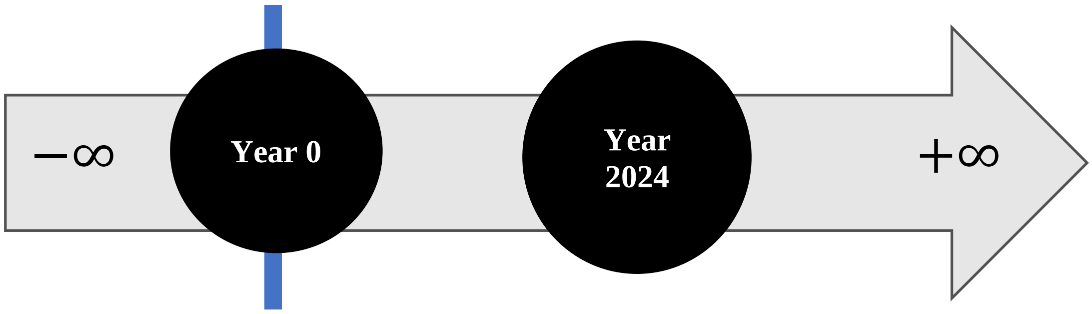


Fig. 5. Absolute time, over which we have no control and which we cannot reverse, pause, or move into the future. This visualization represents the unidirectional nature of time, which flows steadily and cannot be altered, paused, or reversed. The years marked symbolically as "Year 0" and "Year 2024+" represent specific points along the timeline, demonstrating how events are anchored on this uninterrupted axis

4.2. Hypothesis of Relative Time – New Perspectives in Management and Adaptive Technologies

The concept of relative time, formulated by Albert Einstein in 1905 within the framework of the theory of relativity, revolutionized our understanding of time and space in physics. In that context, time is dependent on the speed of objects, leading to a time-dilation effect for objects moving at high speeds relative to a stationary observer. While this concept had profound implications for the natural sciences, its application was primarily limited to cosmic scales and physical phenomena.

The hypothesis of relative time proposed by the author of this work extends this classical concept to the fields of management, production operations, and adaptive technologies. It proposes treating time as a dynamic resource, dependent not only on speed but also on a broad operational, decision-making context, as well as on the subjective experience of process participants. This new interpretation of time finds particular application in management systems and artificial intelligence (AI) algorithms, enabling a more adaptive and precise approach to analysis and optimization.

4.2.1. Key Elements of the New Hypothesis of Relative Time

The hypothesis introduces several foundational elements that expand the classical understanding of time, making it applicable to complex operational contexts.

1) **Multicriteriality and Relativity in the Operational Context**

The hypothesis assumes that the passage of time can be interpreted differently depending on reference points, creating a multicriterial matrix of references (a system of multidimensional references, where various decision-making factors serve as reference points). In this view, time is dynamic and depends on conditions specific to a given situation. For instance, 5 minutes for someone waiting at a cold bus stop will be perceived differently than 5 minutes spent on an intensive task. This relativity forms the basis for more flexible management models, particularly in environments that require rapid decision-making.

2) **Application in Decision-Making and Adaptive Systems**

The author proposes applying this hypothesis in management and adaptive technology systems, where relative time can support decision-making models that adjust to dynamically changing operational conditions. In artificial intelligence (AI) systems, relative time can be treated as a variable that allows for precise resource management and real-time response to changes, which is crucial for enhancing operational efficiency.

3) **Time as a Function of Subjective Experience and Operational Reference Points**

In the new hypothesis, time is defined not only as a linear progression of moments but also as a multidimensional quantity whose perception depends on the subjective experience of process participants and the operational context. The same passage of time can be perceived differently depending on the situation and the reference point, which is significant in management, where subjective perceptions of time influence the quality and efficiency of task execution.

4) **Integration with AI Systems and Forecasting Capabilities**

This hypothesis opens up new perspectives in artificial intelligence, where relative time can be utilized for forecasting and operational optimization. In AI systems, relative time functions as a dynamic factor that adapts algorithms to changing operational conditions, enabling more flexible modeling of future scenarios.

4.2.2. Formulation of the Relative Time Hypothesis

The mathematical model of relative time assumes that the passage of time can be expressed as a function of variable reference points and the operational context:

$$T_{\mathrm{w}} = f\,(t_0, t_1, C) \tag{4}$$

where:
T_w – relative time,
t_0 – initial reference point,
t_1 – final reference point,
C – context vector.

The context vector includes subjective and operational factors such as emotions, environmental conditions, task complexity level, behavioral factors, and others depending on the process. This approach enables precise modeling of relative time by taking into account contextual variability and process specifics, leading to a more nuanced interpretation of time passage.

The formulas below provide the mathematical basis for the relative time hypothesis. Formula 5 defines relative time as the difference between time reference points, while Formula 6 incorporates additional operational factors:

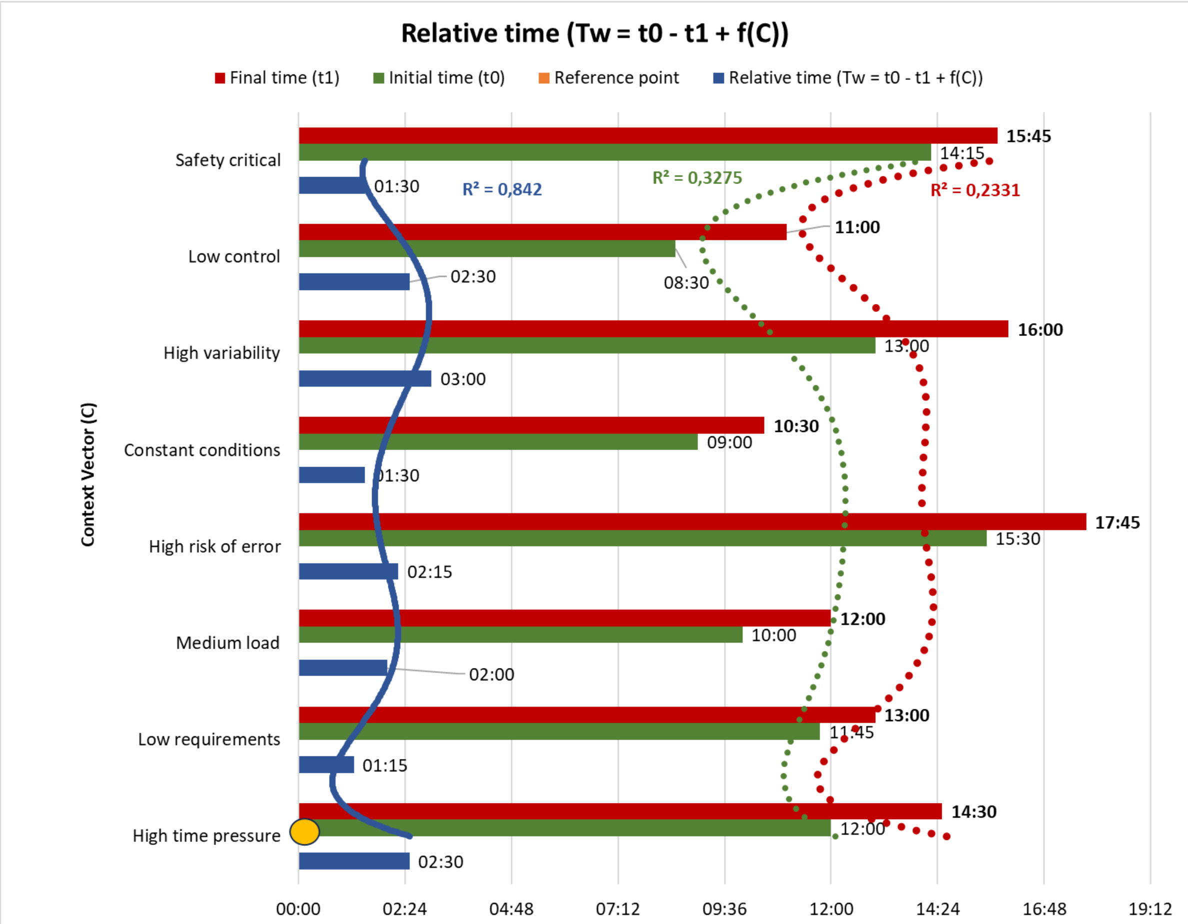
$$T_{\mathrm{w}} = t_0 - t_1 + f\,(C) \tag{5}$$

$$\int_{t_0}^{t_1} T_w dt = \sum_{i=1}^{n} (t_{i+1} - t_i) \cdot C \tag{6}$$

where:
n – denotes the number of reference points,
C – represents the influence of specific process conditions.

Figure 6 depicts dynamic changes in physical parameters such as acceleration and force over time. The graph shows the evolution of these parameters from the initial point t_0 to the final point t_1, illustrating their non-linearity and challenging-to-predict variability. This is an illustration of real-world processes that often exhibit considerable complexity and are sensitive to changes influenced by the operational context. In the context of the relative time hypothesis, this figure emphasizes the importance of forecasting variables in engineering and design processes and highlights the critical need for developing adaptive systems. This allows engineers to design systems that better respond to dynamic environmental changes.

Figure 7 illustrates the multidimensional model of relative time, using the example of vehicles moving along the same route but at different speeds. Each vehicle experiences a distinct operational time, influenced by both internal parameters, such as speed or load, and external conditions, such as traffic density, weather, and traffic management priorities. This figure demonstrates the concept of relative time, which is of particular importance in systems that require rapid decision-making.



	High time pressure	Low requirements	Medium load	High risk of error	Constant conditions	High variability	Low control	Safety critical
Final time (t1)	14:30	13:00	12:00	17:45	10:30	16:00	11:00	15:45
Initial time (t0)	12:00	11:45	10:00	15:30	09:00	13:00	08:30	14:15
Reference point	0	0	0	0	0	0	0	0
Relative time (Tw = t0 - t1 + f(C))	02:30	01:15	02:00	02:15	01:30	03:00	02:30	01:30

Fig. 6. An example illustrating dynamic changes in a process from the initial point (nominally assigned time t_0) to the endpoint (measured time t_1). The chart depicts the multi-criteria and variability of real-world processes, which require flexibility and adaptability within changing operational conditions, described by the Context Vector, presenting an alternative perspective on time across various contexts

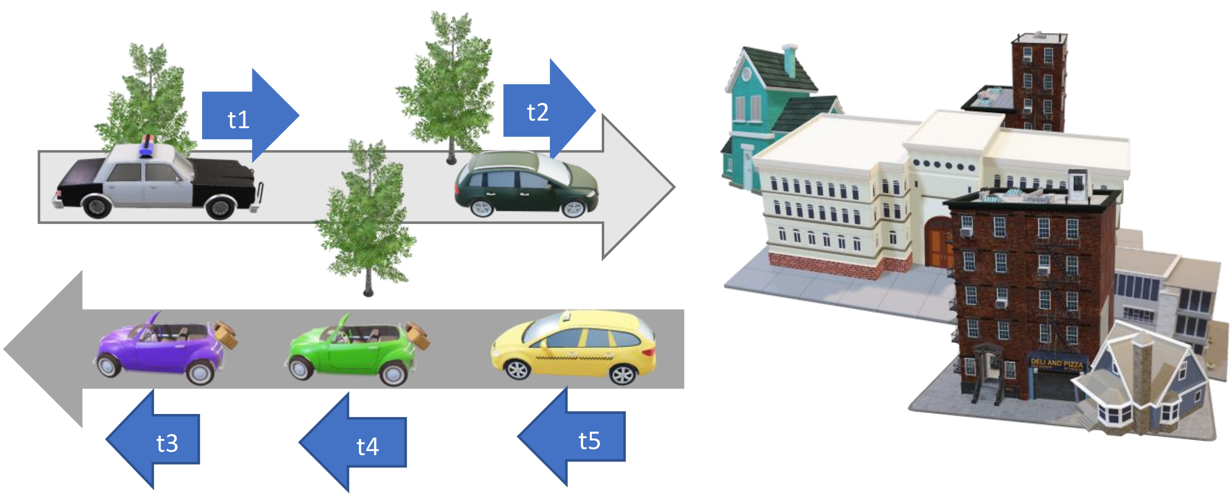


Fig. 7. The diagram illustrates the concept of relative time using the example of vehicles traveling the same route at different speeds. This example demonstrates how the relativity of operational time impacts logistical and operational management in dynamic conditions, which is essential for rapid decision-making and AI system adaptation

4.3. Forecasted Time

Forecasted time refers to phenomena and processes that are subject to influence through the construction and planning of solutions where time is a critical factor, such as machine efficiency, process speed, completion deadlines for various tasks, machine delivery, etc.

When designing a new machine, device, or process, historical indicators from similar solutions can be utilized. This approach allows for the identification of a much-needed reference point, if available, based on staff interviews and archived process records. Based on these sources, a historical indicator of the considered process or operation can be estimated.

$$H_c = \frac{T_c}{T_b} - \frac{(T_1+T_2+T_3+T_4)}{T_b} \tag{7}$$

where:
H_c – historical stoppage indicator for lines and/or processes,
T_C – operating time of similar production lines or other processes under study,
T_1 – registered downtime due to power outage for the historical period (historical information collected and stored in a database),
T_2 – registered downtime caused by preventive and maintenance actions (historical information collected and stored in a database),
T_3 – registered downtimes due to logistical disruptions (historical information collected and stored in a database),
T_4 – time from other causes of production line stoppage (historical information collected and stored in a database),
T_b – absolute time.

To illustrate Equation (7) in a practical example, calculations were performed for a production line based on historical indicators. Suppose we have collected historical data regarding the production process on a similar production line (archived records of all or part of the factors affecting production).

Step 1: Determine the total number of working hours in a year.

A calendar year has 365 days, and the factory operates in a 3-shift system (24 hours a day). However, we need to account for days when production does not occur due to holiday breaks:

a) 2 weeks (14 days) break for Christmas,
b) 2 weeks (14 days) summer break,
c) 1 week (7 days) break for Easter,
d) 3 days break for All Saints' Day.

The number of working days in a year is calculated as follows:

$$365 - (14 + 14 + 7 + 3) = 327 \text{ working days.}$$

The total number of working days in the year is: $327 \cdot 24 = 7\,848$ working hours per year.

Step 2: Division of Working and Downtime by Percentage.

According to the assumptions:

a) 80% of the time is actual production line operating time,
b) 5% is downtime due to failures,
c) 8% is downtime due to logistical issues,
d) 2% is downtime due to major breakdowns,
e) 5% is due to organizational issues, routine maintenance, and other interruptions.

The total percentage must equal 100%. Let's verify:

$$80\%+5\%+8\%+2\%+5\%=100\%$$

Step 3: Calculation of Hours Based on Percentages.

Now, we will calculate the number of hours for each component (effective operation and downtime).

Production Line Operating Time (80%)

$$T_c = 7{,}848 \times 0.80 = 6\,278.4 \text{ godzin.}$$

Downtime Due to Failures (5%)

$$T_1 = 7{,}848 \times 0.05 = 392{,}4 \text{ hours.}$$

Downtime Due to Logistical Issues (8%)

$$T_2 = 7{,}848 \times 0.08 = 627{,}84 \text{ hours.}$$

Downtime Due to Major Breakdowns (2%)

$$T_3 = 7{,}848 \times 0.02 = 156.96 \text{ hours.}$$

Downtime Due to Organizational Issues and Routine Maintenance (5%).

$$T_4 = 7{,}848 \times 0.05 = 392.4 \text{ hours.}$$

Step 4: Calculation of the Historical Line Downtime Indicator (H_c).

We use equation (6) to calculate the historical line downtime indicator (H_c).

$$H_c = \frac{6\,278.4}{7\,848} - \frac{(392.4 + 627.84 + 156.96 + 392.4)}{7\,848}$$

Calculating each term.

$$\frac{6\,278.4}{7\,848} = 0.7999 = 0.8$$

Next, we sum the downtimes:

$$T1+T2+T3+T4 = 392.4+627.84 + 156.96 + 392.4 =$$
$$= 1\,569.6 \text{ hours of downtime.}$$

Now, we calculate the second term of the equation.

$$\frac{1\,569.6}{7\,848} = 0.2$$

Finally, we calculate the historical line downtime indicator (H_c)

$$H_c = 0.8 - 0.2 = 0.6$$

The historical line downtime indicator $H_c = 0.6$ – indicates that the production line operated efficiently for 60% of the time throughout the year. Therefore, 60% of the operational time was effective, while the remaining 40% accounted for downtimes due to breakdowns, logistical issues, maintenance, and other interruptions.

In summary, in the analyzed example, over the course of the year, the production line operated for 7,848 hours, of which:

1) 6,278.4 hours were effective working time (80%),
2) 1,569.6 hours accounted for total downtime (20%), caused by:
   a) 392.4 hours due to breakdowns,
   b) 627.84 hours due to logistical issues,
   c) 156.96 hours due to major failures,
   d) 392.4 hours due to ongoing maintenance and organizational issues.

The $H_c = 0.6$ indicator provides a measure of production line efficiency and can guide decisions on optimizing logistics management and machine maintenance.

5. Displacement as the Second Key Parameter Describing Reality and Random Phenomena

Displacement is considered by the author as the second essential parameter describing dynamic reality. Displacement can be viewed as:

a) **Global displacement relative to the Earth** (Figure 8), based on geographic coordinates such as latitude and longitude. These are expressed as angular measures from the geographic coordinate origin, which is the intersection of the Prime Meridian (Greenwich) and the equator.
b) **Displacement relative to a chosen reference point,** illustrated in Figure 9 as a schematic. The design of a displacement mechanism with respect to a chosen reference point is shown in Figure 10. Relative displacement with respect to sequential measurement planes XY, XZ, and YZ.
c) **Combination of multiple movements**, including translational, curvilinear, and rotational, of a selected point within a single body.

Fig. 8. Global displacement relative to the Earth. The zero reference point of the coordinate system can be taken at the intersection of the Prime Meridian and the equator. Here, we assume a theory that divides our planet into four sections, which can also be divided into smaller areas.

One of the proposed methods involves projecting an element (its characteristic points) onto three planes, with an additional measurement of the distance from the zero reference point. As a phenomenon or element changes position, it also shifts the positions of characteristic points on the surfaces of the solid element relative to the origin of the coordinate system.

In summary, we have four variables:

a) the position of points on the XY measurement plane,
b) the position of points on the XZ measurement plane,
c) the position of points on the ZY measurement plane,
d) the length of the tracking vector r – the position of the characteristic points of the solid relative to the origin of the coordinate system.

The characteristic points of this methodology are based on concepts used in CNC machines for machining:

a) Machine zero point,
b) Workpiece zero point,
c) Machine reference point,
d) Tool reference point.

Machining processes have evolved significantly over the past 30 years, and thus, according to the author, they can be treated as predictable, with randomly changing situations rarely occurring. Such situations may include hidden material defects in workpieces and tools, environmental vibrations, breakdowns, temperature fluctuations, power outages, and extreme events such as floods or earthquakes. Experience gained in the field of machine tool construction can and should be used for designing machines in other technological processes, including those with random variability. The dynamics of spindles, cutting tools, and sensors applied are ideal for other industrial applications, such as assembly processes on a single production line for parts of varying shapes and weights, randomly arranged without positioning.

A proprietary construction solution based on the presented theory is shown in Figure 10. The layout of individual sensors in the form of cameras is depicted in Figure 11. This mechanism enables measurement of the change in position of the tested element within the measurement space. It is designed using sliding axes driven by electric motors equipped with high-resolution position sensors and high-frequency data collection on location. This arrangement allows precise and fast adjustment of measurement cameras monitoring specific characteristic points for the spatial solid planes. The displacement radius is measured using a camera mounted on two rotary tables. Using motor-driven tables equipped with position sensors enables precise and rapid repositioning in two axes, allowing it to keep pace with a randomly changing process. The movement directions along individual axes are marked in Figure 12.

The size of the *XY*, *ZY*, and *XZ* planes and the range of the tracking vector r (also referred to by the author as the tracking radius, depending on the process specificity) depends on the size of the displacement area. The measurement space can be divided into smaller sections, called "virtual measurement cubes." The more predictable the process, the larger these virtual measurement cubes can be (fewer cubes required), and conversely, for less predictable processes. The division of the measurement space into virtual measurement cubes is illustrated in Figure 13. By tracking positional changes on individual measurement planes *XY*, *ZY*, *XZ*, using virtual measurement cubes and changes in the length of the tracking vector, we can visualize the path of the object in terms of points, edges, and planes for randomly variable processes.

When a point moves between the measurement planes of the virtual measurement cube, its positional changes can be observed relative to the intersected plane of that cube. To react properly to such changes, software is required that, based on historical data, can determine the direction of the element's movement and predict shifts of the linear actuator carriages in that direction. When it appears that the element changes direction and moves in a different direction than its previous trajectory indicated, the program, based on data from earlier changes, can adapt and adjust the movement path. Consequently, this leads to the determination of the positioning of measurement cameras, which define both the range of movement and the boundaries of the *virtual measurement cube*.

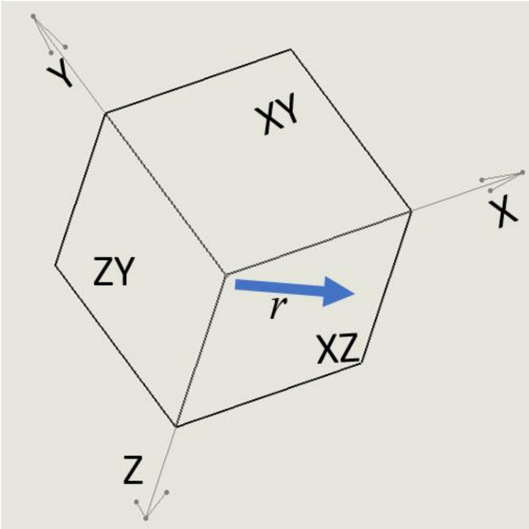


Fig. 9. System of three planes *XY*, *XZ*, *ZY*, projecting the position of the tracking element along with the tracking vector "*r*"

The following section describes a historical example of position changes and an analysis of using this model, where subsequent movements of objects relative to sensors can be observed. The sensor gathers information on position changes and automatically adjusts the linear or non-linear displacement of the element. Graphical representations of these displacements are shown in Figures 14 and 15, respectively.

Displacement relative to a selected reference point can be recorded as a multiple integral of the displacement function:

$$p_1 = \iiint f(x, y, z, r) dx\, dy\, dz\, dr \qquad (9)$$

where:
p_1 – displacement of point 1,
f – four-variable displacement function.

Relative displacement with respect to subsequent measurement planes in randomly changing processes for 4 selected points can be expressed as a function in which:
$[x_{11}, y_{11}]$ – represents the coordinates of selected characteristic points describing the measured body on the XY plane. Subscripts denote successive measurements. The notation is applied similarly to all characteristic elements of the measured body,
$\left|\vec{r}_{11}\right|$ – tracking vector length r.

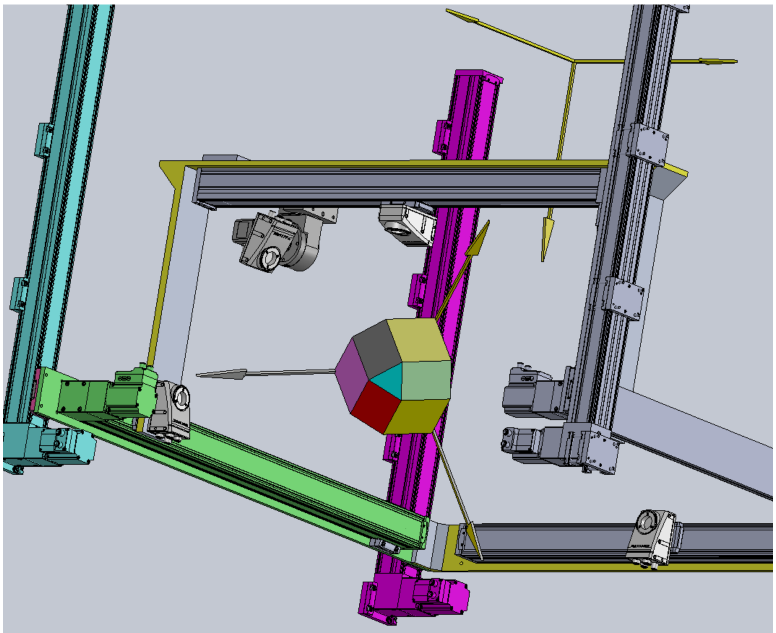


Fig. 10. Mechanism enabling measurements in the planes *XY*, *XZ*, *ZY*, projecting the position of the tracking element along with the tracking vector "*r*"

$$p_1(x,y,z,r) = \begin{cases} [x_{11},y_{11}] \pm [x_{12},y_{12}] \pm [x_{13},y_{13}] \pm [x_{14},y_{14}] + \cdots [x_{1n},y_{1n}] \\ [x_{11},z_{11}] \pm [x_{12},z_{12}] \pm [x_{13},z_{13}] \pm [x_{14},z_{14}] + \cdots [x_{1n},z_{1n}] \\ [y_{11},z_{11}] \pm [y_{12},z_{12}] \pm [y_{13},z_{13}] \pm [y_{14},z_{14}] + \cdots [z_{1n},y_{1n}]\,) \\ \left|\vec{r}_{11}\right| \pm \left|\vec{r}_{12}\right| \pm \left|\vec{r}_{13}\right| \pm \left|\vec{r}_{14}\right| \ldots \pm \left|\vec{r}_{1n}\right| \end{cases}$$

$$p_2(x,y,z,r) = \begin{cases} [x_{21},y_{21}] \pm [x_{22},y_{22}] \pm [x_{23},y_{23}] \pm [x_{24},y_{24}] + \cdots [x_{2n},y_{2n}] \\ [x_{21},z_{21}] \pm [x_{22},z_{22}] \pm [x_{23},z_{23}] \pm [x_{24},z_{24}] + \cdots [x_{2n},z_{2n}] \\ [y_{21},z_{21}] \pm [y_{22},z_{22}] \pm [y_{23},z_{23}] \pm [y_{24},z_{24}] + \cdots [z_{2n},y_{2n}] \\ \left|\vec{r}_{21}\right| \pm \left|\vec{r}_{22}\right| \pm \left|\vec{r}_{23}\right| \pm \left|\vec{r}_{24}\right| \ldots \pm \left|\vec{r}_{2n}\right| \end{cases}$$

$$p_3(x,y,z,r) = \begin{cases} [x_{31},y_{31}] \pm [x_{32},y_{32}] \pm [x_{33},y_{33}] \pm [x_{34},y_{34}] + \cdots [x_{3n},y_{3n}] \\ [x_{31},z_{31}] \pm [x_{32},z_{32}] \pm [x_{33},z_{33}] \pm [x_{34},z_{34}] + \cdots [x_{3n},z_{3n}] \\ [y_{31},z_{31}] \pm [y_{32},z_{32}] \pm [y_{33},z_{33}] \pm [y_{34},z_{34}] + \cdots [z_{3n},y_{3n}] \\ \left|\vec{r}_{31}\right| \pm \left|\vec{r}_{32}\right| \pm \left|\vec{r}_{33}\right| \pm \left|\vec{r}_{34}\right| \ldots \pm \left|\vec{r}_{3n}\right| \end{cases}$$

$$p_4(x,y,z,r) = \begin{cases} [x_{41},y_{11}] \pm [x_{42},y_{42}] \pm [x_{43},y_{43}] \pm [x_{44},y_{44}] + \cdots [x_{4n},y_{4n}] \\ [x_{41},z_{11}] \pm [x_{42},z_{42}] \pm [x_{43},z_{43}] \pm [x_{44},z_{44}] + \cdots [x_{4n},z_{4n}] \\ [y_{41},z_{41}] \pm [y_{42},z_{12}] \pm [y_{43},z_{43}] \pm [y_{34},z_{34}] + \cdots [z_{4n},y_{4n}] \\ \left|\vec{r}_{41}\right| \pm \left|\vec{r}_{42}\right| \pm \left|\vec{r}_{43}\right| \pm \left|\vec{r}_{44}\right| \ldots \pm \left|\vec{r}_{4n}\right| \end{cases}$$

Displacement of a selected point defining the path of movement is recorded as a function of input variables. Assuming that a single point moves through space along a vector

$$\vec{d} = (dx, dy, dz, dr),$$

we can calculate the displacement with respect to all measurement planes XYZ, as well as the initial location. It is assumed that movement occurs in chosen, arbitrary displacement units, which allows precise determination of the new coordinates of each point regardless of the shape of the geometry of the element, e.g., the new position for point A is $A + \vec{d}$.

Continuing, we calculate the new coordinates and *displacement radii* r with respect to the reference systems, enabling precise prediction of linear actuator carriage shifts and adjustment of the motion trajectory relative to changing conditions, where

$$r = \sqrt{x^2 + y^2 + z^2}.$$

In this way, we determine the displacement range, facilitating further prediction of movement and optimization of system operation.

Assume that a solid with 10 faces has 10 vertices initially located within the coordinate system. For simplicity, let's assume that the starting points have coordinates (defined in arbitrary units) as follows:

1. *A* = (1, 1, 0)
2. *B* = (2, 1, 0)
3. *C* = (3, 2, 0)
4. *D* = (3, 2, 0)
5. *E* = (1.5, 3.5, 0)
6. *F* = (0.5, 2.5, 0)
7. *G* = (0, 1.5, 0)
8. *H* = (0.5, 0.5, 0)
9. *I* = (1.5, 0, 0)
10. *J* = 2.5, 0.5, 0)

Assume that the solid moves through space by a vector:

$$\overline{d} = (dx, dy, dz) = (2, 3, 1)$$

Each vertex shifts according to vector $\overline{d}$. We calculate the new coordinates for each point:

1. New coordinates for *A*:

$$A' = A + \overline{d} = (1, 1, 0) + (2, 3, 1) = (3, 4, 1)$$

2. New coordinates for *B*:

$$B' = B + \overline{d} = (2, 1, 0) + (2, 3, 1) = (4, 4, 1)$$

3. New coordinates for *C*:

$$C' = C + \overline{d} = (3, 2, 0) + (2, 3, 1) = (5, 5, 1)$$

4. New coordinates for *D*:

$$D' = D + \overline{d} = (2.5, 3, 0) + (2, 3, 1) = \\ = (4.5, 6, 1)$$

5. New coordinates for *E*:

$$E' = E + \overline{d} = (1.5, 3.5, 0) + (2, 3, 1) = \\ = (3.5, 6.5, 1)$$

6. New coordinates for *F*:

$$F' = F + \overline{d} = (0.5, 2.5, 0) + (2, 3, 1) \\ = (2.5, 5.5, 1)$$

7. New coordinates for *G*:

$$G' = G + \overline{d} = (0, 1.5, 0) + (2, 3, 1) \\ = (2, 4.5, 1)$$

8. New coordinates for *H*:

$$H' = H + \overline{d} = (0.5, 0.5, 0) + (2, 3, 1) \\ = (2.5, 3.5, 1)$$

9. New coordinates for *I*:

$$I' = I + \overline{d} = (1.5, 0, 0) + (2, 3, 1) = (3.5, 3, 1)$$

10. New coordinates for *J*:

$$J' = J + \overline{d} = (2.5, 0.5, 0) + (2, 3, 1) \\ = (4.5, 3.5, 1)$$

Calculate the new radii r relative to the initial reference frame (i.e., the point (0, 0, 0) for each displacement. We use the formula:

$$r = \sqrt{x^2 + y^2 + z^2}$$

1. Radius for A':

$$r_{A'} = \sqrt{3^2 + 4^2 + 1^2} = \sqrt{9 + 16 + 1} = \sqrt{26} \\ \approx 5.1$$

2. Radius for B':

$$r_{B'} = \sqrt{4^2 + 4^2 + 1^2} = \sqrt{16 + 16 + 1} = \sqrt{33} \\ \approx 5.74$$

3. Radius for C':

$$r_{C'} = \sqrt{5^2 + 5^2 + 1^2} = \sqrt{25 + 25 + 1} = \sqrt{51} \\ \approx 7.14$$

4. Radius for D':

$$r_{D'} = \sqrt{4.5^2 + 6^2 + 1^2} = \sqrt{20.25 + 36 + 1} \\ = \sqrt{57.25} \approx 7.57$$

5. Radius for E':

$$r_{E'} = \sqrt{3.5^2 + 6.5^2 + 1^2} = \sqrt{12.25 + 42.25 + 1} \\ = \sqrt{55.5} \approx 7.45$$

6. Radius for F':

$$r_{F'} = \sqrt{2.5^2 + 5.5^2 + 1^2} = \sqrt{6.25 + 30.25 + 1} = \sqrt{37.5} \approx 6.12$$

7. Radius for G':

$$r_{G'} = \sqrt{2^2 + 4.5^2 + 1^2} = \sqrt{4 + 20.25 + 1} = \sqrt{25.25} \approx 5.03$$

8. Radius for H':

$$r_{H'} = \sqrt{2.5^2 + 3.5^2 + 1^2} = \sqrt{6.25 + 12.25 + 1} = \sqrt{19.5} \approx 4.42$$

9. Radius for I':

$$r_{I'} = \sqrt{3.5^2 + 3^2 + 1^2} = \sqrt{12.25 + 9 + 1} = \sqrt{22.25} \approx 4.72$$

10. Promień dla J':

$$r_{J'} = \sqrt{4.5^2 + 3.5^2 + 1^2} = \sqrt{20.25 + 12.25 + 1} = \sqrt{33.5} \approx 5.79$$

Using formula no. 8 to describe displacements:

$$p(x,\, y,\, z,\, r) = \begin{bmatrix} x_{ij} \pm dx & y_{ij} \pm dy & \dots \\ x_{ij} \pm dx & z_{ij} \pm dz & \dots \\ y_{ij} \pm dy & z_{ij} \pm dz & \dots \end{bmatrix}$$

Symbols x_{ij}, y_{ij}, z_{ij} correspond to the initial coordinates of the vertices, and *dx*, *dy*, *dz* represent the displacements. The results are visible in the new positions of the vertices and the calculations of the radii.

Examples of displacement tracking for an irregular solid with 10 faces are illustrated in Figures 11 through 15. These figures demonstrate how characteristic points on a complex geometry are monitored across different measurement planes, allowing precise movement tracking within spatial coordinates. Each face of this solid is paired with specific tracking vectors, highlighting the adaptability of these methods for unconventional geometries. This structured approach enables comprehensive displacement management in dynamic processes, ensuring that even irregular shapes are thoroughly analyzed across relevant planes. To enhance movement speed and zone segmentation, the space has been divided into virtual cubes, as also shown in these figures.

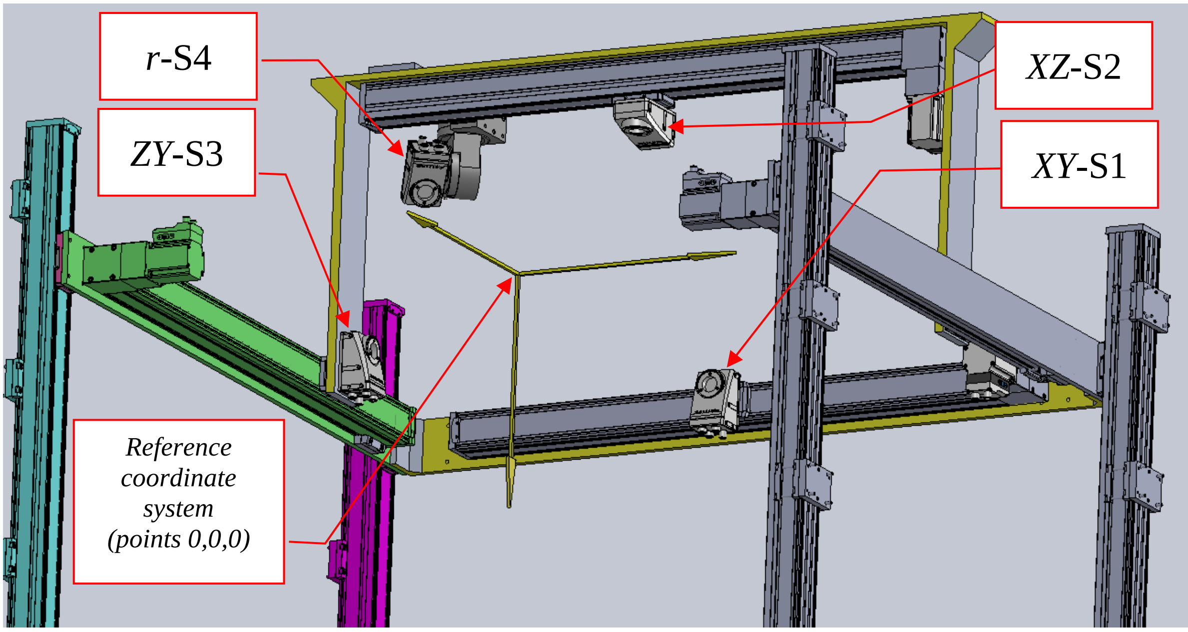


Fig. 11. Structural schematic of the arrangement of measurement cameras within a three-dimensional space. Camera *XY*-S1 monitors movements along the *XY* plane and adjusts on the *Z*-axis, enabling height regulation. Camera *XZ*-S2 controls movements along the *XZ* plane and adjusts on the *Y*-axis, facilitating lateral movement. Camera *ZY*-S3 tracks changes within the *ZY* plane and adjusts on the *X*-axis, allowing precise horizontal movement. Camera *r*-S4, equipped with rotational capabilities, enables 360-degree rotation around the *Y*-axis, providing monitoring of angular changes. This configuration of cameras allows comprehensive analysis of the position and orientation of objects, ensuring high precision in measurement.

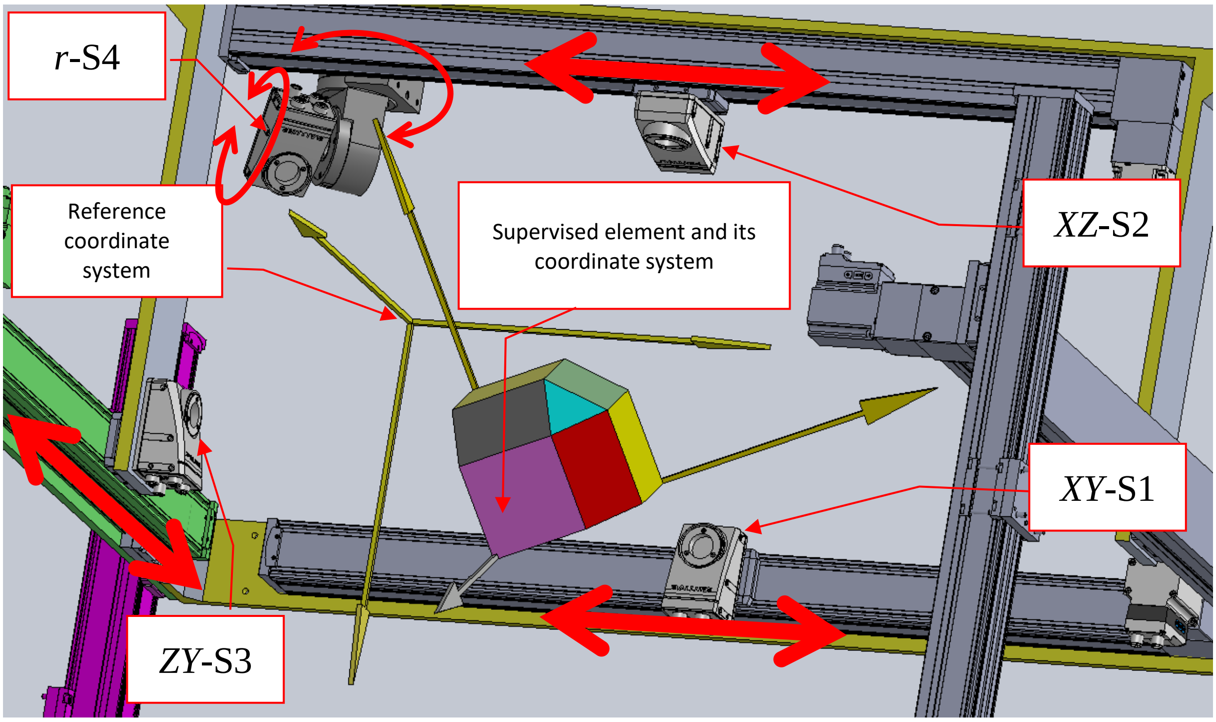


Fig. 12. Spatial configuration of motion and degrees of freedom of measurement cameras. Cameras *XY*-S1, *XZ*-S2, and *ZY*-S3 move along their respective axes: *Z*, *Y*, and *X*, enabling precise positioning of the observed object. Camera *r*-S4 allows full 360-degree rotation around the *Y*-axis, ensuring maximum adaptability and precision in the measurement of object movements. The configuration enables a comprehensive analysis of object orientation within the measurement field, ensuring the reliability of recorded data

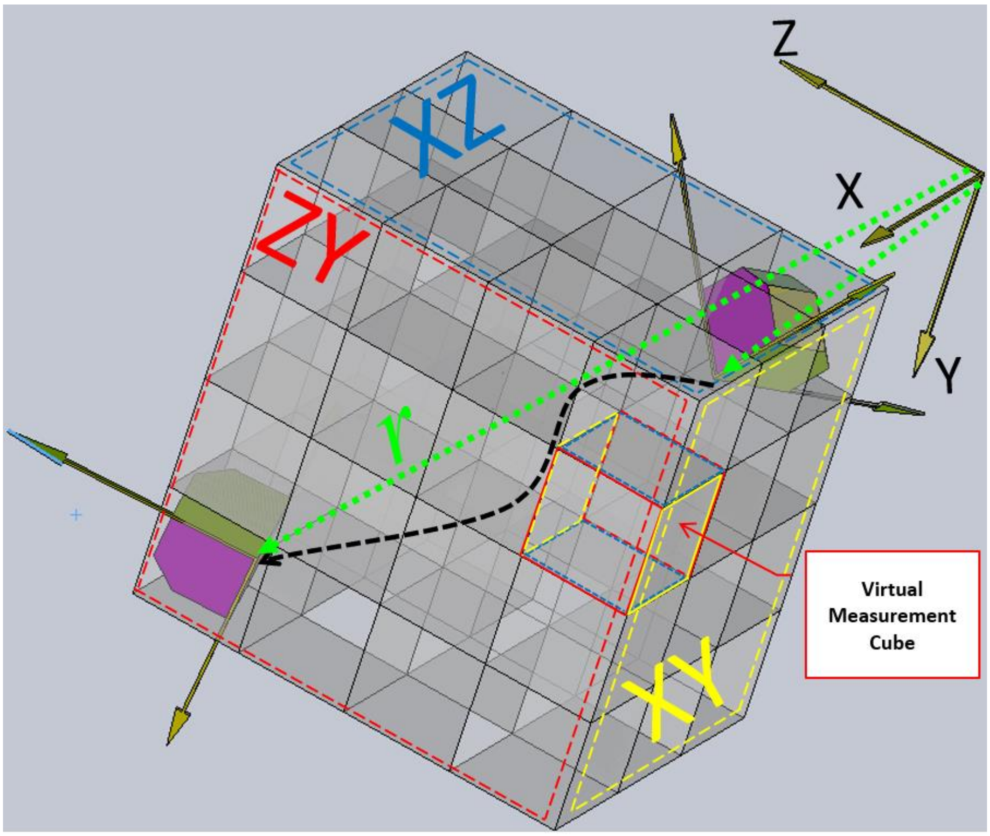


Fig. 13. Division of the measurement space into "virtual cubes," allowing segmentation into smaller measurement areas within the XY, XZ, and ZY planes. Each "cube" corresponds to a specific spatial range, enabling precise tracking of the object's position. Crossing the boundary of one of these areas activates camera movement along the translation axes or its rotation (r), which allows automatic adjustment of camera positions and continuous object tracking. This solution ensures full coverage of the measurement space, enhancing the accuracy and versatility of the measurement process

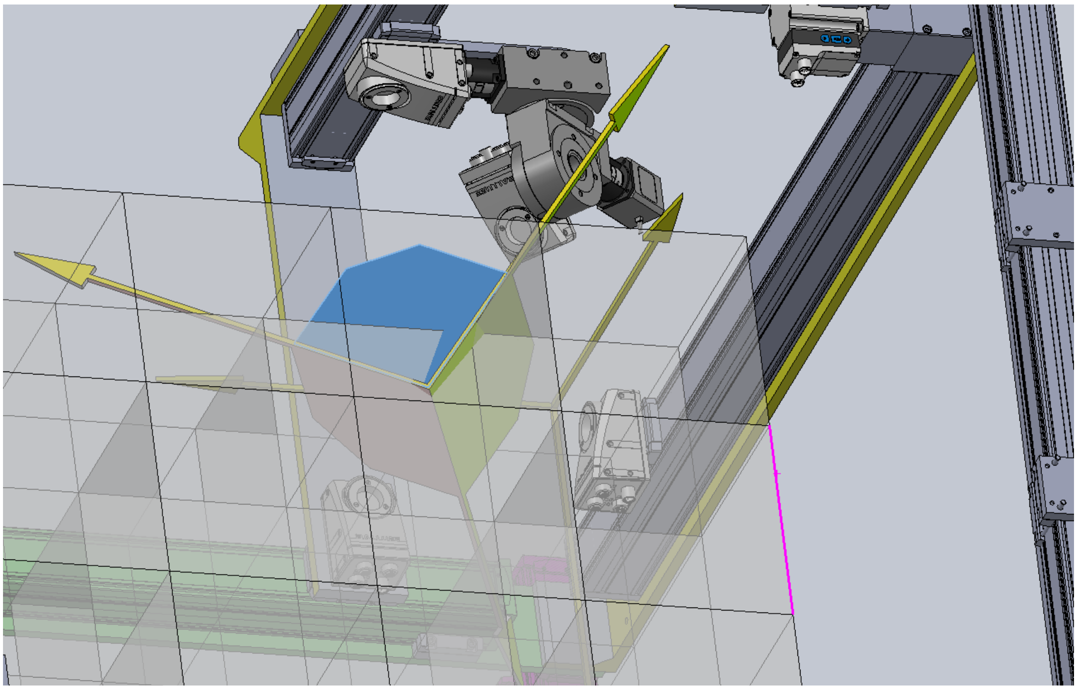


Fig. 14. Illustration of the initial positioning of the measurement system, with the measurement space divided into virtual areas. This setup allows precise tracking of the observed object's position across the XY, XZ, and YZ planes. The system automatically adapts, using dynamic camera positioning to follow the object's movement in all three dimensions. The system is designed for continuous measurement of position changes in high-precision applications

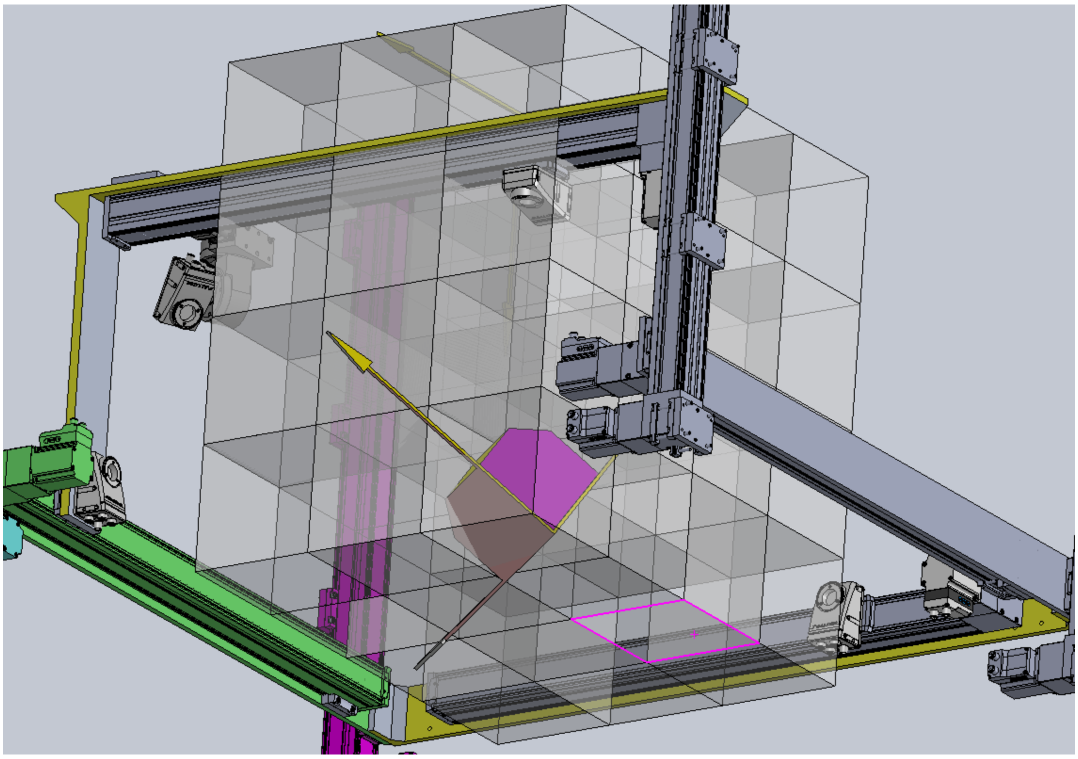


Fig. 15. Continuation of the movement of the measured element shown in Figure 14, depicting the system’s state after a certain amount of time. The moving element crosses additional virtual measurement zones, which automatically triggers camera position adjustments. Cameras dynamically reposition along the translation axes and perform necessary rotations to ensure continuous tracking of the object’s location. The system precisely follows the movement, which is essential in applications requiring high dynamics and precision in real-time monitoring

6. Proposed New Chapter Title: "Temperature as a Key Parameter in Describing Dynamic Processes and Random Phenomena"

Temperature is a crucial parameter that describes changing reality. For a long time, temperature measurement has been used in the diagnostics of machine health and wear, as well as in the search for missing persons. Temperature can be classified as follows:

a) ambient temperaturę D_o – the temperature of the surrounding environment,
b) Measured temperature relative to a selected reference point T_m – the temperature taken in relation to a specific point,
c) temperature of the examined object on specific measurement planes XY, XZ, ZY (T_mXY, T_mXZ, T_mZY) – temperature measurements taken from three sides of the examined object.

Temperature expressed as a difference in temperature, accounting for the specific heat of materials and the amount of heat delivered, according to the formula (Equation 10):

$$\Delta T = \frac{\Delta Q}{m \cdot c} \tag{10}$$

where:
C – specific heat $[\frac{J}{kg \cdot K}]$,
m – mass of the object [kg],
ΔQ – heat delivered [J].

In addition to temperature, similar methodologies can be applied to measure changing volume and indirectly calculate mass and temperature changes occurring on the surface. This approach enables real-time monitoring and control, which is particularly useful in industrial processes involving heating and cooling. By employing this methodology, it is possible to optimize production costs and improve product quality across various industrial sectors.

Depending on the processes, parameters will vary, and each operator aiming to analyze and forecast randomly changing processes must work with a team of specialists to determine which parameters are crucial and relate them to a reference value. The principles for constructing equations to describe additional physical parameters are analogous to those used for time, displacement, and temperature.

In addition to temperature, similar methodologies can be applied to measure changing volume and indirectly calculate mass and surface temperature changes. This approach allows for real-time monitoring and precise control, which is particularly beneficial in industrial processes involving heating and cooling. By employing this methodology, production costs can be optimized, and product quality can be enhanced across numerous sectors of the industry.

7. Historical Data as a Primary Source of Information for Modeling Complex Design Problems in Randomly Changing Technological Processes

History can also be recorded as a function of data changes over time. Anything that occurs outside of this fraction of a second is already history, which can be classified as follows:

1) **absolute history** – events that happen worldwide every day,
2) **documented history** – information recorded on paper,
3) **subjective history** – what people remember and pass on through stories or oral tradition, subject to the imperfections of human senses and vulnerable to suggestions and manipulation,
4) **recorded history** – data registered from measurements of physical and chemical quantities, forming the foundation of science and applicable for predicting randomly changing phenomena.

$$\int_{t_0}^{t_2} \left(\int_{p_{1(\mathrm{t})}}^{p_2(\mathrm{t})} f(p,t)dp \right) dt \tag{11}$$

where:
f (p, t) – function of documented technological parameters (p) over a selected time interval from t_1 to t_2.

A graphical diagram illustrating the use of historical data and the process of building on historical data analysis and forecasting the probability of future events is shown in Figure 16. The measured operational parameters and the history of phenomena that have historically occurred under similar parameters form the basis for decision-making in the presented methodology. Since 1993, the author has been actively involved in machine design and researching technological processes to implement the best possible solutions for improving worker safety and machine operation, as well as enhancing economic efficiency for businesses by raising the quality of technology.

Figure 16 presents a comprehensive schematic illustrating the data collection and comparison process, along with predictive analysis based on historical trends. This process is designed to optimize decision-making in dynamic and variable technological environments by comparing current data to historical benchmarks.

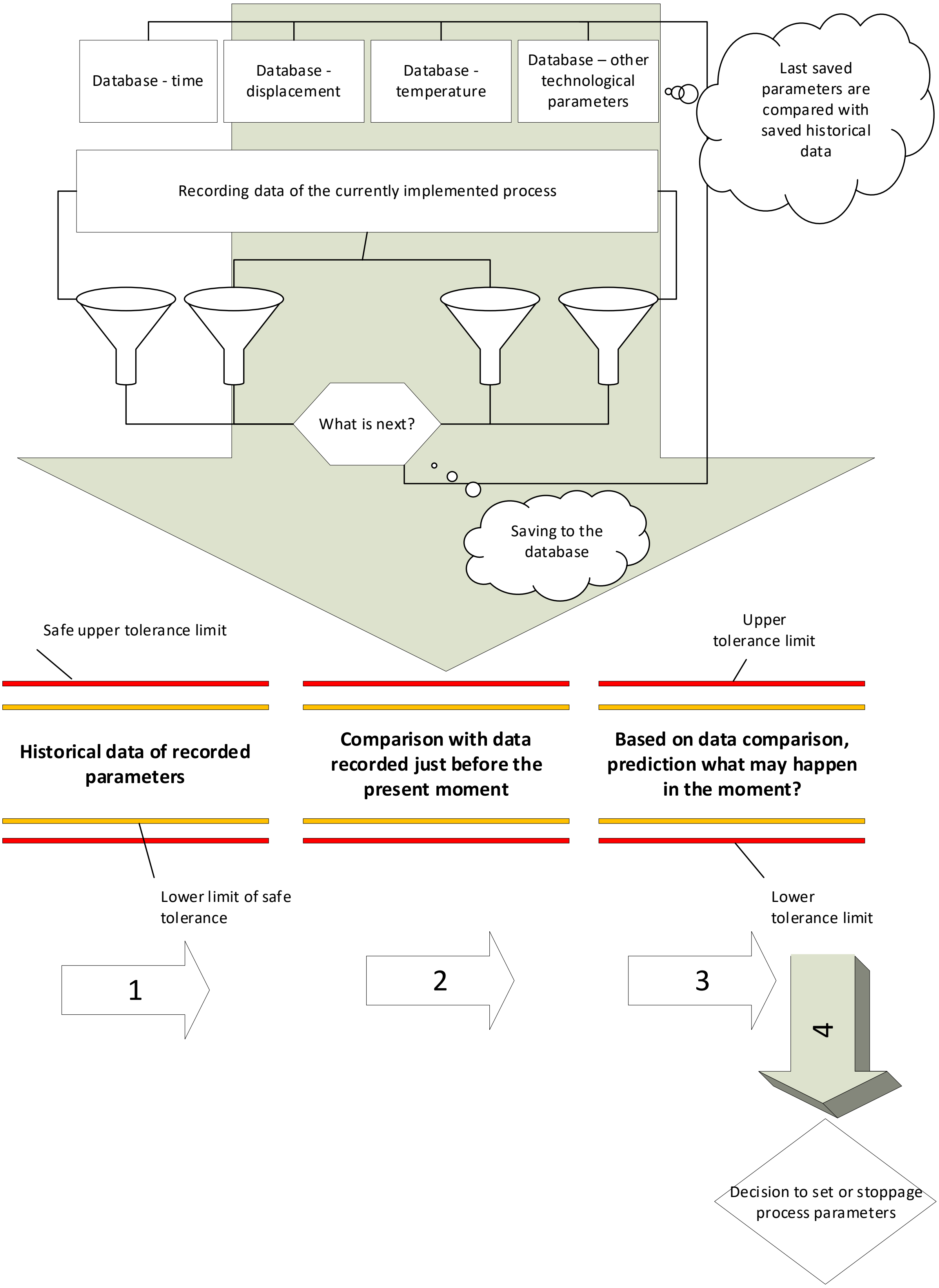


Fig. 16. Graphical representation of the data collection and comparison process with historical events. This system continuously records data related to various operational parameters, such as time, displacement, temperature, and other technological aspects. The recorded data from each moment is compared to historical records to assess deviations and predict upcoming events based on historical trends. This comparison process operates within predefined tolerance limits (upper and lower limits of safe operation) to ensure the system's stability and safety. If the data analysis identifies a potential issue or deviation from safe operational parameters, the system makes an automatic decision to either adjust or halt the process parameters. This predictive approach aids in maintaining optimal functionality and mitigating risks, particularly in dynamic environments where technological changes occur unpredictably

7.1. Diagram Structure and Components:

1. **Data Sources**. The top section shows multiple data sources, each representing different operational parameters (e.g., displacement, temperature, pressure). These sources feed into a central processing unit for data analysis.
2. **Data Recording and Historical Comparison**. Data from ongoing processes are continually recorded and archived in a historical database. This archived data provides a benchmark, capturing typical process fluctuations and tolerance limits.
3. **Comparative Analysis**. The current data is compared with historical data to detect deviations from typical trends. This comparison helps determine whether the present conditions are within the established safe tolerance limits or approaching risky levels.
4. **Predictive Decision-Making**. Based on comparative analysis, predictive algorithms project the likelihood of upcoming changes. If patterns emerge that deviate significantly from safe thresholds, the system triggers alerts or adjustments to prevent errors or inefficiencies.
5. **Tolerance Limits and Adaptive Response**. The lower and upper tolerance limits shown in the diagram represent the operational thresholds. If data indicates a potential breach of these limits, the system adapts by adjusting process parameters to stabilize conditions.

7.2. Using the Diagram for Process Management.

1. **Step 1**: Begin by collecting current data across all relevant operational parameters.
2. **Step 2**: Feed this data into the system, where it is recorded in real time and archived for future reference.
3. **Step 3**: Compare the present data with historical values. Look for trends or anomalies that may indicate a deviation from safe operational conditions.
4. **Step 4**: Use predictive analysis to anticipate future states. If the system predicts a potential breach of safe limits, immediate adjustments should be made to avoid disruptions.

This process ensures that operators maintain optimal control over processes, leveraging historical data and real-time analysis to enhance decision-making.

8. Discussion on the Analysis and Modeling of Design Problems in the Context of Random Technological Changes

8.1. Introduction to the Discussion

The purpose of this discussion is to analyze the results of modeling complex design problems in the context of random technological changes, integrating the author’s innovative hypotheses regarding time, displacement, mass, and temperature. This methodology's primary objective is the adaptive management of resources and processes in variable operational environments. The approach combines advanced analytical techniques with dynamic integration of historical data, allowing for enhanced forecasting and adaptation to future technological challenges.

8.2. Application of Time and Displacement Hypotheses in Adaptive Monitoring Systems

Time and displacement are key parameters describing the dynamics of technological reality. The author expands the concept of time by emphasizing its irreversibility and directionality – time progresses unidirectionally and cannot be reversed, forming a foundation for numerous technological processes in which parameters are functions of time. The concept of relative time adds a dynamic aspect to time, making it dependent on operational context and the subjective perception of process participants. Analogous to Einstein's theory of relativity, time in this methodology ceases to be merely a linear flow of moments; it becomes an adaptive resource that enables more flexible management of resources and processes.

Displacement, as the second key parameter, enables precise monitoring of movement and the position of elements in three-dimensional space. The introduction of virtual “measurement cubes” allows dynamic adjustment of these zones' sizes, depending on the object being monitored. This means that for smaller objects, these cubes can achieve microscopic dimensions, while for large objects, such as in military applications, they may span several meters or even kilometers. The segmentation of space into measurement cubes enables detailed tracking of movements, where any deviation or change in position is immediately detected and analyzed, which is crucial in environments that demand high precision and adaptability.

8.3. The Role of Historical and Predictive Data in Process Forecasting and Optimization

A fundamental element of this methodology is using historical data as the foundation for constructing predictive models. The author’s core hypothesis suggests that every moment in the past is an information resource for forecasting the future – even a fraction of a second ago is part of history that can be analyzed and used to model future scenarios. This approach supports the systematic collection of operational data, which can be leveraged to precisely model and forecast technological conditions that exhibit randomness.

Integrating historical data with current measurements and using adaptive analytical models enables dynamic adjustments of operational parameters to current conditions. An example of this approach is a real-time monitoring system for temperature and displacement, which adjusts its parameters in response to ongoing conditions, allowing for faster adaptation to changes and minimizing the risk of failure. Thus, the presented methodology is a groundbreaking tool for managing highly dynamic and variable processes, ensuring operational stability and efficiency.

8.4. Integration of Time, Displacement, Mass, and Temperature Parameters

This methodology is based on the interrelationships between four key parameters: time, displacement, mass, and temperature. Each of these parameters plays a crucial role in describing dynamic technological processes, and their integration enables a more comprehensive analysis and control of complex industrial processes.

Temperature, as the third key parameter, is particularly significant in processes involving heating and cooling. Temperature changes are monitored in real-time, enabling precise adjustments to production processes. This approach is invaluable for industry, as temperature control directly impacts the quality of the final product and production costs. Furthermore, the methodology allows for measuring volume changes and the indirect calculation of mass and temperature on surfaces, which can be used to optimize and improve process control..

8.5. Importance of Process Variability and Adaptability

Adaptability is a critical aspect of this methodology, enabling effective management of technological processes characterized by random changes. Variability can be the result of both external factors, such as fluctuations in resource availability or changing market demands, and internal factors, such as equipment failures or unpredictable changes in operational parameters. Integrating historical data with current measurements allows for the identification of patterns and trends, enhancing the system's ability to forecast and respond rapidly to changes. This approach, therefore, increases operational efficiency and minimizes the risk of downtime and losses.

8.6. Practical Applications and Examples of Process Optimization

The theoretical and empirical investigations demonstrate that real-time adjustment of system parameters is achievable and can significantly enhance operational efficiency. Monitoring systems equipped with proprietary analytical algorithms can detect even minimal deviations and automatically adjust device settings, ensuring continuous process optimization. An example includes the application of these algorithms in industrial processes, where dynamically adjusting operational parameters enables optimized energy and resource consumption, essential for maintaining competitiveness and minimizing costs.

8.7. Summary and Directions for Future Research

In summary, the presented methodology provides a comprehensive and adaptive tool for managing highly variable technological processes. The integration of historical data with dynamic measurements, combined with adaptive predictive models, enables precise modeling of future scenarios and resource optimization. This methodology stands out for its flexibility, allowing adaptation to rapidly changing operational conditions, making it suitable for various industrial sectors.

8.8. Significance of the Author's "What Next?" Methodology

A central innovation in this work is the "What Next?" methodology, developed by the author as a systematic approach for continuous decision-making, particularly well-suited to environments characterized by random technological changes. This methodology underpins the adaptive framework presented in the study, which is designed to dynamically adjust in response to unpredictable process fluctuations. Unlike traditional methods that rely on fixed-stage planning, the "What Next?" approach introduces an iterative, flexible decision-making model that promotes ongoing assessment and adjustment at every phase of a process. This feature is essential for optimizing responses in environments that require high reactivity and precision.

The core strength of the "What Next?" methodology lies in its structure, which encourages constant evaluation and alignment with real-time data. Each step in the process is not an endpoint but a checkpoint that raises the question of "What Next?" This continuous loop of analysis and decision-making fosters greater adaptability, ensuring that processes remain resilient to unanticipated shifts. By facilitating dynamic recalibration of key parameters like time, displacement, temperature, and mass, the methodology supports a robust approach to maintaining process stability and optimizing operational efficiency.

Moreover, the "What Next?" methodology provides a foundation for implementing advanced predictive models by linking historical data analysis with forward-looking scenario planning. Through this integration, the methodology enables anticipatory adaptation, allowing systems to proactively address potential challenges before they impact performance. This capability is particularly relevant for designing intelligent technological systems and production machines capable of self-adjustment in changing environments.

The significance of this methodology is further underscored by its potential applications in developing technological artificial intelligence (AI) and production machine intelligence. According to the author, technological AI is a system that autonomously optimizes process parameters based on real-time data and predictive modeling, while production machine intelligence refers to self-regulating systems that adjust operational variables in response to environmental fluctuations. Together, these concepts represent the next frontier in industrial automation, where machines and systems autonomously improve performance by continuously analyzing their environment and adapting to new conditions.

8.9. Limitations of the Methodology and Future Research Directions

Despite promising results, this methodology has certain limitations. One of the primary challenges is the significant demand for computational resources and IT infrastructure, which may pose a barrier in environments with limited access to advanced technologies. Another limitation is the dependence on accurate historical data; its absence or inaccuracy can reduce the precision of forecasts and adaptive efficiency. Additionally, this methodology requires advanced real-time monitoring, which may be costly and complex to implement in less advanced environments.

Despite these limitations, this methodology holds great development potential. Future research should focus on optimizing adaptive algorithms to increase their speed and accuracy. Additionally, further development of predictive modeling using more advanced artificial intelligence approaches could significantly enhance responsiveness to changing operational conditions.

9. Conclusions

This study, *"Analysis and Modeling of Design Problems in the Context of Random Technological Changes,"* offers a novel approach to understanding and managing the complexities of design in environments marked by unpredictable technological shifts. The central goal of developing a universal methodology for modeling design challenges in such variable contexts has been successfully achieved, enabling new possibilities for adaptive design management.

The proposed methodology, grounded in four key parameters–time, displacement, mass, and temperature–introduces a cohesive framework that supports the dynamic adaptation of processes to variable operational conditions. A five-axis measurement system was developed to monitor and predict process changes in real time, integrating both relative and absolute time references to enable flexible tracking of fluctuations within segmented "virtual measurement cubes." This arrangement significantly enhances the system's capacity to respond to random process fluctuations with improved accuracy, which is crucial in settings demanding high reactivity and precision.

The hypotheses presented in the study have proven effective in defining these parameters with sufficient breadth and relevance to achieve the study’s objectives. Each parameter’s definition and integration into the framework contribute practically to the model's applicability, reinforcing its utility as an engineering tool. This model facilitates the adaptive management of design processes in dynamically changing conditions, positioning it as a valuable asset for real-world industrial applications. By incorporating multi-criteria decision analysis and integrating historical data systematically, the model not only enriches the understanding of dynamic production processes but also provides a foundation for adaptive systems that can evolve with technological demands.

Moreover, this work introduces two pivotal concepts: *technological artificial intelligence* and *manufacturing machinery artificial intelligence*. Technological artificial intelligence, as conceptualized here, is an adaptive algorithmic system optimized to predict and respond to dynamic technological conditions, while manufacturing machinery artificial intelligence denotes autonomous systems within machinery that monitor, analyze, and adjust production parameters based on real-time and historical data. These definitions establish new research avenues for intelligent, adaptive control systems across various industries, marking a significant theoretical advancement in automated process management.

Future Research Directions, to build upon the theoretical and practical foundation established in this study, the following directions are recommended:

1) **refinement of adaptive algorithms** to further improve real-time responsiveness and precision in fluctuating conditions.

2) **advancement in predictive modeling** to leverage the virtual cube model for more granular forecasting in high-precision environments.
3) **integration with artificial intelligence** to enable autonomous system adjustments informed by both historical data and live feedback, enhancing automation.
4) **validation in industrial settings** to confirm model efficiency and adaptability through iterative testing in real-world conditions.

In conclusion, this study introduces a systematic and forward-looking approach to modeling and managing design processes within unpredictable environments. The proposed framework, designed to facilitate adaptive intelligence, may offer valuable contributions to the field of engineering technology. Its applications suggest promising avenues for enhancing efficiency and adaptability in contemporary production systems and could provide a robust foundation for future advancements in intelligent, adaptive design.

References

Chang, C.-C., Lin, C.-J. (2011). "LIBSVM: A Library for Support Vector Machines." *ACM Transactions on Intelligent Systems and Technology*, 2(3), 27. DOI: https://doi.org/10.1145/1961189.1961199.

Cortes, C., Vapnik, V. (1995). "Support-Vector Networks." *Machine Learning*, 20, pp. 273–297. DOI: https://doi.org/10.1007/BF00994018.

Du, X., Chen, W. (2004). "Sequential Optimization and Reliability Assessment Method." *Journal of Mechanical Design*, 126(2), pp. 225–233. DOI: https://doi.org/10.1115/1.1649968.

Galindo-Rueda, F., Verger, F. (OECD Science, Technology and Industry Working Papers). *OECD Taxonomy*. DOI: https://doi.org/10.1787/5jlv73sqqp8r-en.

Pham, H. (2006). *Reliability Modeling, Analysis, and Optimization*. World Scientific. DOI: https://doi.org/10.1142/5870.

Platt, J. (1998). "Sequential Minimal Optimization." *Microsoft Research Technical Report* MSR-TR-98-14.

Saleh, J.H., Marais, K. (2006). "Highlights from the Early (and pre-) History of Reliability Engineering." *Reliability Engineering & System Safety*, 91, pp. 249–257. DOI: https://doi.org/10.1016/j.ress.2005.01.003.

Trott, P., Hartmann, D., van der Duin, P., Scholten, W., Ortt, R. (2016). *Managing Technological Innovation and Entrepreneurship*. Routledge, ISBN: 9780415677219.

World Intellectual Property Indicators 2021. WIPO Publication No. 941E/21, ISBN: 978-92-805-3329-3.

Knast, P., (2021). The theory of efficient preparation and operation of the industry producing products for the needs of the army and in the event of an emergency, *edited by: Jarosław Wołejszo, Konrad Malasiewicz, Norbert Prusiński, Praxeology in security sciences, Efficiency of action in national security, Kalisz 2021*, Wydawnictwo Naukowe Akademii Kaliskiej, pp. 209–236, ISBN 978-83-65872-48-7.