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Intelligent Methods for Predicting Technological Risks Based on Simulation Modeling

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ABSTRACT

This article explores modern approaches to forecasting technological risks using simulation modeling and machine learning algorithms. It analyzes typical failure scenarios, methods for constructing digital twins, and the architecture of interaction between simulation environments and intelligent modules. The effectiveness of hybrid systems is emphasized in the context of unstable technological regimes, including aggressive environments and equipment failure prevention. The study presents simulation results of a manufacturing process using the SimPy environment and embedded ML classifiers, which demonstrated a reduction in emergency shutdowns and production losses. The findings confirm the practical applicability of intelligent systems for adaptive control and enhanced resilience of industrial processes under uncertainty.

Key words : simulation modeling, digital twin, technological risk, machine learning, predictive analytics, intelligent systems, process resilience.

1. INTRODUCTION

New manufacturing systems are becoming automated and complex, and this is accompanied by expansion in technological hazards of equipment instability, departures from operating regimes, and the effects of hostile environments. With high downtime costs and potential environmental effect, the importance of proactive risk management is increasingly rising. Traditional control processes, based on predetermined checks and expert appraisal, are inadequate for timely response in the context of fluctuating environments. Smart systems with an integration of simulation modeling and machine learning algorithms are of particular importance in this context because they enable forecasting of emergency development and making real-time recommendations.

The goal of the research is to compare intelligent methods of forecasting technological risks based on simulation modeling. The study presents the application of digital twins and trainable models to approximate the probabilities of failure and establish process parameters in actual production conditions.

2. MAIN PART. THEORETICAL FOUNDATIONS OF TECHNOLOGICAL RISK FORECASTING USING SIMULATION MODELING

Technological risks in production systems represent a set of probabilities associated with events that may disrupt the stable operation of technological processes, leading to economic losses, environmental incidents, or threats to personnel safety. For instance, in the oil and gas industry, where equipment operates under aggressive chemical and thermobaric conditions, risk classification becomes particularly important for constructing digital models and trainable predictive systems (table 1).

Table 1: Classification of technological risks and typical failure scenarios (based on the oil and gas industry)

Risk category	Description	Typical failure scenarios
Technical	Arises from equipment wear, design flaws, or mechanical failure.	Pump housing rupture, motor overheating, valve unit breakdown (e.g., during inhibitor injection).
Technological	Caused by deviations from operational parameters.	Reactor overpressure, uneven inhibitor distribution, pH imbalance in the water treatment loop.
Physicochemical	Related to aggressive environments, corrosion, deposits, or chemical reactions.	Local pipeline wall failure due to acid corrosion, cavitation, paraffin deposition in flowlines.
Energy-related	Caused by failures in power supply or transmission systems.	Voltage fluctuations, shutdown of pumping stations, UPS failure during drilling operations.
Software / algorithmic	Control system errors, logic faults	Incorrect activation of inhibitor valve, SCADA

	in automation	system crash, flow control script failure.
Human factor	Operator mistakes, procedural violations, insufficient training.	Incorrect inhibitor concentration setting, delayed response to alarm signals.
External influences	Natural or technogenic events beyond the plant's control.	Reservoir breakthrough, inflow of aggressive components into formation water, external thermal or vibrational stress.

Despite differences among industries, the nature of technological risks in most production systems is fundamentally similar. They are the result of an interaction among technical, organizational, human, and environmental factors. Equipment failure, deviations from regulatory parameters, operator error, and destabilization of environmental conditions are all typical sources of potential failure. Therefore, a detailed elaboration and introduction of general risk modeling techniques are of particular significance, since they allow for the potential creation of adaptive digital models capable of reproducing the real dynamics of processes in diverse industrial sectors.

Simulation modeling offers the ability to imitate the behavior of complex systems in the virtual world, taking into account a myriad of variables and interdependences. According to a report by Grand View Research, the global simulation software market was valued at $23.56 billion in 2024, with North America dominating the market share with 36.5% (figure 1).

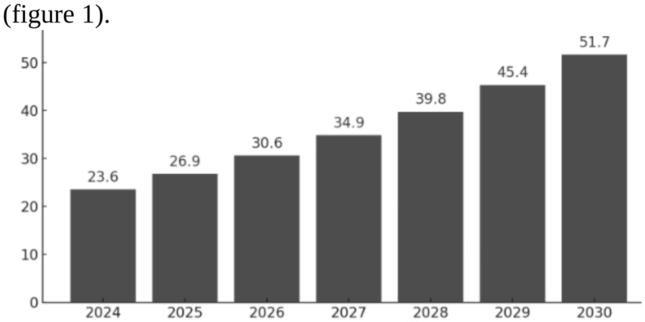

Figure 1: Simulation software market size, billion dollars [1]

Simulation modeling, as a method of engineering analysis, is utilized to model the behavior of large technological systems in situations that are nearly identical to real operating situations. With this method, nonlinear system dynamics, random changes in parameters, and multiple point failures can be considered, an important condition when controlling high-risk industrial processes.

2.1 Technological risk forecasting methods

With the increasing complexity of production systems and growing demands for the reliability of technological processes, traditional risk assessment methods – such as expert judgment, statistical analysis, or regulatory inspections – are increasingly giving way to intelligent approaches that enable adaptive, predictive, and self-learning control.

The intelligent methods applied in this domain can be broadly classified based on how they interact with the simulation model: ranging from passive data analysis to active control and agent-based learning through feedback. Some algorithms utilize the simulator as a source of training datasets; others are embedded directly into the simulation environment as surrogate components; and still others treat the simulator as a training environment for reinforcement learning agents (table 2).

Table 2: Intelligent methods for predicting technological risks based on simulation modeling [2, 3]

Method class	Description	Typical algorithms	Applications
ML on synthetic data	ML models are trained on datasets generated by the simulator, including rare or failure scenarios	XGBoost, Random Forest, SVM, Logistic Regression	Failure classification, remaining useful life estimation, critical state prediction
ML as a surrogate in simulation	Trained models replace complex or resource-intensive blocks inside the simulation environment	MLP, CNN, GPR (Gaussian Process Regression), LSTM	Approximating heat transfer, corrosion rates, flow dynamics
Anomaly detection	Identifies deviations from normal behavior modeled or learned from simulation data	Autoencoder, One-Class SVM, Isolation Forest	Fault detection, early warning systems, deviation monitoring

Reinforcement Learning (RL)	The simulator is used as an environment to train agents for optimal control strategies	Q-Learning, DQN, PPO, SAC	Inhibitor dosage control, operational mode optimization
Probabilistic methods	Forecasts are generated based on probabilistic distributions and confidence intervals	Bayesian Neural Networks, Monte Carlo Dropout.	Risk estimation, failure probability mapping
Simulation-based optimization	Optimization of system parameters using the simulator as a black-box evaluator	Genetic Algorithms, Bayesian Optimization.	Parameter tuning, fault-tolerant configuration, scenario analysis

The advantage of these methods lies in their ability to account for complex, nonlinear, and stochastic characteristics of processes that are difficult to formalize through analytical equations. However, their successful application requires careful selection of the simulation platform to ensure compatibility with external ML libraries, as well as a reliable data exchange architecture between system components. Collectively, intelligent methods based on simulation modeling provide the technological foundation for developing adaptive and predictive production systems.

These approaches are particularly important in technological domains characterized by physicochemical instability, where process dynamics are highly sensitive to slight deviations in input parameters. This is especially relevant for systems involving the treatment of aggressive environments and the prevention of corrosion-related degradation [4]. In such cases, not only accurate reproduction of current system states is required, but also timely correction of control actions. For instance, in systems for the metered injection of inhibitors, an effective control strategy can be implemented through the integration of predictive algorithms with chemical interaction models. This approach enables adaptation to variable conditions, optimization of dosing regimes, and, consequently, increased equipment reliability while reducing operational costs.

2.2 Digital twins as a tool for simulation modeling

In the context of increasing complexity and interdependence of industrial processes – particularly in sectors with a high degree of automation and elevated risk of failure – the digital twin has emerged as a critical component of forecasting systems [5]. It enables the integration of a physical object with its corresponding mathematical and informational representation. A digital twin is a high-fidelity virtual replica of a physical asset, synchronized with real-time data from the operational system (figure 2).

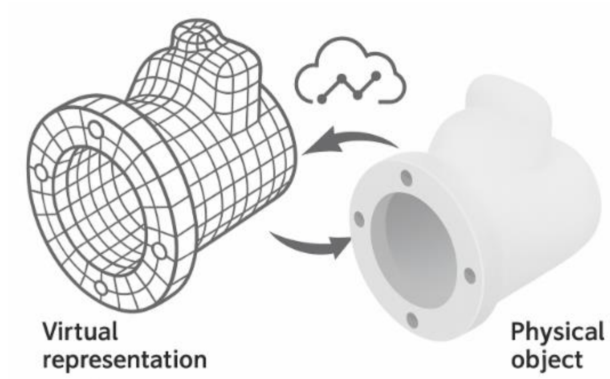

Figure 2: Digital twin architecture

A digital twin not only replicates the current parameters of a system but also enables predictive analysis, failure scenario evaluation, optimization of operating modes, and simulation of external influences. In industrial practice, digital twins are employed for equipment condition monitoring, process control, maintenance planning, and risk assessment during transitions to new operational regimes.

The construction of digital twins is based on discrete-event, agent-based, system dynamics, or hybrid models, depending on the nature of the production process. The implementation of such models relies on specialized software tools (table 3).

Table 3: Approaches to building digital twins and corresponding modeling tools [6, 7]

Model type	Brief description	Applications	Modeling tools
Discrete-event	Models the system as a sequence of events occurring over time.	Production lines, queuing systems, logistics, service systems.	AnyLogic, FlexSim, Arena, SimPy.
Agent-based	System is represented as a set of autonomous agents interacting with each other.	Human behavior modeling, transport systems, autonomous entities,	AnyLogic, NetLogo, GAMA Platform.
System dynamics	Uses differential equations and	Chemical and energy processes,	Vensim, Stella, Dymola, Matlab

	feedback loops to represent accumulations and flows.	high-level process control.	Simulink
Hybrid	Combines two or more modeling paradigms within a single model.	Complex industrial systems, full-scale digital twins, integration with SCADA/PLC.	AnyLogic, Modelica, OpenModelica, Matlab Simulink, custom Python.

The practical implementation of a digital twin requires the construction of a multi-layered architecture that includes the physical layer (sensors, actuators), a data acquisition and preprocessing layer (e.g., SCADA, OPC UA, MQTT), simulation and analytics modules, and a user interface. As an intermediate layer, cloud-based solutions and industrial IoT platforms – such as Siemens MindSphere, GE Predix, and Azure IoT Hub – are increasingly employed to provide scalability and connectivity for distributed components [8]. The simulation module itself can be deployed either locally or in a cloud environment, supporting asynchronous scenario processing and feedback interaction with the physical asset.

Special attention is given to synchronization between the physical and virtual states of the system. This can be implemented as real-time synchronization or in quasi-real-time mode (batch updating), depending on the required response time. In industrial and supply chain environments, maintaining up-to-date digital representations plays a critical role in enabling timely decision-making and enhancing system fault tolerance [9]. The efficient operation of a digital twin also necessitates the implementation of model calibration mechanisms based on new incoming data, which is typically achieved through integration with learning algorithms (e.g., online learning or transfer learning). Thus, the digital twin becomes not merely a static simulation model, but a continuously evolving system capable of adapting to changes in both the external environment and the internal structure of the object.

3. EVALUATION OF THE EFFECTIVENESS OF INTELLIGENT MODELS FOR FORECASTING TECHNOLOGICAL RISKS IN A PRODUCTION SYSTEM

As part of this study, a digital model of a production process was developed to simulate the operation of a continuous manufacturing line consisting of four sequential modules: raw material loading, thermal processing, packaging, and quality control. The model incorporated stochastic elements, including random delays, component failure probabilities, and fluctuations in technological parameters such as temperature, speed, and pressure. It was implemented in the SimPy environment, enabling multiple scenario runs under varying initial conditions.

The experiment assessed the potential for improving the resilience of the technological process by integrating predictive mechanisms based on existing machine learning algorithms. In particular, standard built-in classifiers from MATLAB (Classification Learner) were used to analyze the simulator-generated data and predict the likelihood of deviations beyond acceptable process limits. The model functioned as a predictive module capable of issuing early warnings about the accumulation of deviations that could lead to production stoppages or increased defect rates. Parameter adjustment scenarios were implemented through control signals in the simulator – such as conveyor speed changes, activation of cooling systems, or skipping of dosing cycles.

The comparison was conducted across three operational modes:

- standard (without prediction),
- intelligent (with failure forecast-based adjustments),
- stress (including external disturbances such as raw material supply interruptions, temperature spikes, and malfunctions in the packaging unit).

Table 4 presents the averaged performance indicators based on 1,000 simulation iterations for each mode.

Table 4: Performance indicators of the production process under different control modes

Indicator	Standard mode	Intelligent mode	Stress mode
Number of critical shutdowns (per 1000 cycles)	62	19	87
Average downtime duration, min	178	71	239
Defective product rate, %	7.3	3.0	11.5
Energy/resource savings, %	–	11.8	–
False alarm rate of the prediction system, %	–	4.6	–

The modeling results demonstrated that integrating a predictive module based on existing machine learning tools significantly enhances the resilience of the production process to both random and cumulative disturbances. By utilizing forecasts of the probability of exceeding acceptable technological parameter ranges, the simulation model exhibited a more than threefold reduction in the frequency of critical shutdowns, as well as reductions in product loss and downtime duration. These outcomes confirm the applicability of intelligent modeling not only for scenario analysis but also as a foundation for digital process control under uncertainty.

4. CONCLUSION

The advancement of intelligent methods based on simulation modeling represents a promising direction in engineering analytics aimed at proactive risk management in complex technological systems. The use of hybrid architectures that combine mathematical models with trainable components enables not only the reproduction of production system behavior under uncertainty but also the formulation of adaptive response strategies to potential deviations. Digital twins integrated with machine learning modules serve as a foundation for predictive diagnostics, parameter optimization, and improved robustness to abnormal situations.

The results of the analysis confirm the high practical relevance of such approaches in real industrial environments, particularly in sectors with a high degree of automation and sensitivity to internal and external fluctuations. Intelligent risk forecasting systems allow for a reduction in the number of emergency shutdowns, a decrease in defect rates, and optimization of resource consumption through anticipatory control. Future research in this area may focus on the development of online learning techniques, scalable architectures for digital twins, and standardization of data exchange models between simulators and ML services in industrial settings.

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