DIGITAL TRANSFORMATION OF BUSINESS DECISION-MAKING: AN ALGORITHM FOR THE APPLICATION OF PRESCRIPTIVE ANALYTICS

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Abstract. *The rapid digitalization of modern enterprises has significantly increased the complexity of business environments, requiring advanced analytical approaches to support effective decision-making. This study examines the role of prescriptive analytics in the digital transformation of business decision-making, with a particular emphasis on simulation modeling as a core methodological tool. The research aims to develop a generalized algorithm for constructing digital decision-making systems capable of analyzing complex and dynamic business processes. The study integrates multiple simulation approaches, including discrete-event simulation, agent-based modeling, and hybrid modeling, to support scenario analysis, resource optimization, and risk mitigation.*

A structured methodological framework is proposed, encompassing problem formulation, conceptual modeling, data modeling, experimental design, validation, and integration into digital platforms. The results demonstrate that simulation-based prescriptive analytics enables organizations to evaluate multiple decision scenarios without real-world risks, improving operational efficiency and strategic planning. Furthermore, the integration of simulation with optimization techniques enhances decision accuracy and adaptability. The study concludes that digital decision platforms based on simulation modeling significantly contribute to sustainable and data-driven business process management in dynamic environments.

Keywords: *prescriptive analytics, Simulation modeling, Digital decision-making, Business process optimization, Discrete-event simulation, Agent-based modeling, Hybrid simulation systems.*

1. Introduction

The transformation of business environments under the influence of digital technologies has fundamentally altered how organizations approach decision-making. Increasing levels of uncertainty, system complexity, and interdependence among processes require analytical tools capable of handling dynamic and stochastic conditions. Traditional decision-making approaches, which rely on historical data analysis and managerial intuition, are no longer sufficient for addressing the multifaceted challenges faced by modern enterprises.

Prescriptive analytics has emerged as a critical component of the analytics paradigm, extending beyond descriptive and predictive approaches by providing actionable recommendations based on advanced computational models (Delen & Zolbanin, 2018). Among the various techniques used in prescriptive analytics, simulation modeling has gained particular importance due to its ability to replicate the behavior of complex systems over time. Simulation modeling allows decision-makers to experiment with different scenarios in a controlled digital environment, thereby reducing risks and improving the quality of decisions.

Simulation modeling in business process management involves the creation of a digital representation of real-world systems that incorporates stochastic variables and dynamic interactions. Several modeling approaches are commonly used, including discrete-event simulation (DES), system dynamics (SD), and agent-based modeling (ABM). Discrete-event simulation focuses on sequential processes and event-driven changes, making it suitable for logistics and manufacturing systems (Banks et al., 2014). System dynamics provides a macro-level perspective by modeling continuous flows and feedback loops (Shannon, 1998), while agent-based modeling captures interactions among autonomous agents, enabling the analysis of emergent behaviors in complex systems (Wallentin & Neuwirth, 2017).

Despite the widespread application of these techniques, existing research often treats them as independent methodologies rather than components of an integrated decision-making framework. This fragmentation limits their effectiveness in addressing complex, real-world problems that require multi-level analysis and coordinated decision-making. Moreover, there is a lack of generalized algorithms that systematically integrate simulation modeling with optimization techniques to support prescriptive decision-making.

Business process reengineering (BPR) further highlights the need for advanced analytical tools. Redesigning business processes requires a comprehensive understanding of current operations, resource allocation, and potential future scenarios. Testing alternative configurations in real-world conditions is often impractical due to high costs and associated risks. Simulation modeling offers a viable alternative by enabling virtual experimentation and performance evaluation under controlled conditions.

Therefore, this study aims to address the existing research gap by developing a generalized algorithm for the application of prescriptive analytics through simulation modeling. The proposed framework integrates multiple modeling approaches and provides a structured methodology for building digital decision-making systems capable of optimizing business processes and supporting strategic decision-making.

2. Methodology

This study adopts a conceptual and methodological research design aimed at developing a comprehensive algorithm for prescriptive analytics based on simulation modeling. The proposed methodology is grounded in established principles of operations research and systems analysis, incorporating best practices from existing literature on simulation modeling and optimization techniques (Law, 2007; Pritsker, 1998).

The research process begins with **problem formulation**, which involves clearly defining the objectives of the study and identifying the key variables and constraints of the system under consideration. This stage ensures alignment between analysts and decision-makers and provides a foundation for subsequent modeling activities. It is important to note that problem formulation is often iterative, as new insights may require adjustments to the initial problem definition.

The next stage involves **defining research objectives and developing a project plan**. This includes identifying the specific questions to be addressed through simulation modeling and determining whether simulation is an appropriate methodology for the given problem. The project plan outlines the scope of the study, including the number of scenarios to be analyzed, required resources, and expected outcomes.

Model conceptualization follows, where the system is abstracted into a simplified representation that captures its essential features. This process involves identifying system components, defining relationships among variables, and selecting the appropriate modeling approach. Depending on the nature of the system, a discrete-event, agent-based, system dynamics, or hybrid modeling approach may be used. Conceptual modeling should strike a balance between simplicity and accuracy to ensure that the model remains both manageable and representative of the real system.

The **construction of the digital model** involves translating the conceptual model into a computer-readable format using specialized simulation software. Tools such as AnyLogic, FlexSim, and AutoMod are commonly used for this purpose. This stage requires careful consideration of computational requirements and model scalability.

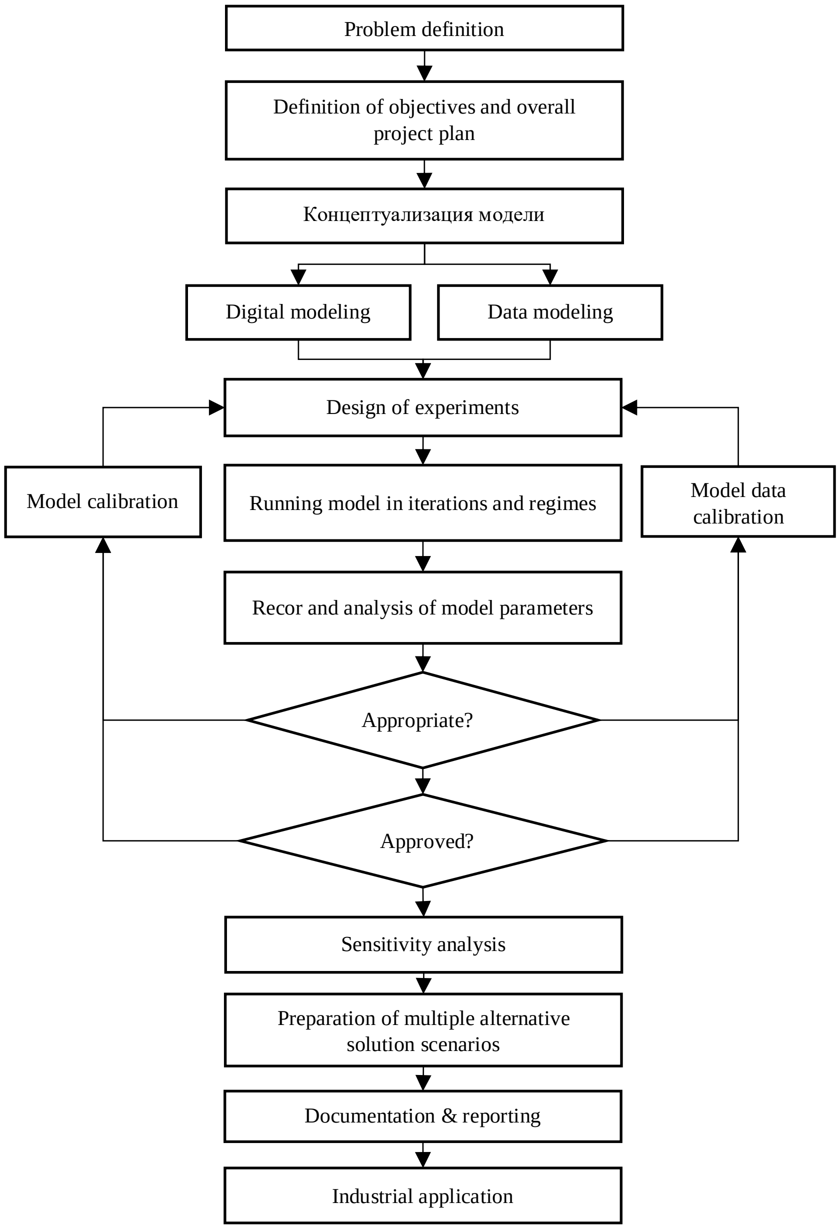

Figure 1. A general algorithm for implementing prescriptive analytics for building a digital decision-making system.

Data modeling is conducted concurrently with model construction. This stage involves collecting, processing, and analyzing input data required for the simulation. Data may be obtained through electronic recording systems, direct observation, or expert assessment. Statistical analysis is used to determine data distributions and ensure that the model accurately reflects real-world conditions (Gavilan et al., 2021).

The **experimental design** phase defines the parameters of the simulation, including the duration of simulation runs, number of iterations, and variation of input variables. Multiple simulation runs are conducted to account for stochastic variability and ensure the reliability of results (Sanchez, 2007).

Model verification and validation are critical steps in ensuring the accuracy and reliability of the simulation model. Verification involves checking that the model is implemented correctly, while validation ensures that the model accurately represents the real system. Validation may involve comparing simulation outputs with real-world data or relying on expert judgment when empirical data are unavailable (Sargent, 2007).

A **sensitivity analysis** is then performed to evaluate the impact of changes in input variables on system performance. This analysis helps identify critical variables and assess the robustness of the model under different conditions.

Finally, the results are integrated into a **digital decision-making platform**, where alternative scenarios are evaluated, and optimal solutions are identified. This integration enables real-time decision support and enhances the practical applicability of the simulation model.

3. Results

The application of the proposed methodology resulted in the development of a generalized algorithm for implementing prescriptive analytics in business decision-making. The algorithm consists of a sequence of interconnected stages, including problem formulation, conceptual modeling, data modeling, experimental design, simulation execution, validation, sensitivity analysis, and integration into a decision-support system.

The results demonstrate that simulation modeling provides a robust framework for analyzing complex systems and evaluating alternative decision scenarios. By enabling virtual experimentation, simulation reduces the risks associated with real-world testing and allows organizations to identify optimal strategies for resource allocation and process optimization.

The integration of optimization techniques with simulation modeling further enhances decision-making capabilities. Optimization methods enable the identification of the best configuration of system parameters, improving performance metrics such as efficiency, cost, and service quality (Collison, 2022). This combination of simulation and optimization provides a powerful tool for prescriptive analytics.

Additionally, the use of hybrid simulation models allows for a more comprehensive representation of complex systems by combining the strengths of different modeling approaches. For example, integrating discrete-event simulation with system dynamics enables the modeling of both operational processes and strategic-level interactions. Similarly, combining agent-based modeling with other approaches allows for the analysis of individual behaviors and their impact on system-level outcomes.

The results also highlight the practical applicability of the proposed algorithm across various industries, including logistics, manufacturing, energy systems, and e-commerce. Simulation-based decision-making systems can be used to optimize delivery services, improve production efficiency, and support strategic planning in dynamic environments.

4. Discussion

The findings of this study underscore the transformative potential of prescriptive analytics and simulation modeling in modern business environments. The proposed algorithm provides a systematic framework for integrating simulation models into digital decision-making platforms, enabling organizations to make informed and data-driven decisions.

One of the key advantages of simulation modeling is its ability to capture the dynamic and stochastic nature of real-world systems. This allows decision-makers to analyze the impact of various factors on system performance and identify potential bottlenecks and inefficiencies. Furthermore, the integration of optimization techniques enhances the effectiveness of simulation models by identifying optimal solutions based on predefined criteria.

The use of hybrid simulation models represents a significant advancement in modeling complex systems. By combining different modeling approaches, hybrid models provide a more comprehensive understanding of system behavior and improve the accuracy of predictions. This is particularly important in industries where systems are highly interconnected and influenced by multiple variables.

The integration of artificial intelligence and machine learning into simulation modeling presents additional opportunities for improving decision-making processes. These technologies can automate the optimization process, reduce computational time, and enhance the adaptability of decision-making systems (Alalwan, 2020).

However, several challenges remain. The development of simulation models is a complex and time-consuming process that requires significant expertise and computational resources. Data availability and quality also play a critical role in determining the accuracy of simulation results. Furthermore, the successful implementation of simulation-based decision-making systems depends on the involvement of end users throughout the modeling process and their understanding of the model's outputs.

5. Conclusion

This study demonstrates that prescriptive analytics, supported by simulation modeling, plays a crucial role in the digital transformation of business decision-making. The proposed algorithm provides a comprehensive framework for developing digital decision-making systems capable of analyzing complex business processes and supporting optimal decision-making.

Simulation modeling enables organizations to evaluate multiple decision scenarios without real-world risks, improving operational efficiency and strategic planning. The integration of optimization techniques further enhances decision accuracy and adaptability, allowing organizations to respond effectively to changing environments.

In conclusion, the implementation of simulation-based prescriptive analytics contributes significantly to the development of effective digital decision-making platforms. These platforms enable organizations to navigate complexity, optimize resources, and achieve sustainable competitive advantages in an increasingly dynamic business landscape.

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