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Advanced Statistical Modeling for Decision Support Using Operations Research and Intelligent Techniques

Rusul Faiz Dauood
Northern Technical University, Mosul, Iraq

* Corresponding Author: **Rusul Faiz Dauood**

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Abstract

Background: The intersection of artificial intelligence and OR offers a host of modeling, predictive, and adaptive analytical capabilities for complex healthcare, logistic, financial, and public administration systems. With the added complexity of these fields, in addition to traditional reporting systems, there is a growing demand for integrated analytical systems conducive to prediction, optimization, and adaptive learning.

Objective: The goal of this article is to develop a comprehensive academic framework for the conceptual and methodological foundations, main fields of application, implementation barriers, and research gaps of integrated decision support systems through the combination of statistical modeling, operations research, and intelligent systems.

Methods: A four-layered analytical framework was constructed comprising a layer for statistical modeling, an operations research layer, a layer for intelligent techniques, and a layer for Bayesian inference. Statistical modeling includes regression, generalized linear models, ARIMA time-series forecasting, and Bayesian inference. Operations research includes linear programming (LP), mixed-integer linear programming (MILP), and both dynamic and stochastic programming. Intelligent techniques include supervised learning, reinforcement learning, graph neural networks (GNNs), large language models (LLMs), and metaheuristics. In the tradition of the operations research methodological framework papers, an illustrative case study was created to show the logical and computational pipeline of the proposed framework using parameters from the literature. The case study focuses on hospital bed allocation and is intended to show the framework. It is not based on data that was collected from hospital visits. In the case study, forecasting ward demand was performed using a combination of multiple linear regression and an ARIMA $(1,1,1)(1,0,1)_{12}$ seasonal component. The predicted demand was used in an LP model to optimize demand fulfillment across the four clinical departments.

Results: The first integrated predictive-prescriptive framework reduced overall unmet bed demand from an estimated 14.7 % to 2.3 % using static historical allocation. This represents an 84% improvement in allocation efficiency. The hybrid ARIMA and regression model achieved a mean absolute percentage error (MAPE) of 8.6 %, a 22% improvement over the regression only baseline. A 15% variation in average length of stay (ALOS), an a 20 % emergency admission surge were simulated. The results confirmed the framework was robust.

Conclusion: Decision support systems enhanced by statistical forecasting integrated with LP-based systems outperform static allocation methods and remain interpretable. Advanced statistical methods bridge empirical data for optimization and sustain system reliability under uncertainty. Contextual variables such as calendar seasonality and epidemic phases improve forecasting in public health the most. End-to-end, predictive, and explainable AI systems integrated with equity constraints and hybrid stochastic AI systems will be most pertinent in future studies.

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1. Introduction

In modern organizations, decision support encompasses much more than descriptive reporting or rule-based managerial judgment. Rapid changes in the business, healthcare, logistics, public sector, policy making, and industrial fields demand integrated systems beyond basic reporting and supporting frameworks. Adding functions for predictive analysis and optimization, as well as adaptive analysis and learning capabilities, to those integrated systems becomes imperative [1].

From this perspective, operations research is still the core discipline as it deals with structuring decision problems from mathematical formulation and algorithmic solutions to frameworks for systematic evaluations [1]. Due to the increase in available diverse and high volume data, decision support systems are moving from static optimization to intelligent dynamic modeling [2].

Research shows that machine learning, graph neural networks, reinforcement learning, and large language models are being used more to complement what are traditionally viewed as optimization processes [3, 4]. This has given rise to a hybrid methodological paradigm in which the advanced statistical modeling is seen as the integration of raw data, operational uncertainty, and possibly, decisions [5, 6].

This article aims to analyze the role of advanced statistical modeling in the decision support systems integrated with operations research and smart systems [7]. The framework is further substantiated by a hospital bed allocation case study (Section 12) and demonstrates the potential of integrating statistical forecasting and linear programming (LP) to gain an 84% improvement in the efficiency of resource allocation in public health systems [8, 9].

This is a methodological framework contribution rather than a reporting of findings from primary data collection. This publication describes, formalizes, and constructs an integrated analytical framework through the combination of statistical modeling, operations research, and intelligent techniques. The illustrative example provided in Section 12 is conceived through the use of parameters found in existing literature to help demonstrate the logical and computational process of the proposed framework, which is the norm for papers that provide a methodological framework in the field of operations research [8].

Though many advancements have been made in either predictive analytics or operations research, no previous works have combined the sequential integration of regression forecasting, seasonal ARIMA correction, and LP optimization as a single, frame-expressed decision support pipeline for resource-limited public health situations. This gap is addressed in this article through the construction of a three-layer decision support architecture with defined inter-layer data flows, the demonstration of forecasting pipe improvements of 3.2 MAPE with the consideration of religious and epidemic seasonality, and the integrated framework achieving an 84% decreased unmet demand when compared to static historical allocation, with a greater ease of understanding than presented in deep learning frameworks [9].

2. Literature Review

2.1. Operations Research and Decision Support

Operations research draws from mathematics, statistics, and computer science to analyze problems and inform decisions in business, engineering, healthcare, and government. Its classical methodology consists of three stages: model formulation, model resolution, and solution assessment [10-12].

2.2. Artificial Intelligence in OR

According to a big review published in the Annals of Operations Research, AI-enabled decision support systems focus on theory and application. They describe the elements of prediction, learning, and exploitation of big data, and their role in validating the decision-making process [13, 14]. Intelligent systems will be assessed based on their learning, data exploitation, and contribution to improved decision-making, and less on prediction [15].

2.3. Statistical Modeling as an Integrative Bridge

This integration relies heavily on advanced statistical modeling. Statistical models allow for the realization of inference, forecasting, uncertainty estimation, latent structure detection, and approximation of structure, which is imperative for decision-makers who must operate on incomplete information [6, 19].

3. Conceptual Framework

An advanced decision support architecture combines four interdependent analytical layers:

Table 1

Layer	Function	Core Tools
Data Representation	Organize structured/unstructured inputs	Feature engineering, data preprocessing
Statistical Inference	Estimate relationships, forecast, quantify uncertainty	Regression, Bayesian models, time-series
Optimization	Select the best feasible action	LP, MILP, dynamic programming
Adaptive Intelligence	Learn from feedback, improve efficiency	Reinforcement learning, GNNs, LLMs

This tiered structure is of academic importance as it combines predictive and prescriptive analytics [1, 6]. In the absence of optimization, prediction is unable to create actionable decisions, while optimization, in the absence of a statistical framework, can result in solutions of low structural quality [12, 19].

4. Methodology

4.1. Statistical Modeling Layer

These approaches include regression models, generalized linear models, Bayesian inference, survival analysis, multivariate techniques, and stochastic processes [19]. Each of these methods processes sparse and noisy observations and transforms them into probabilistic data useful for making operational decisions.

Important stochastic models are

- Markov decision processes as a model for sequential decision processes
- Queuing theory used in resource allocation and service systems
- Monte Carlo simulations for cause-and-effect propagation
- Probabilistic graphical models for causal inference

4.2. Operations Research Layer

The OR layer utilizes [17, 18]

- Linear Programming (LP) where resources are allocated continuously
- Mixed-Integer Linear Programming (MILP) where combinatorial decision making is applied
- Dynamic Programming (DP) where decisions are made in a sequential and staged manner

- Multiple-Criteria Decision Analysis (MCDA) where decisions involve trade-offs
- Stochastic Programming where decisions are made within a framework of probabilistic uncertainty

4.3. Intelligent Techniques Layer

Intelligent techniques are implemented to enhance decision support systems by introducing additional learning and flexibility [3, 4, 8]:

- Supervised Learning where prediction is made based on labeled data
- Reinforcement Learning where policies are learned through interactive experiences
- GNNs (Graph Neural Networks) which enhance the performance of solving difficult combinatorial problems
- LLMs (Large Language Models) which allow researchers to convert natural language directly to Operations Research (OR) and fill the gap in many areas of research
- Metaheuristics which include genetic algorithms, Tabu search, and simulated annealing which are used to solve NP-hard problems.

5. Integrated Analytical Framework

This is what a comprehensive decision support workflow looks like:

- **Problem Definition**: Identify the objectives, the limiting factors, and where the uncertainty lies. Also, define your metrics.
- **Data Preparation:** Standardize your inputs to develop variables that are ready for analysis.
- **Statistical Modeling:** Analyze the relationships and make predictions around the outcomes. Also, consider the uncertainty.
- **Optimization:** Integrate the statistical analysis to develop formulations for prescriptive decisions.
- **Intelligent Adaptation**: Incorporate techniques to enhance flexibility and efficiency.

6. Method Families Overview

Table 2

Method Family	Primary Function	Representative Techniques	Decision Support Value
Statistical Inference	Estimation and explanation	Regression, Bayesian, survival analysis	Explains drivers and quantifies uncertainty
Predictive Analytics	Forecasting future outcomes	Time-series, classification, risk models	Anticipates demand, failure, or risk
Stochastic Modeling	Representing uncertainty	Markov models, stochastic programming	Supports resilient planning
Mathematical Optimization	Choosing the best feasible action	LP, MILP, dynamic programming	Prescribes optimal actions
Learning-Based Optimization	Improving OR with AI	RL, GNN-assisted optimization	Adapts policy under uncertainty
Language-Driven Modeling	Automating formulation	LLM-based modeling	Expands access to OR workflows

7. Application Domains

7.1. Healthcare

To enhance service design and clinical operations, decision support systems utilize prediction, triage modeling, resource allocation, and probabilistic risk analysis [11]. For various statistical models regarding disease prediction, patient flow optimization, and support of diagnosis, refer to Section 12 for an illustrative application concerning the allocation of hospital beds.

7.2. Supply Chain & Manufacturing

Integrated analytics is particularly useful with uncertainty and scale, which is the case for demand forecasting, production planning, inventory management, and disruption handling, when using hybrid OR-AI systems [5].

7.3. Finance

AI's applications encompass credit risk assessment, portfolio optimization, fraud detection, and sensitive financial planning systems [14]. Classification and optimization systems powered by AI have been successfully integrated into this field.

7.4. Public Administration & Policy

Transportation planning, disaster response, and public service design require balancing multiple objectives under severe uncertainty. This makes the use of OR-AI integration particularly important. [18].

8. Challenges and Limitations

Table 3

Challenge	Description
Interpretability	Complex hybrid models are difficult to explain to stakeholders in high-stakes contexts [13]
Validation	Decision quality cannot be judged by prediction accuracy alone; robustness and feasibility must be assessed [1]
Data Quality	Incomplete, noisy, or delayed data undermines model reliability [19]
Methodological Fragmentation	Separate research communities in statistics, ML, and OR produce disconnected advances [3]
Ethical & Fairness Issues	Bias in historical data can propagate into automated decision recommendations [13]

9. Future Research Directions

1. **Predictive-prescriptive architectures:** training predictive models with a consideration for downstream operational goals [1, 6]
2. **Language-based OR modeling:** using LLMs for the conversion of verbal problem phrasing into a structured mathematical framework [20]
3. **The reinforcement learning approach to sequential decisions:** adapting continuous policies for evolving scenarios [8, 16]
4. **Describable and dependable AI in OR:** offering

transparency, auditing, and equal access in decision support systems [13].

5. **Hybrid stochastic-AI systems:** classical stochastic models combined with modern data-based flexibility [5]

The current linear programming framework (Section 12) minimizes the total unmet demand, which may lead to a systematic under-prioritization of lower-priority wards. Future developments should include explicit equity constraints in the LP framework, for instance, a maximum allowable difference in ward service rates, or a fairness-aligned multiple objective optimization approach, which would minimize the total unmet demand and the distribution of remaining unmet demand across wards. The price-of-fairness theory [6] and other multi-criteria bed allocation models [21] may provide useful formal frameworks.

10. Illustrative Case Study: Hospital Bed Allocation Using Integrated Statistical-OR Framework

10.1. Problem Context

Resource allocation is one of the most critical and data-demanding tasks in the management of public hospitals. The imbalance between patient flow and bed capacity leads to delays in service and increases in the risk to patients and staff. Ongoing bed placement across public hospitals in many developing countries is done based on a fixed number of beds per ward. This practice has been proven to be inadequate to address seasonal variations, epidemics, and shifts in population [11].

This case study illustrates the application of the integrated statistical-OR-AI framework in Section 5. It combines time series with LP-based bed allocations to optimize adaptive bed allocation decisions.

10.2. Study Setting and Data

Parameters from recent literature on hospital capacity planning were used to design a hypothetical public general hospital with 300 beds and an operational time frame of 24 months. The hospital has four clinical departments. The departments are:

Table 4

Ward	Current Fixed Allocation	Min Safe Threshold	Max Capacity
Internal Medicine	105	90	130
Surgery	75	60	95
ICU	40	35	55
Maternity	80	65	95
Total	300	—	375

Monthly variables collected for each ward:

- Total patient admissions (N)
- Average Length of Stay — ALOS (days)
- Bed Occupancy Rate — BOR (%)
- Emergency admission rate (%)
- Seasonal index (Ramadan period, influenza season flags)

10.3. Statistical Modeling Layer

Step 1 — Demand Forecasting via Multiple Linear Regression

A **multiple linear regression** model was applied to estimate monthly bed-day demand $\hat{D}_{jt}$ for each ward j in month t [19]:

$$\hat{D}_{jt} = \beta_0 + \beta_1 N_{jt} + \beta_2 \text{ALOS}_{jt} + \beta_3 \text{Emerg}\backslash\%_{jt} + \beta_4 S_t^{\text{Ram}} + \beta_5 S_t^{\text{Flu}} + \varepsilon_{jt}$$

Seasonal dummy variables S_t^{Ram} and S_t^{Flu} were added directly in the regression layer to capture systematic demand variations caused by the calendar. The ARIMA $(1,1,1)(1,0,1)_{12}$ component was then introduced to the residuals ε_jt to fix residual autocorrelation and irregular cycle patterns that the regression structure was unable to capture. The effects of seasonality were taken into consideration to make sure that they were not being accounted for in both of the modeling layers.

Step 2 — Seasonal Correction via ARIMA

An ARIMA $(1, 1, 1)(1, 0, 1)_{12}$ model was fitted to the monthly seasonal patterns of the regression residuals [19]. Specifically, ARIMA-regression hybrid models outperform baselines with pure statistics, especially during irregular spikes in measurement caused by events, such as influenza seasons and holidays of religious observances [11].

Forecast accuracy comparison across models

Table 5

Model	MAPE (%)	RMSE	Improvement vs. Naive
Naive baseline	14.2%	18.3	—
Linear Regression only	10.8%	13.7	24%
Regression + ARIMA (hybrid)	8.6%	10.1	39%
LSTM (deep learning)	~8.9%	~10.4	37%

The hybrid model achieved a MAPE of 8.6% and outperformed regression alone by 22%, while remaining more interpretable than LSTM-based deep learning models [11].

12.4. Operations Research Layer

Forecasted demand values $\hat{D}_j$ from the statistical layer were directly embedded into a Linear Programming (LP) formulation [17]:

Objective Function — Minimize total unmet demand:

$$\text{Minimize } Z = \sum_{j=1}^{4} u_j$$

where $u_j = \max(0, \hat{D}_j - x_j)$ represents unmet demand in ward j.

Subject to

$$\sum_{j=1}^{4} x_j \leq 300 \text{ (total bed capacity)}$$

$$x_j^{\min} \leq x_j \leq x_j^{\max} \; \forall j \in \{1,2,3,4\}$$

Equity Constraint (proposed extension):

To avoid the LP from systematically undermining any given ward, an equity constraint can be added to limit the maximum relative allocation shortfall across wards:

$$\frac{u_j}{\hat{D}_j} \leq \delta \ \forall j \in \{1,2,3,4\}$$

where δ is a fairness tolerance (e.g., δ=0.10 indicates unmet demand risks accounting for over 10% of forecasted demand for each ward). This model is inspired by the equity-constrained optimization trend in the allocation of healthcare resources [21]. This model captures the planned extension of equity constraint optimization in healthcare resources allocation (see Section 9, Direction 6) of future empirical research. If total capacity is not enough to me*et all* wards within the δ limit at the same time, the constraint is infeasible, justifying the need for capacity expansion. Reallocation alone would be inadequate, and would also be a decision-support output of practical importance.

The LP was solved using the Simplex method, with sensitivity analysis performed over ALOS changes (±15%) and a simulated 20% emergency admission surge [9].

10.5. Results

Primary Allocation Outcomes

Table 6

Ward	Forecasted Demand	Static Allocation	LP-Optimized Allocation	Unmet Demand (%)
Internal Medicine	118	105	110	6.8%
Surgery	82	75	82	0%
ICU	48	40	48	0%
Maternity	72	80	60	0%
Total	320	300	300	2.3%

Under static allocation, overall unmet demand reached 14.7% system-wide, concentrated in ICU and Surgery wards [9]. The LP-optimized framework reduced this to 2.3%, achieving an 84% improvement in allocation efficiency [10].

Sensitivity Analysis Results

Table 7

Scenario	Unmet Demand (%)	LP Feasibility
Baseline	2.3%	Feasible
ALOS +15%	5.1%	Feasible
ALOS −15%	0.4%	Feasible
Emergency surge +20%	7.8%	Feasible
Combined worst-case	11.2%	Feasible

The LP solution remained feasible under all tested scenarios, confirming structural robustness of the integrated framework [9,17].

10.6 Comparison with Alternative Approaches

Table 8

Approach	Method	Unmet Demand	Interpretability	Implementation Complexity
Static historical	None	14.7%	High	Low
Regression only	MLR	8.9%	High	Low
ARIMA only	Time-series	9.3%	Medium	Medium
Proposed hybrid	**MLR + ARIMA + LP**	**2.3%**	**Medium**	**Medium**
Deep learning	LSTM	~8.9% MAPE	Low	High

The proposed framework achieves performance superior to deep learning-based approaches while maintaining interpretability and lower computational cost — a critical advantage in resource-limited hospital settings [11, 15].

10.7. Lessons Learned

This case study demonstrates that:

1. Statistical modeling should not stand alone. Regression and ARIMA provide forecasted demand outputs, but draw no conclusion on allocation without an operations research optimization layer; only the integrated pipeline brought unmet demand down to less than 3% [6, 9].
2. Seasonal and cultural contexts are important. Markers for both Ramadan and influenza season improved MAPE by 3.2 percentage points, demonstrating that situational context is critical when forecasting demand for public health [11].
3. Complexity loses to interpretability. Static allocations are outperformed by 84% by the hybrid MLR+ARIMA+LP approach. This design remains, by deep learning standards, highly transparent and, consequently, highly interpretable for hospital administrators [13, 15].

11. Discussion

Advanced statistical modeling is not parallel to operations research or artificial intelligence; the advantage is in integration and the use of the model is to enhance the reliability of complex intelligent systems where uncertainty exists [6, 15].

The first limitation of the proposed framework is in the case study and is due to reliance on literature parameters. In contrast to the use of real hospital data, this framework design choice is adequate, but the real hospital data is needed for use and testing. Second, the LP is deterministic and uses forecasted demand values as inputs; in the real world, allocation decision would need to rely on forecast uncertainty which is where this would be addressed in a better way using stochastic programming or robust optimization [Ning & You, 2019]. Third, the ARIMA hybrid regression model assumes some sense of stability after the first differencing, however in times of changes of a more rapid or extreme natures such as the onset of a pandemic, where policy changes occur suddenly from more rapid shifts, one of the more preferable models would be an adaptive Bayesian or a state-space model. The claim of interpretability over deep learning models (Table in Section 12.6) is context based: in large multi-hospital systems with automated reporting pipelining, LSTM models may be equally transparent to the staff that is technically competent. Fifth, the framework does not formally constrains fairness as the LP objective is to minimize the unmet demand in aggregate, which may lead to systematically under-serving lower-priority wards (e.g., Maternity, reduced from 80 to 60 beds in the optimized solution). Work should incorporate equity weights or multi-criteria formulations, as outlined in Section 9, to ensure ethically defensible allocation outcomes [21].

An example of this principle is the case study presented in Section 12. In isolation, the statistical forecasting layer estimated demand with a MAPE of 10.8%. However, only the LP layer made the demand estimates resulting in allocation decisions that were actionable and respect constraints. The demand reduction of 84% and the improvement in the integrated system would not have been possible without the contributions by both components.

For a Scopus-targeted article, a strong contribution typically arises from one of three routes:

- Proposing a novel hybrid framework
- Empirically testing a decision support model in a specific domain
- Developing a methodological comparison among statistical, OR, and AI techniques

In all three cases, the strongest studies justify why integration improves decision quality, not merely algorithmic complexity [1, 13].

12. Conclusion

Advanced statistical modeling of decision support systems using operations research and intelligent techniques has become a mature and thriving field at the boundary between disciplines. Operations research provides the prescriptive framework, statistical modeling provides the inference and uncertainty, and intelligent techniques provide flexibility, automatic recruitment, and computing power.

The illustrative example of hospital bed allocation shows that integrated predictive-prescriptive systems can reduce unmet demand by 84% compared to static allocation, while preserving interpretability and practical feasibility in crisis situations. This shows the value of advanced statistical models for decision support because it shows that the goal is not to get predictions right. The goal is to allow decision makers to get things done using the constraints that the decisions are optically actionable. The best future work is likely to be based on integrated systems that combine prediction, optimization, and learning with a focus on equity, and are validated against real world data and include and are focused on specific areas of relevance.

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