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The Role of Intelligent Technologies in Advancing Operations Research Models and Statistical Methods: A Review

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Abstract

This article reviews the evolving role of smart technologies in advancing operations research models and statistical methods. The article begins by asserting that operations research and statistics have developed relatively separately despite their natural complementarity, as statistical methods provide the data and standards needed for operations research models. The article identifies three main categories of smart technologies: Artificial Intelligence and Machine Learning (sub-categories: supervised learning, unsupervised learning, and reinforcement learning), data infrastructure and big data analytics (including data processing and feature engineering), and automation, simulation, and digital twining. The article reviews the synergies between these technologies and process research modeling through three main areas: model formulation and solution techniques, by integrating machine learning predictions, surrogate modeling, and designing hybrid structures, data-driven calibration and validation: using data to derive model parameters and estimating uncertainty, instantaneous optimization and adaptive decision-making: through rapid re-optimization and multi-stage optimization. The article also discusses the enhancement of statistical methods through intelligent technologies, especially in AI-powered Bayesian and probabilistic modeling, non-parametric methods, and powerful methods in intelligent data environments, causal reasoning, and experimental design with learning-enhanced tools. The article concludes with applications across multiple sectors, including supply chains and logistics, healthcare and epidemiology, energy systems and sustainability, and finance and risk management, emphasizing that the integration of smart technologies with operations research and statistics opens up new avenues for improving decision-making in complex and data-rich environments.

Keywords: Operations Research, Statistical Methods, Smart Technologies, Artificial Intelligence, Machine Learning, Big Data Analytics.

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1. Introduction

Operations Research (OR) has been integral to management science, business analytics, and applied economic decision-making since the mid-20th century. The discipline assists in selecting the optimal course of action through the construction and solution of mathematical models derived from realistic real-world decision-making challenges. Statistical methods—built upon probabilistic modeling and the design of experiments—help specify stochastic components (noise, demand, processing times, etc.) of OR models and either

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generate data for model calibration or evaluate model performance (1,2).

Despite notable advances in OR, the interplay with statistical methods—also an essential scientific focus with an extensive history—has been relatively weak (3). Using straightforward definitions for OR, statistical methods, and intelligent technologies, this review explores how recent, sophisticated, and broadly applicable intelligent technologies offer potential for overcoming long-standing challenges in both disciplines (4,5).

2. Foundations of Operations Research and Statistical Methods

Operations Research (OR) and Statistical Methods constitute decision analytical methodologies widely applied in diverse industry settings. Despite considerable advancements since their inception, their core models and statistical counterparts still await a thorough examination of the opportunities presented by recent developments in Intelligent Technologies (3).

During World War II, operations research was developed to aid in military strategy. Since then, it has developed into a broad field that uses a variety of modeling paradigms and approaches to solving problems. OR's interactions with allied topics, such as stochastic modeling, queueing theory, reliability, game theory, system dynamics, and constraint satisfaction, demonstrate its interdisciplinary nature (6). A variety of mathematical and computational methods intended to support optimum decision-making in complex systems are together referred to as OR. These techniques, which have gained popularity in supply chain management, transportation systems, production scheduling, network design, inventory control, and many other domains, find the best solutions for mathematical models that represent operational settings. In order to improve knowledge of the organization and its operations and help decision-makers make better decisions, OR models, techniques, and systems often extract information from relevant data (7).

Operations Research (OR) is greatly enhanced by Statistical Methods, which deal with the extraction of information from observable data. A significant and mutually beneficial synergy has grown over time between OR and statistical methods. On the one hand, OR technologies help with data analytics in high-dimensional, more complicated data models. On the other hand, many Statistical Methods regularly give OR information that helps with model building, calibration, validation, and even optimization (6). This interaction is especially noticeable in the field of supply chain analytics, where relevant data is collected to accurately model different target decision variables and statistical insights are used to improve the performance of the company (8).

2.1. Core Models in Operations Research

The area of operations research (OR) focuses on using advanced analytical methods to support better decision-making. It makes use of techniques from related fields of mathematics, such as statistics, optimization algorithms, and mathematical modeling. Linear programming (LP), integer programming (IP), network flow models (NF), and stochastic programming (SP) are examples of fundamental OR analytical models. Deterministic mathematical models such as LP, IP, and NF have been extremely popular in OR, having been extensively studied by researchers and implemented at scale by enterprises. A mathematical programming model typically consists of three elements: the decision variables, the objective function, and the set of constraints within which optimal solutions must lie (6,9). These analytical models have facilitated a wide variety of application areas, from supply chain network design to facility location planning, both in deterministic and stochastic settings. The LP model deals with problems having continuous decision variables, while integer programming deals with discrete decision variables and is computationally challenging. Network models are an important subclass of LP models that deal with flow problems in a directed/undirected network. SP deals with the uncertainty in future realization of certain data, supports fast and easy modelling, avoids complex non-linear relationships among random variables, provides probability guarantees for constraint violations, and out-of-sample performance (10,11). Typical SP models include Chance Constrained Programming, Distributionally Robust Optimization, and Robust Optimization. Thus, OR has not only gained prominence as a scientific discipline but is also widely recognized by practitioners as a powerful tool for improving decision making (3, 8).

2.2. Statistical Methodologies in OR

Operations Research (OR) plays an important role within decision science, supporting systematic modeling and optimizing complex systems through analytical methodologies and intelligent technologies. OR emerged during World War II, when mathematicians investigated military asset and troop allocation problems at the request of the British and American military; the term "OR" (short for "Operational Research") was subsequently adopted in the United Kingdom (12). The first linear programming (LP) problem was formulated in 1939, while the first simplex algorithm for solving LP problems was published in 1947. Operational Research (OR) analyzes societal problems ranging from energy conservation to health service planning by applying mathematical methods for system modeling, optimization, and decision-making. Statistical methodologies are integral to OR because they support key aspects and facilitate model integration with optimization (3). Statistics play an important role in operations research (OR), where it was applied in the formulation of many studies and models (13).

Five statistical methods underlie a broad range of OR applications: estimation (determining system parameters based on observed data), statistical hypothesis testing (determining whether two processes are the same to inform, say, equipment choice), regression (directly predicting system outputs based on inputs to minimize the gap), experimental design (gaining information about uncertain parameters to improve the model formulation and, consequently, decision quality), and forecasting (predicating future unobserved values based on known observations). These methodologies can be applied to the formulation of the problem itself and subsequently incorporated into the optimization model (14).

3. Intelligent Technologies: Definitions and Core Capabilities

Intelligent technologies automate various aspects of modeling, problem solving, and decision support. Data–driven problems allow data–intensive modeling of the underlying system, meanwhile enabling real–time tracking to update model parameters. Intelligent technologies empower dynamic planning over an extended horizon with uncertain requirements, support better–informed decision making in both well-structured and unstructured situations, allow a richer consideration of interdependencies among state variables, enhance performance at a lower model fidelity, and extend the applicability of established models to new domains (15).

3.1. Artificial Intelligence and Machine Learning

Artificial intelligence (AI) and machine learning (ML) comprise fundamentally different paradigms. AI embodies the endeavor to conceive intelligent machines capable of executing tasks typically necessitating human intelligence. Its goal is to counter the limitations of conventional programming by enabling machines to acquire knowledge, integrate diverse information, form associations, and draw conclusions. MLM forms a subset of AI. It addresses knowledge acquisition:

training computers to have knowledge is often arduous; employing sample data to induce algorithms that can generalize to unobserved data is a more feasible alternative. As a result, machine learning permeates every aspect of daily life, business, science, and technology. However, its contribution to operations research is still rather small. Supervised learning and unsupervised learning are two well-known and well-acclaimed subfields in artificial intelligence. A labeled dataset—inputs coupled with their precise targets—is essential to supervised learning. Configurations like traits and features—dimensions considered essential for solving the problem—are carried by the inputs, or objects. Finding a function that skillfully maps inputs to targets is the goal of supervised learning. In order to reduce the difference between expected outputs and actual objectives, this function often takes the form of a model whose parameters are adjusted during training (16-18).

As a result, machine learning permeates many different fields, including science, technology, business, and daily life. However, its impact on operations research is still rather small. Supervised learning and unsupervised learning are two promising, well-explored avenues for the development of artificial intelligence. A labeled dataset that matches inputs with their actual goals is used in supervised learning. The inputs, or objects, include combinations of traits and features, the crucial parameters selected to address the issue. The objective is to create a function that can accurately map inputs to their objectives. Typically, this is accomplished by creating a model whose parameters are adjusted during training to reduce the difference between expected and actual results (19,20).

The third major area of machine learning is reinforcement learning (RL). In reinforcement learning, an agent dances with its surroundings; the environment changes and evolves with each transition, and the agent chooses actions that can influence those changes. The environment gives the agent incentives when the dust settles, a chorus of feedback that directs the path. The RL agent's primary objective is to create a policy that maximizes the overall long-term received reward. Many OF issues may be converted into RL problems by integrating OR models into the environment framework or by using OR models to provide the reward function (21).

AI—particularly ML—has tangible theoretical potential to improve operations research and facilitate its implementation. However, deciding on real-value samples, determining appropriate model structures, and obtaining comprehensive sample sets remains challenging within this field (22).

3.2. Data Infrastructure and Big Data Analytics

Data infrastructure in operations research refers to the sources, structures, and collection methods that enable business models and software tools. Data routes include digital footprints (e.g., click patterns, influencer activities), market transactions (e.g., purchase order patterns, bill of lading activities), communication channels (e.g., emails, corporate memos), and information exchanges (e.g., online questionnaires). Both molecular (individual micro-sessions to discover customer journey patterns) and macroscopic (aggregate customer cohorts to detect bottleneck- and turnover-types) analytics are fueled by commercial transactions. Digital trails provide preferences and intention patterns, communication streams illuminate current concerns, and questionnaires investigate knowledge gaps, satisfaction levels, and deviations from requirements (23).

Processing underpins the various operational research functions. Data quality manifests in attributes such as formal correctness, semantic precision, storage integrity, and temporal consistency. Generating enhanced data-ready supply chain structures can require hundreds of hours (24).

Data preprocessing entails tasks like cleaning, transformation, integration, and reduction. For example, mapping the entire supply chain network may combine data on physical flows, document transactions, financing arrangements, and supply-demand aspects encompassing prices, target indicators, and contract durations (25).

Feature engineering increases coverage through suitable conversions (attribute reformulation, expansion, creation, and aggregation) and replacements (change of location from the source to the destination); or reduced dimension via filtering (maximizing relational relevance or correlation), extraction (pca, fda, lda), and construction (gradient boosters). Explainability refers to acquiring essential attributes with low coverage of the business model, or fewer feature changes (demand, lead time, etc.) during optimizations (26).

Big data and analytics can enhance decision-making (27). Business intelligence concentrates on information access; data mining and advanced analytics augment prediction and modeling. Ensuring data acquisition aligns with recognizable business models and transparent decision metrics is crucial for optimizing actions at the operational level (28).

3.3. Automation, Simulation, and Digital Twins

Automation clears the grind of repetitive tasks and fuels nimble decision-making. A secure environment for experimenting with complex systems is created via simulations. Digital twins enable fast decisions and quick reconfigurations by fusing simulation-driven models with real-time data to deliver prescriptive and predictive insights (29). Automation, which frequently threads across engineering workflows, data management, and model building, is at the core of intelligent technology. Adjusting models or refining solutions as circumstances change, it allows for real-time optimization and adaptable decisions. Machine learning (ML) technologies are used to create surrogate models, which offer data-driven stand-ins for complicated systems to guide improvement. It takes work to choose the best machine learning (ML) algorithms and adjust hyperparameters; automated machine-learning (AutoML) technologies make this process easier and accelerate preliminary studies (30).

Object-oriented, agent-based, and similar modeling domains are supported by dynamic simulation, which allows creativity to leap over time spans and conflicting goals as design possibilities are tried quickly one after the other. It establishes the foundation for digital twins, which enhance rather than replace conventional simulation and open up new avenues for predictive and prescriptive analytics across sectors. Digital twins combine dynamic simulation models with real-time monitoring to understand the present, forecast future events, and provide remedial actions (31). They may be found in manufacturing systems, healthcare, supply chains, and energy transformation. They can be used for pandemic response, inventory control, and production schedule optimization. Probing alternate scenarios, technology, or design principles throughout significant overhauls or policy upheavals is made feasible by digital twins. They are essential to smart factories because they allow for quick evaluation of possible enhancements (32).

4. Synergies Between Intelligent Technologies and OR Modeling

Intelligent technologies encompass a wide range of digital resources that enhance data collection and modeling, thereby improving decision support. Operations research (OR) focuses on the development and resolution of decision-making models to optimize the allocation of resources within given constraints (33). There is a substantial role for intelligent technologies at the interfaces of decision-making models. Such models find wide application in supply chains, healthcare, resource management, and finance (34).

The interface between intelligent technologies and OR modeling is framed in three categories. The first addresses model formulation and solution techniques, extending optimization problems by embedding machine learning (ML) predictions, constructing surrogate models, applying decomposition principles, and designing hybrid architectures. The second focuses on data-driven model calibration and validation, leveraging observed data for parameter estimation, augmenting traditional practices with cross-validation and out-of-sample testing, and quantifying uncertainty in settings with limited data. The third covers real-time optimization and adaptive decision-making, integrating online learning systems, a rolling-horizon scheme, rapid re-optimization capabilities, and control mechanisms addressing uncertainty throughout the temporal evolution of the model (35).

Model formulation and solution techniques. Extending first-stage decision problems with ML predictions (open-loop control) encourages comprehensive exploration of decision processes, addresses situations where standard analytical tools do not exist, and helps surmount the computational intractability of large-scale problems. Surrogate models approximate the underlying relationships between decision variables and system outputs, thereby guiding the solution process towards optimality, supporting benchmarking, or constraining decision space with valid inequalities. Decomposition techniques simplify highly complex optimization problems, and hybrid architectures blend derivative-free, gradient-based, and heuristic methods (36).

4.1. Model Formulation and Solution Techniques

Intelligent technologies can enhance model formulation and solution techniques for Operations Research (OR) problems. Intelligent technologies can augment the solution of decision systems in OR via intelligent technologies through two main avenues: via intelligent technologies and via ML technology. Various intelligent technology capabilities can contribute to OR modelling efforts through (1) the intelligent acquisition of observations that inform models, (2) sophisticated modelling to build OR representations that incorporate a problem's data, and (3) intelligent decision support that leverages mathematical models to focus on decisions (3,9).

Machine Learning techniques can improve general modelling, estimation, representation, and solution paradigms in OR systems. Embedding off-line ML predictions into mathematical or simulation-based modelling frameworks can contribute to describing mathematical relationships that are otherwise opaque. Surrogate modelling can provide the density of potential solutions in a high-cost optimisation environment. Decomposition strategies can partition problems into simpler subproblems whose formulations span different structures, while retaining a shared data-conditional component. Hybrid model architectures can connect a general predictor with an OR model, a strategy already common in other disciplines, that still awaits broader adoption (3).

4.2. Data-Driven Model Calibration and Validation

The determination of parameters in operational research (OR) models is often based on expert judgment or handbook values, potentially limiting model effectiveness. Leveraging data to derive suitable model parameters enables a more informed characterization of the underlying system. Methods for estimation, verification, and uncertainty characterization of parameters constitute fundamental components in addressing the modelling problem (37). These activities are usually referred to as model calibration and validation. The objective of model calibration is to identify relevant values for the parameters of an OR model that are consistent with the observed input-output behaviour generated by the system under study. Model validation allows evaluating the degree to which a model, once calibrated, replicates the behaviour of the system under scrutiny. Validating and quantifying the uncertainty associated with the estimated/calibrated parameters are instrumental in establishing confidence in model-based predictions. The capability of automatic learning from past data in intelligent technologies provides a potential means for addressing these activities (38). Embracing an estimation-prediction-validation process provides a coherent framework to specify the four-stage sequence followed to carry out model calibration and validation, starting from data acquisition. The process encompasses parameter estimation from the available data; model prediction of the response variable; validation through out-of-sample analysis assessing how well the model-predicted values approximate the observations; and uncertainty quantification associated with the estimated parameters (39).

4.3. Real-Time Optimization and Adaptive Decision Making

Real-time optimization and adaptive decision-making become necessary when the problem parameters are uncertain or when they vary due to their stochastic nature or rapidly changing environments. One setting that has gained extensive attention is an optimization problem in which the solution needs to be re-optimized over time when new information becomes available, such as due dates in project scheduling and customer demand in inventory control (40). This problem is referred to as rolling-horizon optimization or, in the case that the system needs to be re-optimized at multiple points in time, multi-stage optimization. The state-of-the-art re-optimization approaches are grouped into two categories: fast re-optimization, which speeds up the solving of the mathematical model issued when new information arrives, and adapted optimization, which optimizes a system where new information is gradually revealed, such as Markov decision processes and adaptive robust optimization (41). One branch of fast optimization is the development of customized solvers that exploit the specific structure of individual use cases and constraints, for example, optimizing crew pairing through workforce management or crew scheduling (3).

5. Enhancements in Statistical Methods through Intelligent Technologies

Operations Research (OR) encompasses a diverse range of activities that support decision-making in an uncertain, dynamic, and data-rich environment, as described in a companion study (3). OR planning problems involve optimizing the performance of limited physical and organizational resources, supply chains, disease control, and other systems. Data requirements for decision-making can be categorized into four areas: demand (quantity and timing), cost (fixed and variable), capacity (gaining insight from historical time series), and system constraints. Intelligent Technologies (IT) offer opportunities to enhance Statistical Methods through statistics and data science; allow the construction of Statistical Method-based classifiers, robust methods, Bayesian approaches, hypothesis testing, and data aggregation of uncertain parameters; play a growing role in Developing Theory, delaing and solving problems with a set of assumptions and providing insights beyond the specific aspects; and support ethical considerations in supply chain management, healthcare issues, environmental factor, strategies of public goods items, and redevelopment of occupied area by integrating precision and socio-economy data for specific policy evaluation (22,42).

Statistical Methods represent a mainstream branch of Modern Applied Mathematics, alongside Mathematical Modelling, Optimization, and Data Analysis. Comprising acquisition and evaluation of knowledge, description of dependences, causing factors, and effects, Statistical Methods support the modelling of relationships among inputs and outputs and address the evolution of a system. Systems evolve to meet changes in external environments affecting the core technological process. While Statistical Methods develop approximately when Mathematics started to be a formal study and constituted a separate discipline, they continue to evolve rapidly under the growing complexity of systems without a formal definition of Statistical Methods in the first half of the Twentieth Century (43). Statistics help decision-makers to identify valid conclusions, provide justifications, refute wrong claims, and improve forecasts in a multitude of fields. According to a survey on ORAA literature from 2009 to 2015, OR practitioners use Statistics more than other sub-disciplines; Statistics finds wider applications in ORAA and remains a core research direction of OR, to tackle new challenges from existing-found systems comprising uncertainty, imprecision, reliability, and robustness (8).

5.1. Bayesian and Probabilistic Modeling with AI Support

The rise of data-centric intelligent technologies has stimulated fresh advancements in operations research (OR) and statistical methods by leveraging the vast amount of data collected in the decision-making process 3. Such advancements include developments in AI for data collection and knowledge acquisition, statistics for data regularization, and OR for creating targeted decision-making models. The advantages gained from these intelligent technologies significantly push the boundaries of the use of models and the level of analysis carried out (3). Together, they enable the rapid and reliable creation of insightful models that encompass a higher potential of impactful decisions and whose treatments are reached with a higher level of confidence. In particular, intelligent technologies allow scalable high-dimensional data acquisition, knowledge integration, and an understanding of data dependency, establishing a more realistic decision-making environment (44).

Intelligent technologies have substantially modernized conventional statistical methods through a better understanding of data structure, enabling the precise formulation of decision-regulated distributions under longer observation horizons and fewer samples. Bayesian and probabilistic modeling have taken on a more central role, gaining further enhancement from AI techniques. Guidance on sophisticated prior construction, scalable data-dependent inference, model diversity and averaging, and data-adaptive sequential learning of integrated prior and likelihood modeling is readily available in the increasingly informative literature. Nonparametric and robust methods are also receiving increasing attention (45). The former focuses on the acquisition of information from a more extensive support and privileged availability of data description without parameter fluctuations as the situation evolves. In contrast, the latter seeks to minimize the adverse impact of uncontrollable circumstance perturbed noise, interference, or other distracting disturbances that may cloud the incoming data, leaving the original content of essential information as intact as possible and remaining unaffected (46,47).

5.2. Nonparametric and Robust Methods in Smart Data Environments

Advances in machine learning and statistics have brought noticeable benefits to the implementation of nonparametric and robust techniques on high-dimensional data sets. With the rise of intelligent technologies, kernels, trees, and other nonparametric constructions integrated within nonparametric optimal transport frameworks have been used not only for density estimation and regression but also for frequently studied topics like model selection, outlier detection, and dependency analysis (44,48).

In most estimation scenarios, model noise occurs at the observation level, preventing a clear separation of data into systematic and random components. Under such conditions, the embedding of statistical requirements into the optimization framework permits recovery of a nontrivial signal from a seemingly random observation (49). Because the estimated optimal transport plan or density does not directly depend on the observations, the structure of the estimated field remains valid even when data errors are large, making these strategies inherently robust to data noise. At the same time, a significant portion of machine learning literature increasingly recognizes that many queries in data science can be formulated in terms of transport, leading to the development of nonparametric strategies (50).

5.3. Causal Inference and Experimental Design with Learning-Augmented Tools

Determining the presence of causal effects, the estimation of effect sizes, and the design of instruments for identifying causal effects become far more difficult when these data-collection efforts must be undertaken in an environmentally friendly manner, with a minimum of unnecessary or artificial interventions. Learning-augmented methods, which rely upon the analysis of pre-existing or automatically collected data, provide the promise of inferring causation without the need for further environmentally intrusive experimental work (51). Data-driven experimentation and auxiliary data provide alternative, less intrusive means of learning which causal effects are stronger or weaker, potentially permitting individualized recommendation systems to be constructed at low environmental cost (52).

6. Applications Across Sectors

Operational research (OR) encompasses a wide range of applied problems in various sectors, from healthcare and public service to logistics and finance. Smart operational research enhances decision-making in networks through the combination of mathematical modeling, data analytics, and artificial intelligence (AI) (33). With a focus on operations rather than strategic aspects, supply chain logistics addresses configuration design, logistic pricing policies, routing, mode selection, and distribution network optimization. AI models equipped with machine-learning algorithms optimize demand forecasts, allowing for inventory management at different levels with limited data and implementing effective replacement policies (8). In vibrant, sprawling networks that span sites, products, and distribution paths, thorough scenario analysis lights the way from visibility to hands-on operational command. Meanwhile, ensemble learning built from decision trees sharpens the forecast of how quickly each product needs replacement (53).

6.1. Supply Chain and Logistics

Reliable forecasts anchor countless applications across industries, shaping the very quality of decisions (54). As disruptions grow more frequent and sprawling, the call for sturdy yet nimble models grows louder. Tweaking existing models' parameters alone won’t cut it; smarter, more inventive designs are essential (55). Three sector-spanning examples, retail demand forecasting, transportation network optimization, and safety stock determination for an energy supplier, show how tailored models or fresh takes on traditional methods can emerge from hands-on operational wisdom. These examples demonstrate that the most relevant intelligent technology to integrate depends on the decision to be supported, the nature of the data available, and the preliminary knowledge on the process governing the data generation (56). Consequently, transferring ideas across domains is feasible and often fruitful, provided one maintains an open yet critical perspective on the applicability of the prior model and the specificities of the new context (43).

6.2. Healthcare and Epidemiology

Healthcare occupies a vital position in society and has drawn increased attention from academics and practitioners seeking to improve its efficiency and efficacy (57). Various aspects of the healthcare process can be expressed mathematically, such as appointment scheduling, staffing, routing, and bed management. Recent advancements render the development and deployment of health-impacting operations research (OR) models easier and more pertinent than in the past. These include greater availability of health-related data; burgeoning interest in machine-learning (ML) techniques for predictive analytics; more accessible software for predictive analytics; emerging protocols for personalized experimentation and quasi-experiments that facilitate learning; and the proliferation of accumulation and transmission systems—especially in a pandemic context—that aid outbreak transmission modelling (58).

Epidemiological models have long been used to help understand and control the spread of infectious diseases in communities. As the world has departed from the initial COVID-19 outbreak, various interested parties have sought to exploit lessons learned from the pandemic. The involuntary acquisition of relevant data by government entities, combined with a desire to monitor, evaluate, and adjust emerging control policies, has revived interest in two components of the standard SEIR (susceptible-exposed-infectious-recovered) approach: the model itself and the way attachment to the model may derive from how well it fits science-grounded curves that reflect control impacts (59,60).

6.3. Energy Systems and Sustainability

Energy system optimization must consider the balance between energy generation and demand. Various approaches are used, such as generation planning, load balancing, decentralization and control, and capacity optimization, to characterize load flexibility and develop demand response strategies (61). Optimization can occur in short timeframes with frequent reconfiguration and coordination of distributed resources. The interest in carbon-aware optimization—where the environmental impact related to $CO2$ emissions encapsulated in the carbon footprint is taken into account alongside classical cost functions—grows as $CO2$ emissions restrictions at specific time slots and locations increase (62). Modeling solutions for energy systems largely depend on digital transformations, which use multiple paradigms to increase comprehensiveness (63). An exhaustive, non-collapsing overview of the use of digital-transformation-oriented methods and models to support the design, planning, operation, and management of energy systems is provided (64).

6.4. Finance and Risk Management

Innovations in feedback-based supervision, anomaly detection through causal domains, and stress testing via degradation modelling illustrate how intelligent technologies enhance system design and analysis in finance and risk management. Methods seek to maximise returns on diversified portfolios while controlling exposure to operational, credit, liquidity, and market risk. Numerous machine-learning models fitting sensor data have been adopted in hybrid architectures with analytical models for feedback and diagnostics, and for supervised anomaly detection that identifies faulty components and offers repair guidance. Causal-detection techniques can identify the cause or control of anomalies and suppress proposals implicating causal factors with unclear physical mechanisms. Degradation-modelling approaches render stress tests interpretable and facilitate recovery-curve estimation by analysing scan patterns to describe fitting and stress processes, or by embedding a stress-deformation submodel into cyclic probe-compatible models. Proposals for hybridised structures are already emerging, alongside avenues for broader application and transfer to other vital sectors (65, 66).

7. Conclusion

Operations Research (OR) and statistical methods, which are widely used for modeling and analyzing complex real-world systems, often rely on data as a crucial component for obtaining practically relevant solutions. With the ever-increasing volume of data generated in daily operations, intelligent technologies are advancing at a rapid pace and opening up new opportunities for improving these models. The objective of this review is to explore the emerging synergies between intelligent technologies and OR models and statistical methods, and to provide a comprehensive overview of how the combination of these two fields advances each of them. In particular, the article investigates the specific roles that intelligent technologies play in their interactions with OR and statistical models and identifies avenues for enhancing OR formulations and solution methodologies, as well as for extending the scope of statistical methodologies through greater integration with optimization.

In the context of an overall advancement of OR, intelligent technologies and their characteristics, including Artificial Intelligence and Machine Learning, data infrastructure and big-data analytics, and automation, simulation, and digital twins, are first defined. These technologies support models and systems through the various phases of decision-making—data acquisition, modeling, and decision support—and help improve the modeling of decisions in environments characterized by such intelligent technologies.

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References:

1. Pachura P. The space industry-mapping the challenges for management science The space industry-mapping the challenges for management science. Polish Journal of Management Studies. 2024. icm.edu.pl
2. Tsoni E, Lazanaki V, Katsaros K. The influence of organizational climate on work engagement: evidence from the Greek industrial sector. Administrative Sciences. 2025. mdpi.com
3. Fan Z, Ghaddar B, Wang X, Xing L et al. Artificial Intelligence for Operations Research: Revolutionizing the Operations Research Process. 2024. [PDF]
4. Ma J, Li J, Chen Y, Yang Z et al. Poor statistical power in population-based association study of gene interaction. BMC Medical Genomics. 2024. springer.com
5. Spake R, Bowler DE, Callaghan CT, Blowes SA, Doncaster CP, Antao LH, Nakagawa S, McElreath R, Chase JM. Understanding 'it depends' in ecology: a guide to hypothesising, visualising and interpreting statistical interactions. Biological Reviews. 2023 Aug;98(4):983-1002. wiley.com
6. Petropoulos F, Laporte G, Aktas E, Alumur SA, Archetti C, Ayhan H, Battarra M, Bennell JA, Bourjolly JM, Boylan JE, Breton M. Operational research: Methods and applications. Journal of the Operational Research Society. 2024 Mar 3;75(3):423-617. tandfonline.com
7. Gopinath M. … MODELLING IN COMPLEX SYSTEMS: INTEGRATING MATHEMATICAL OPTIMIZATION AND STATISTICAL METHODS FOR ENHANCED DECISION-MAKING. International Journal of Applied Mathematics. 2025. ijamjournal.org
8. Kobbacy KAH, Vadera S. A survey of AI in operations management from 2005 to 2009. 2011. [PDF]
9. Silva C, Ribeiro R, Gomes P. Algorithmic optimization techniques for operations research problems. InProceedings of the Computational Methods in Systems and Software 2023 Apr 12 (pp. 331-339). Cham: Springer Nature Switzerland. [HTML]
10. Costa Y, Melo T. Facility location modeling in supply chain network design: Current state and emerging trends. The Palgrave Handbook of Supply Chain Management. 2022. [HTML]
11. Fazlollahtabar H. A Mathematical Model for Optimizing Postal Supply Chain Networks and Facility Location. J. Intell. Manag. Decis. 2025. acadlore.com
12. Scott TG. Financing National Defense in the United States: Comparing Post World War II to the 21st Century Global War on Terrorism–Punctuated Equilibrium Theory in …. 2022. [HTML]
13. A Fildes R, Nikolopoulos K, Crone S, Syntetos A. Forecasting and Operational Research:A Review. 2008. [PDF]

14. Smeeton N, Spencer NH, Sprent P. Applied nonparametric statistical methods. 2025. ertongbook.com
15. Sarker IH. AI-based modeling: techniques, applications, and research issues towards automation, intelligent, and smart systems. SN computer science. 2022. springer.com
16. Setzer VW. AI-Artificial Intelligence or Automated Imbecility? Can machines think and feel?. Ann Arbor. 2022. usp.br
17. Arin H. AI and the Human Experience: Embracing the Age of Intelligent Machines. 2023. [HTML]
18. Ren L, Dong J, Liu S, Zhang… L. Embodied intelligence toward future smart manufacturing in the era of AI foundation model. IEEE/ASME transactions …. 2024. ieee.org
19. Almuqati MT, Sidi F, Mohd Rum SN, Zolkepli M, Ishak I. Challenges in Supervised and Unsupervised Learning: A Comprehensive Overview. International Journal on Advanced Science, Engineering & Information Technology. 2024 Jul 1;14(4). researchgate.net
20. Ali A, Mashwani WK. A supervised machine learning algorithm: applications, challenges, and recommendations. Proceedings of the Pakistan Academy of Sciences: A. Physical and Computational Sciences. 2023 Dec 8;60(4):1-2. ppaspk.org
21. Wang X, Wang S, Liang X, Zhao D, Huang J, Xu X, Dai B, Miao Q. Deep reinforcement learning: A survey. IEEE Transactions on Neural Networks and Learning Systems. 2022 Sep 28;35(4):5064-78. [HTML]
22. Gupta S, Modgil S, Bhattacharyya S, Bose I. Artificial intelligence for decision support systems in the field of operations research: review and future scope of research. Annals of Operations Research. 2022 Jan;308(1):215-74. [HTML]
23. Mishra S, Shinde M, Yadav A, Ayyub B, Rao A. An AI-driven data mesh architecture enhancing decision-making in infrastructure construction and public procurement. arXiv preprint arXiv:2412.00224. 2024 Nov 29. [PDF]
24. Alexakis T, Adamopoulou E, Peppes N, Daskalakis E, Ntouskas G. Evaluating Data Quality: Comparative Insights on Standards, Methodologies, and Modern Software Tools. Electronics. 2025 Jul 30;14(15):3038. mdpi.com
25. Borrohou S, Fissoune R, Badir H. Critical role of data transformation in preprocessing: methods, algorithms, and challenges. In International Conference on Model and Data Engineering 2024, Nov 18 (pp. 108-122). Cham: Springer Nature Switzerland. [HTML]
26. Boeschoten S, Catal C, Tekinerdogan B, Lommen A, Blokland M. The automation of the development of classification models and improvement of model quality using feature engineering techniques. Expert Systems with Applications. 2023 Mar 1;213:118912. sciencedirect.com
27. Zhan Y, Hua Tan K. An analytic infrastructure for harvesting big data to enhance supply chain performance. 2020. [PDF]
28. Jayaram Y, Sundar D. Enhanced Predictive Decision Models for Academia and Operations through Advanced Analytical Methodologies. International Journal of Artificial Intelligence, Data Science, and Machine Learning. 2022 Dec 30;3(4):113-22. ijaidsml.org
29. Hartmann D, van der Auweraer H. Digital Twins. 2020. [PDF]
30. Mahavarpour S. Integrating Adaptive Reinforcement Learning and Robotic Process Automation for Real-Time Decision-Making in Dynamic Environments. Majlesi Journal of Telecommunication Devices. 2025 Mar 1;14(1). [HTML]
31. Walton RB, Ciarallo FW, Champagne LE. A unified digital twin approach incorporating virtual, physical, and prescriptive analytical components to support adaptive real-time decision-making. Computers & Industrial Engineering. 2024 Jul 1;193:110241. ssrn.com

32. Dasaklis TK, Tsoulfas GT. The future of healthcare supply chains: integrating industry 4.0 technologies for improved resilience and sustainability. InHospital Supply Chain: Challenges and Opportunities for Improving Healthcare 2024 Oct 30 (pp. 533-551). Cham: Springer Nature Switzerland. [HTML]
33. Burger K, White L, Yearworth M. Developing a Smart Operational Research with Hybrid Practice Theories. 2019. [PDF]
34. Mehdiyev N, Majlatow M, Fettke P. Quantifying and Explaining Machine Learning Uncertainty in Predictive Process Monitoring: An Operations Research Perspective. 2023. [PDF]
35. Danry V, Pataranutaporn P, Mao Y, Maes P. Don't just tell me, ask me: AI systems that intelligently frame explanations as questions improve human logical discernment accuracy over causal AI explanations. InProceedings of the 2023 CHI Conference on Human Factors in Computing Systems 2023 Apr 19 (pp. 1-13). acm.org
36. Wang G, Lin Z, Chen Y, Ji H, Chen D, Zhang H, Li P, Yan J. Ai-optimized decision-making in energy systems: Toward a decision-aware machine learning framework. Engineering. 2025 Jul 14. sciencedirect.com
37. Laña I, J. Sanchez-Medina J, I. Vlahogianni E, Del Ser J. From Data to Actions in Intelligent Transportation Systems: A Prescription of Functional Requirements for Model Actionability. 2021. ncbi.nlm.nih.gov
38. Bhatnagar S, Chang W, Kim Jiali Wang S. Computer Model Calibration with Time Series Data using Deep Learning and Quantile Regression. 2020. [PDF]
39. Whiting NW, Roy CJ, Duque E, Lawrence S, Oberkampf WL. Assessment of model validation, calibration, and prediction approaches in the presence of uncertainty. Journal of Verification, Validation and Uncertainty Quantification. 2023 Mar 1;8(1):011001. asme.org
40. Albogamy FR, Paracha MY, Hafeez G, Khan I, Murawwat S, Rukh G, Khan S, Khan MU. Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. IEEE Access. 2022 Mar 23;10:35498-520. ieee.org
41. Kamali A, Kantere V, Zuzarte C. Robust query optimization in the era of machine learning: State-of-the-art and future directions. In 2024 IEEE 40th International Conference on Data Engineering (ICDE) 2024, May 13 (pp. 5371-5375). IEEE. [HTML]
42. Eiselt HA, Sandblom CL. Operations research: A model-based approach. 2022. [HTML]
43. Ivanovich OA. Basic requirements for statistical methods of data analysis. Политематический сетевой электронный научный журнал Кубанского государственного аграрного университета. 2022(181):316-43. cyberleninka.ru
44. Wilson A, Anwar MR. The future of adaptive machine learning algorithms in high-dimensional data processing. International Transactions on Artificial Intelligence. 2024 Nov 22;3(1):97-107. pandawan.id
45. Zhang C, Li W, Zhang H, Zhan T. Recent advances in intelligent data analysis and its applications. Electronics. 2024. mdpi.com
46. De Felice S, Hamilton AF, Ponari M, Vigliocco G. Learning from others is good, with others is better: the role of social interaction in human acquisition of new knowledge. Philosophical Transactions of the Royal Society B. 2023 Feb 13;378(1870):20210357. royalsocietypublishing.org
47. Zheng R, Li Z, Na S. How customer engagement in the live-streaming affects purchase intention and customer acquisition, E-tailer's perspective. Journal of retailing and consumer services. 2022. sciencedirect.com

48. Xia Y. Application of non parametric Bayesian methods in high dimensional data. Journal of Computational Methods in Sciences and Engineering. 2024 Mar;24(2):731-43. [HTML]
49. Li JJ, Shi C, Li L, Collins AGE. Dynamic noise estimation: A generalized method for modeling noise fluctuations in decision-making. Journal of Mathematical Psychology. 2024. sciencedirect.com
50. Shi K. Applications of Some Robust Statistics in Forestry. 1995. [PDF]
51. Abbasi M, Khadivi M, Ahang M, Lasserre P, Lucet Y, Najjaran H. An innovative data-driven and adaptive reinforcement learning approach for context-aware prescriptive process monitoring. arXiv preprint arXiv:2501.10543. 2025 Jan 17. [PDF]
52. C. Sales A, B. Prihar E, A. Gagnon-Bartsch J, T. Heffernan N. Using Auxiliary Data to Boost Precision in the Analysis of A/B Tests on an Online Educational Platform: New Data and New Results. 2023. [PDF]
53. Ding S, Ward H, Cucurachi S, Tukker A. … hidden potentials of Internet of Things (IoT)-An integrated approach using agent-based modelling and system dynamics to assess sustainable supply chain …. Journal of Cleaner Production. 2023. sciencedirect.com
54. M. Badole C, Rakesh Jain D, A.P.S. Rathore D, Bimal Nepal D. Research and Opportunities in Supply Chain Modeling: A Review. 2013. [PDF]
55. Katsaliaki K, Galetsi P, Kumar S. Supply chain disruptions and resilience: a major review and future research agenda. Annals of Operations Research. 2022. nih.gov
56. Alahmari N, Mehmood R, Alzahrani A, Yigitcanlar T, Corchado JM. Autonomous and Sustainable Service economies: Data-Driven optimization of Design and Operations through Discovery of Multi-perspective parameters. Sustainability. 2023 Nov 16;15(22):16003. mdpi.com
57. Savva N, Keskinocak P. A review of the healthcare-management (modeling) literature published at Manufacturing and Service Operations Management. 2020. [PDF]
58. Samaras L, García-Barriocanal E, Sicilia MA. Syndromic surveillance using web data: a systematic review. 2019. ncbi.nlm.nih.gov
59. Peddinti S, Sabbani Y. Mathematical modeling of infectious disease spread using differential equations and epidemiological insights. Journal of Nonlinear Analysis and Optimization. 2024. jnao-nu.com
60. Yameny, A. Characterization of SARS-CoV-2 Omicron XBB.1.5 sub-lineage: A review. *Journal of Medical and Life Science*, 2023; 5(2): 96-101. doi: 10.21608/jmals.2023.305080
61. Nouiri M, Trentesaux D, Bekrar A. Towards Energy Efficient Scheduling of Manufacturing Systems through Collaboration between Cyber Physical Production and Energy Systems. 2019. [PDF]
62. Priesmann J, Münch J, Ridha E, Spiegel T et al. Artificial Intelligence and Design of Experiments for Assessing Security of Electricity Supply: A Review and Strategic Outlook. 2021. [PDF]
63. Bale CSE, Varga L, Foxon TJ. Energy and complexity: New ways forward. 2015. [PDF]
64. Martusewicz J, Wierzbic A, Łukaszewicz M. Strategic transformation and sustainability: Unveiling the EFQM Model 2025. Sustainability. 2024. mdpi.com
65. Bansal A, J. Kauffman R, M. Mark R, Peters E. FINANCIAL RISK AND FINANCIAL RISK MANAGEMENT TECHNOLOGY (RMT): ISSUES AND ADVANCES. 1991. [PDF]
66. Andriosopoulos D, Doumpos M, M. Pardalos P, Zopounidis C. Computational approaches and data analytics in financial services: a literature review. 2019. [PDF]