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COMPARATIVE ANALYSIS OF ARTIFICIAL INTELLIGENCE-BASED APPROACHES TO FORECASTING AND OPTIMIZATION OF COMPLEX SYSTEMS

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Abstract. Forecasting and optimization form an integrated foundation for the intelligent management of complex systems in industry, logistics, energy, transportation, and service operations. The interaction of multiple components, changing operating conditions, and interconnected decisions creates valuable opportunities for data-driven modeling and adaptive resource allocation. This study presents a comparative literature-based analysis of statistical forecasting, machine learning, deep learning, mathematical optimization, and reinforcement learning approaches. Their suitability is examined in relation to temporal patterns, explanatory variables, uncertainty representation, computational requirements, and decision objectives. Particular attention is given to hybrid architectures that connect probabilistic forecasts with optimization models and continuously updated decisions. The synthesis establishes a conceptual framework for evaluating forecasting quality alongside operational performance and identifies promising directions for intelligent management of dynamic complex systems.

Keywords: complex systems, artificial intelligence, forecasting, optimization, machine learning, deep learning, probabilistic models, reinforcement learning, hybrid algorithms.

INTRODUCTION. Complex systems are characterized by interconnected components, dynamic relationships, feedback processes, and operating conditions that evolve over time. Such characteristics are observable in production networks, transport infrastructure, energy systems, healthcare service operations, and supply chains. Effective management depends on the ability to anticipate future system states and select coordinated actions that support efficiency, resilience, service quality, and sustainable resource utilization. Forecasting estimates future demand, workload, energy consumption, equipment condition, or traffic

intensity, while optimization converts these estimates into practical decisions regarding scheduling, routing, allocation, inventory, and capacity planning. Their joint application creates a unified analytical basis for intelligent decision support.

Digital environments supply operational and contextual observations through enterprise systems, sensors, and connected devices. Artificial intelligence models learn temporal patterns and relationships among predictors, while optimization methods transform these forecasts into coordinated operational actions. This research compares their complementary strengths and outlines a hybrid methodology for forecasting and optimization in complex systems.

MATERIALS AND METHODS. The study applies comparative literature synthesis and conceptual modeling to statistical time-series forecasting, tree-based machine learning, deep temporal architectures, mathematical optimization, and reinforcement learning. Comparisons address nonlinear behavior, temporal structure, uncertainty assessment, interpretability, computational resources, and integration into management decisions.

For a system state x_t, available observations H_t, and external factors z_t, the prediction task can be represented as $\hat{x}_{t+h} = F(H_t, z_t, \theta)$, where h denotes the prediction horizon and θ denotes model parameters. A subsequent decision is selected by minimizing an operational objective $J(u, \hat{x})$ subject to resource and system constraints, where u represents a control or allocation action. Under probabilistic forecasting, the predicted state is described by a conditional distribution $p(x_{t+h} \mid H_t, z_t)$, allowing the optimization component to assess multiple plausible scenarios. This mathematical relationship highlights the essential distinction between predicting future conditions and identifying effective management decisions based on those predictions.

COMPARATIVE ANALYSIS AND DISCUSSION. Statistical forecasting approaches, including exponential smoothing and autoregressive models, provide transparent representations of trends, seasonal effects, and temporal dependence. Their parameters and model structure support analytical interpretation and offer valuable baseline forecasts for dynamic systems with regular patterns. These methods are especially useful when compact

models, reproducibility, and efficient recalibration are central implementation priorities. The selection of an appropriate statistical specification can be guided by the frequency of observations, periodic behavior, and the required forecasting horizon. Statistical benchmarks also create a meaningful reference against which more complex artificial intelligence models can be evaluated.

Machine learning methods such as Random Forest and XGBoost expand the ability to incorporate heterogeneous explanatory variables and capture nonlinear relationships. A forecasting system for production or logistics can combine historical workload with calendar variables, prices, environmental conditions, and operational indicators. Tree-based ensembles learn interactions among these predictors through recursive partitioning and model aggregation. XGBoost, introduced by Chen and Guestrin [1], offers scalable gradient-boosted tree learning and supports systematic parameter optimization. These approaches are particularly suitable for structured tabular datasets and can produce informative feature-importance analyses, supporting both forecasting and operational interpretation.

Deep learning architectures facilitate the modeling of longer temporal relationships and shared patterns across interconnected time series. Recurrent networks can represent sequences of system observations, while probabilistic neural forecasting provides information about the distribution of future outcomes. Salinas and colleagues proposed DeepAR as an autoregressive recurrent approach that learns probabilistic forecasts from related time series [2]. The resulting predictive distributions can support reserve planning, flexible scheduling, and decisions that explicitly account for uncertainty. Temporal Fusion Transformer, developed by Lim and colleagues [3], combines specialized variable-selection mechanisms, recurrent processing, and attention-based representations for interpretable multi-horizon forecasting. Such architectures offer useful capabilities when a complex system contains numerous interacting signals and several planning horizons.

Optimization methods serve a complementary function by transforming predicted conditions into coordinated actions. Linear and mixed-integer programming offer explicit

representations of resource limits, technical requirements, operational costs, and service constraints. Scenario-based and robust formulations connect decisions with possible future system states, while multiobjective optimization supports the simultaneous consideration of cost, environmental impact, service level, and operational stability. Reinforcement learning offers an additional perspective for sequential decisions, where an agent learns a policy through interaction and cumulative performance feedback. Sutton and Barto [4] describe the conceptual foundations of this learning paradigm. In complex-system management, reinforcement learning can be investigated for adaptive routing, energy dispatch, dynamic scheduling, and inventory replenishment.

A comparative interpretation suggests that model suitability depends on the decision setting and information structure. Statistical approaches provide compact and transparent models; tree ensembles contribute flexible learning from diverse structured predictors; deep neural methods offer representations of high-dimensional temporal relationships and predictive uncertainty; mathematical programming provides explicit constraint handling; and reinforcement learning addresses repeated decisions in evolving environments. Consequently, these methods can be treated as complementary elements of a coordinated architecture. The most informative evaluation considers forecast accuracy together with the feasibility, cost, robustness, and quality of decisions produced using those forecasts.

A promising hybrid framework includes five connected stages. The first stage collects and aligns sensor measurements, enterprise records, and external variables. The second stage identifies characteristic operating regimes and develops suitable statistical or machine learning benchmarks. The third stage combines point and probabilistic forecasts to represent expected system behavior and alternative scenarios. The fourth stage employs constrained optimization or a sequential decision policy to select actions for the current planning horizon. The fifth stage evaluates outcomes, updates predictive models, and refines operational policies. This feedback structure links data processing, forecasting, optimization, and continuous improvement within one methodological cycle.

Hybrid frameworks can be assessed through rolling-origin validation and operational simulations. Forecast quality can be measured with mean absolute error, root mean squared error, and probabilistic scoring rules, while decision quality can be evaluated through cost, service levels, resource utilization, and constraint satisfaction. Aligned evaluation periods and shared operational scenarios support reproducible comparisons. This literature-based conceptual synthesis provides a basis for future real-world experiments.

CONCLUSION. Artificial intelligence-based forecasting and optimization provide complementary capabilities for the management of dynamic complex systems. Statistical models contribute clear and efficient temporal baselines, machine learning algorithms support flexible analysis of structured factors, and deep learning architectures facilitate multi-horizon and probabilistic forecasting. Mathematical optimization converts predictive information into feasible operational plans, while reinforcement learning offers a framework for adaptive sequential decision-making. Their coordinated application supports a holistic approach to intelligent planning in logistics, energy, transport, manufacturing, and service systems. The proposed hybrid framework links data integration, predictive modeling, uncertainty assessment, constrained decision-making, and feedback-based updating. Further empirical studies can evaluate this framework across different system types and determine how combined forecasting and optimization improve operational quality, resource efficiency, and adaptive performance.

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