A Data-Driven Neuro-Operations Research Model for Urban Drone Delivery Optimization

Authors Names	**ABSTRACT**
Ali Kadhim Yaqooba[*], Publication date: 28 /8 /2026 ***Keywords:*** Neuro-Operations Research, Strategic Decision-Making, Decision Support Systems, Hybrid Optimization Models	This study examines the use of Neuro-Operations Research (Neuro-OR) in strategic decision-making for businesses operating in a dynamic, complex, and uncertain environment. In order to provide cutting-edge decision assistance in strategic management and improve accuracy and efficiency in strategic choices, Neuro-OR focuses on integrating the concepts of operations research into artificial neural networks. Dealing with nonlinear interactions between the variables, dynamic changes, and uncertainty factors influencing a strategic decision has been proven to have certain general flaws. In order to solve this problem, this study develops a hybrid strategy in which mathematical models of optimization identify the optimal course of action, while neural networks analyze and forecast choice variables at the data analysis level. As a result, it uses the descriptive-analytic approach to develop the theoretical underpinnings of Neuro-Operations Research and applied technique in the development of a mathematical model in conjunction with a neural network. The model that is being provided will be tested using either simulated or real data, and its performance will be evaluated by comparing it to traditional models in three areas: accuracy, efficiency, and robustness of the results against uncertainty. The hybrid technique of Neuro-OR significantly enhances the results of the tests.

1- Introduction

Today's organizational environments are marked by extremely intricate decision-making procedures. [10-11] Decision-making has become a difficult challenge for companies due to the introduction of quickly evolving technologies and organizational dynamics within the external setting.[4 ,11] Modern organizations look for better options that can effectively handle organizational complexities, like non-linear systems with uncertain variables that affect organizational performance, in contrast to traditional organizational settings that relied on operations research as a tool for organizational decision-making.[8-9]

Neuro-OR allows decision models to be more adaptable in addition to increasing accuracy. [4]

Neuro-Operations Research, or Neuro-OR, has been recognized as an appealing way to get around these problems by combining the analytical capabilities of artificial neural networks with those of operations research approaches. Decision-makers can foresee important drivers, find hidden patterns in a set of data, or make the best choices in dynamic or uncertain situations with the help of Neuro-OR. [6-7] The main issue under investigation is the insufficiency of conventional operations research models in handling non-linear issues and shifting trends in contemporary strategic contexts. [8,10] Neuro-OR uses ANNs to accomplish all of this. [11,14]

The core problem being investigated is related to the inadequacy of traditional models of operations research in dealing with non-linear problems and changing patterns in modern strategic settings. The core problem often gives rise to inappropriate or untimely decision-making, which can prove counterproductive to organizational performance and resource allocation. [10-11] As a result, there are

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approaches that can effectively integrate the benefits of operations research optimization with predictive analysis capabilities of neural networks for improved strategic decision-making. [4,6]

Design a model of Neuro-OR that unifies classical OR methods and neural networks. Assess the effectiveness of the proposed model for improvement of decision quality and speed. The proposed model designed using neurocomputing and OR can be tested and compared for performance and adaptability to uncertainty with classical OR models. The proposed model can be applied to actual or hypothetical business situations that can produce recommendations for strategic management. [1-2] The contribution of the research lies in the potential for development of a novel Neuro-driven decision model that can fill the generation gap between classical OR and current prediction analytics. [4,7]

This is because strategic decision-making is essential for organizational success, especially where there is complexity, uncertainty, or change. Classical Operations Research Models are therefore essential for strategic decision-making, although there are difficulties associated with these models. These difficulties include:

Dealing with nonlinear relationships between decision variables.

Adjusting for changes in the operational or market environment.

Handling big data or uncertain data effectively.

Such constraints could lead to nonoptimal decisions, late reactions, and exposure, which in turn affect the efficiency of organizational performance. [4 ,8] [10-11,13]

2- Literature Review

The application of OR technique in strategic decision-making that involves allocation of resources, production planning, and selection of projects has been previously covered in literature. [8-9] Linear programming, integer programming, and multi-objective optimization model are known as

classical OR models that perform well under structured and deterministic environments. [8-9] Nevertheless, various literature has focused on the failure of these models in nonlinear systems that are complex and uncertain with the effects of dynamic changes being very influential on the outcome of the decision alternatives. [10-11]

Recent works have started to focus on hybrid approaches that integrate neural-based techniques with Operations Research models. [6-7] These works highlight the added value given by the integration of predictive models with optimization frameworks in significantly enhancing the quality of decisions, as well as their adaptability under uncertainty. [4-6] Nevertheless, it was observed that there exists a large research gap regarding the integration of NN prediction outputs within OR models of optimization for decision-making purposes. [7] The problem tackled in this study involves filling this gap in research through the design of a Neuro-Operations Research model that combines NN approaches and models of optimization. [6-7] More recent work has been focused on decision theory under uncertainty and dynamics, with increased interest in the role of robustness and adaptability in optimization problems. [10] Methods such as stochastic programming, robust optimization, and fuzzy systems modeling have been proposed that account for uncertainty, although these models often impose significant modeling requirements on probability distributions or membership functions that may not be tractably available in practice. [15,16]

Over the years, with the improvement in machine learning, numerous studies have investigated the use of data-driven models and optimization models in an integrated way. [4][6] The combined approach of forecasting models and operations research has proved fruitful in enhancing the efficiency and accuracy of decisions. [6-7] Notwithstanding the increasing attention from the research community regarding hybrid decision support systems, the subject of Neuro-Operations Research is still not extensively investigated in the existing literature, notably in connection to strategic-level decision-making. [6,7]

The majority of the existing research efforts are relevant to tactical decisions, and as such, there is a research gap as regards the utilization of Neuro-OR paradigms for strategic planning. However, in many of these models, traditional statistical models are used for forecasting instead of neural models. [12] [13]

Most of the current ORS models have assumed deterministic conditions and recent hybrid approaches merge the prediction from the ML with optimization methodologies for better quality decision-making for uncertainty. [4] Demonstrated the potential of machine learning for combinatorial optimization, but most studies deal with algorithmic acceleration rather than the embedding of predictive outputs in decision models. Likewise, applications with neural-assisted optimization have shown encouraging performance in logistics and scheduling, but such strategies typically fall within the operational or tactical decision-levels. [4]

A notable limitation recognized in the current literature is the dichotomy between forecasting and optimization. In numerous works, demand forecasts have been produced in isolation of performance estimation and are not included dynamically in the optimization planning. In addition, most frameworks consider static environments and fail to exhibit much robustness to uncertainty. To overcome these limitations, the proposed Neuro-OR framework builds upon neural network demand predictions into an extensive optimization model and supports adaptive decisions in unstable operational conditions. [8, 10]

Demonstrated further that neural-network-based decision support systems improved logistics planning and utilization of decision support systems for management logistics resources more efficiently than conventional optimization methods and can effectively improve the performance of logistics planning and resource allocation. [7]

While there are methods for addressing uncertain environments in which robust optimization methods, stochastic programming or fuzzy optimization techniques are required in the form of robustness of decision-making, some of them tend to rely on strong assumptions regarding probability distributions or uncertainty sets that are not necessarily available to the practical world. [10]

Moreover, hybrid frameworks are evaluated under much restricted experimental conditions, and there is a scarcity of evidence of their robustness between competing operational states and variable demand. Neuro-Operations Research, also known as Neuro-OR, has emerged as a promising approach to address these hurdles. Neuro-OR aims to leverage the predictive learning capabilities of artificial neural networks and the formal optimization strategies deployed in operations. While classical decision models rely only on deterministic parameters, in the context of Neuro-OR the use of data provides greater quality and adaptive decision making. Neural forecasts directly in optimization formulations enhance better predictions and thus ensure better decision making under uncertainty. Urban drone delivery presents the perfect application area of Neuro-OR systems. The recent rapid growth of e-commerce and last mile delivery services have gained a significant interest in the use of drones to assist logistics. Prior studies have employed optimization techniques to explore drone routing, fleet deployment, battery management and delivery scheduling. [1,3,5,16]

Although these studies have shown the effectiveness of optimization-based approaches, there is typically a generalized assumption of a deterministic or defined pattern of demand. Thus, resource allocation decisions can be suboptimal when real demand changes from expected demand. One such advantage of artificial neural networks in this area is that they are able to learn nonlinear demand from historical data and create realistic estimates of demand. [2]

To fill this gap, the study proposes a data-driven Neuro-Operations Research framework that merges artificial neural network demand forecasting with multi-objective optimization on the allocation schedule of urban drone delivery. Unlike other optimization techniques that are based on deterministic demand assumptions, the framework we proposed combines predicted demand into optimization step one and evaluates performance under uncertain conditions using sensitivity analysis. This integration may provide enhancements in operational effectiveness, resource management, and robust decision making and may contribute to the continuous flow of studies on learning-enhanced optimization techniques.

3- Research Gap

Although several studies have been conducted on drone routing, vehicle allocation and logistics optimization, relatively few studies have explored the direct integration of neural demand forecasting with optimization-based drone allocation decisions. Some work has been done, but not much in terms of integrating neural demand prediction with optimization-based drone allocation frameworks.

Moreover, there is little existing research investigating the stability of such combined systems on diverse demand conditions. As a result, there is a large research void for the construction of unified Neuro-OR systems, which can serve to solve the demand prediction, optimization, and uncertainty, all concurrently within urban drone delivery space. [1-5] [15]

4- Contribution and Novelty

The novelty of this proposed Neuro-Operations Research framework is attributable to 4 things:

1. Unification of neural demand forecasting and optimization within the context of decision-support.
2. Direct integration of neural network outputs into a robust multi-objective optimization model instead of treating forecasting and optimization as separate processes.
3. Use of Neuro-OR in urban drone delivery systems, where high demand uncertainty significantly affects operational performance.
4. Incorporation of robustness analysis to assess system stability in the face of demand fluctuations, improving the reliability of decision making in uncertain conditions.

These contributions establish the proposed framework apart from classical optimization methods and previously mentioned optimization methods using machine learning.

5- Methodology

This work tackles an urban drone delivery allocation problem with a set of integrated quantitative and analytical methods. Artificial Neural Networks are installed as predictive tools for handling the uncertainty related to future delivery demand in each zone. The neural networks should be trained from historical data on delivery for accurate estimation of the expected demand in each zone.

Moreover, the optimization problem can also be solved with the help of the Operations Research models. The issue is mathematically modeled with its goal to minimize the delivery time and operation costs with the significant constraints in the capacity of the drone, the distance of travel, and the time of flight.

5.1 Research Design

This study adopts a hybrid methodological framework based on the integration of neural computational models with operations research techniques. The research follows a descriptive-analytical approach aimed at developing a Neuro-Operations Research (Neuro-OR) model for decision-making under uncertainty. The proposed framework combines neural network-based prediction with mathematical optimization to enhance decision efficiency and system adaptability.

5.2 Neural-Based Demand Prediction

To predict demand of delivery across different operational zones, neural network models are used as prediction tools. To identify nonlinear correlations and patterns in demand behavior, the neural model is trained using simulated delivery-demand data. The expected demand for each zone is represented by the output of the neural network, which is then used as input parameter in the optimization model. Because of the neural prediction, the system is able to account for demand variations and uncertainty, and therefore is more realistic in the decision-making.

5.3 Neuro-OR Decision Framework

Step 1: Collect and preprocess the simulated delivery-demand data.

Step 2: Train the neural network with the simulated demand data.

Step 3: Generate the predicted demand values for each operational zone.

Step 4: Transfer the predicted demand values to our optimization model.

Step 5: Solve the robust multi-objective optimization problem.

Step 6: Obtain the best drone allocation decisions.

Step 7: Perform scenario-based sensitivity analysis.

Step 8: Compare results with traditional optimization methods.

Step 9: Evaluate operational performance and decision quality.

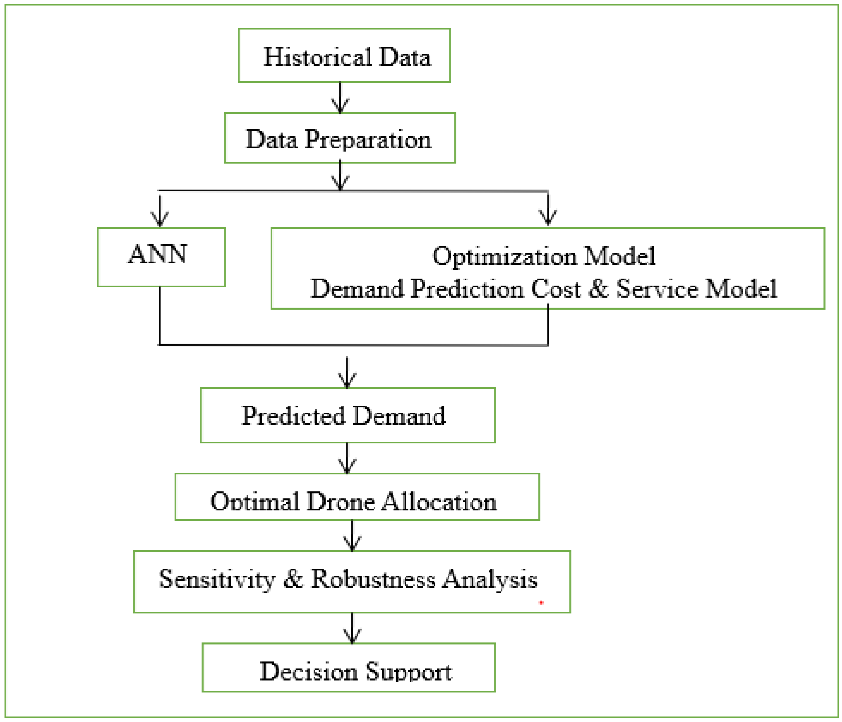

Figure 1. Proposed Neuro-Operations Research (Neuro-OR) Framework for Urban Drone Delivery Optimization.

5.4 Neural Network Architecture and Network Training Methodologies.

First, the simulated delivery-demand data were cleaned, normalized, and standardized. The inputs were delivery requests, delivery distances, demand indicators and operational zone characteristics. Missing values were discarded and all numeric values normalized to [0,1]. A feed-forward ANN (Artificial Neural Network) was used to predict demand. The network consisted of:

• Input layer: 4 neurons representing operational features.

• Hidden Layer 1: 16 neurons with ReLU activation.

• Hidden Layer 2: 8 neurons with ReLU activation.

• Output Layer: 1 neuron representing predicted delivery demand.

The proposed ANN architecture is designed to showcase the prediction element of the proposed Neuro-OR framework and represent a typical example for forecasting demand in the case-study scenario. The architecture is intended to show that demand predictions can be modeled as part of an optimization rather than as a separate ML model.

5.5 Mathematical Optimization Model

$i \in I$: set of operational zones

$j \in J$: set of available resources (e.g., drones / units)

t_{ij}: operational time required for resource j to serve zone i.

$\widehat{D_\iota}$: predicted demand at zone i obtained from neural networks

C_{ij}: operational cost of assigning resource i to zone j.

T_j: maximum available time for resource j.

C_j: capacity of resource j.

5.5.1 Objective Function [5, 8, 14]

Objective 1: Minimize Operational Cost

$$\min z = \sum_{i \in I} \mathrm{Cij} \sum_{j \in J} \mathrm{Xij} \qquad (1)$$

Objective 2: Minimize Demand Deviation (Service Quality)

$$\min Z_2 = \sum_{i \in I} \left| \widehat{D_\iota} - \sum_{j \in I} C_j X_{ij} \right| \qquad (2)$$

$$\mathrm{Min}\ \mathrm{Z}=\mathrm{aZ}_1 + (1-\mathrm{a})\mathrm{Z}_2 \qquad \mathbf{1} \leq \mathrm{a} \leq 0 \qquad (3)$$

Robust Optimization $\widehat{\mathrm{D}_\iota} \in \left[\underline{\mathrm{D_i}}, \overline{\mathrm{D}_\iota}\right]$ **,** $\sum_{i \in I} \mathrm{C_j X_{ij}} \geq \widehat{\mathrm{D}_\iota} \ \forall\ \mathrm{i}$

5.5.2 Formulating of the optimization problem: [1–3, 14–15]

Objective Function

$$\min z = \sum_{i \in I} \mathrm{Cij} \sum_{j \in J} \mathrm{Xij} \qquad (4)$$

Subject to

Demand satisfaction:

$$\sum_{j \in J} Q_j\, x_{ij} \geq d_i \forall i \qquad (5)$$

Drone capacity:

$$\sum_{i \in I} d_i\, x_{ij} \leq Q_j \forall j \qquad (6)$$

Time constraint:

$$\sum_{i \in I} t_{ij}\, x_{ij} \leq T_j \forall j \qquad (7)$$

Binary constraint:

$$x_{ij} \in \{0,1\}$$

5.6 Robust Demand Satisfaction Constraint

Multi-objective and resilient optimization, which strikes a compromise between service quality and cost effectiveness in the face of demand volatility, enhances the proposed Neuro-OR framework. This formulation builds on conventional deterministic models and provides a more realistic representation of operational decision-making.

5.7 Solution Approach

The methodological approach of the current study is anchored on an integrated framework that entails both prediction and optimization. The strategy entails the data gathering and processing and training of neural networks in coming up with predictions of anticipated demand in the urban areas. This is important because it enables the element of uncertainty to be converted into optimized data. Then the results obtained are further applied in operations research formulation, which assists in determining the best distribution of drones to the delivery requests. The operations research formulation at this stage targets the reduction of delivery time, as well as the optimal utilization of the available resources. Finally, the best solution is then interpreted and then the scenario analysis is done to determine the stability of the solution to different scenarios.

5.8 Urban Drone Delivery Optimization

Case Study Description The practicum example demonstrates that the Neuro-OR model could be applied to streamline drone delivery in the cities. The solution proposed is to ensure that deliveries are made with optimal drone allocations in response to demands for delivery in different zones of the city.

6- Data and Forecasts of Neural Network:

In this part, the suggested Neuro-Operations Research framework is implemented to a hypothetical operational case. The purpose is to show the potential to incorporate predicted demand in an optimization model to assist in making decisions in times of uncertainty.

Table 1: Results of Neuro-OR Optimization on Drone Delivery in Urban Areas

Request	Predicted Demand (number of deliveries) ($\widehat{D_i}$)	Distance (km)	Assigned Drone	Allocated Time (min)
Zone A	25	5	Drone 1	30
Zone B	15	8	Drone 2	40
Zone C	30	12	Drone 3	60
Zone D	10	6	Drone 4	20
Zone E	20	10	Drone 5	50

Table 1 presents the results from the proposed Neuro-OR model. A neural network generates predicted demand values. The optimization model then allocates resources based on demand level and operational distance. In particular, areas with a higher predicted demand are selected more, indicating the adaptive nature of our framework. The finding that neural network predictions play an important role in the optimization process is more relevant and practical than the deterministic methods, which can make the approach work in terms of adaptability in case of the predicted demand. The model adapts the resource allocation based on the predicted demand change dynamically, which is strong evidence that it is performing well.

Table 2: Performance Comparison Between Models

Model	Total Cost ($)	Total Delivery Time (min)	Average Time per Zone (min)
Traditional OR	520	210	42
Neuro-OR	430	180	36

The "Traditional Operations Research (Traditional OR)" model and the proposed "Neuro-OR" model for optimization of urban drone or intelligent delivery operations are compared in Table 2. The results show that the "Neuro-OR" model outperformed the traditional OR on all operation metrics. In particular, the "Neuro-OR" model reduced the total operating costs from $520 (Traditional OR) to $430, which is a reduction of $90 or about 17.3%. The cost reduction shows how the use of AI and neural network techniques with operations research can increase the efficiency of resource allocation and reduce operating expenses.

The Neuro-OR model improved the "total delivery time" by about 14.3%, from 210 minutes to 180 minutes. This means the suggested model is better at route optimization and delivery scheduling, which means drones will be assigned more effectively and order distribution decisions can be made faster.

In the Neuro-OR model, the average delivery time per zone dropped from 42 minutes in the Traditional OR model to 36 minutes. This result shows how the suggested framework can enhance service responsiveness and speed up delivery performance across different operational zones.

6.1 Quantitative Improvement Analysis

$$\text{Improvement (\%)} = \frac{\text{Baseline} - \text{Proposed}}{\text{Baseline}} \times 100$$

1. Cost Reduction

$$\text{Reduction} = \frac{520 - 430}{520} \times 100 = 17.3\%$$

Neuro-OR reduced operational cost by 17.3%

2. Time Reduction

$$\text{Reduction} = \frac{210 - 180}{210} \times 100 = 14.3\%$$

6.2 Delivery time reduced by 14.3%

The improvement percentages were calculated by comparing the performance of the proposed Neuro-OR model against a baseline traditional optimization model.

The values are derived from simulated case study results to demonstrate the relative performance gain.

6.3 Sensitivity Analysis

To evaluate robustness, demand was increased by 20%.

Scenario	Total Cost ($)	Delivery Time (min)
Base Case	430	180
+20% Demand	470	205

Interpretation:

- Cost increased by ~9.3%
- Time increased by ~13.9%

This indicates that the model remains stable under moderate demand changes

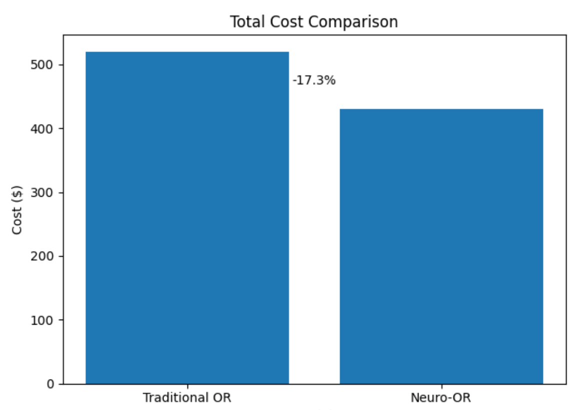

Figure 2. Total cost comparison between Traditional OR and Neuro-OR models

Figure 2 shows that the Neuro-OR model achieved a noticeable reduction in overall cost, decreasing from approximately $520 to $430, which corresponds to a 17.3% reduction

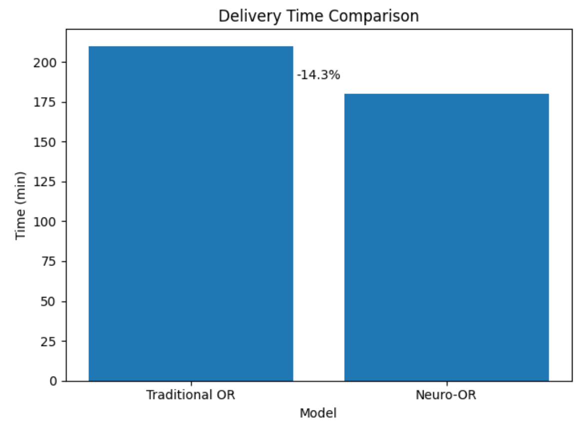

Figure 3. Delivery time comparison between Traditional OR and Neuro-OR models

Figure 3 shows the Neuro-OR, which reduced the overall delivery time from approximately 210 minutes under the Traditional OR model to 180 minutes, representing a 14.3% improvement.

The robustness analysis is mandatory as one of the decision support directives to apply and address decision support systems analysis in uncertain and dynamic environments. Demand patterns in urban drone delivery applications are subject to climatic variations in the form of seasonality, customer demand, and unexpected operational disruptions when considering weather events or sudden changes that trigger unexpected interruptions in the system execution. Consequently, an evaluation of the capability of neuro-operations research (Neuro-OR) framework offered to achieve moderate performance with respect to demand variability is vital for support of its practical implications. In order to assess the strength of the proposed framework, a sensitivity analysis was implemented by increasing the expected demand 20% relative to the baseline condition. Hence, the costs were raised from \$430 to \$470 in operation, and the total delivery time from 180 to 205 minutes. Even though the performance measures grew in all cases, the optimization model could provide realistic allocation recommendations while satisfying all operational constraints regarding resource usage, delivery needs, and coverage. The increase in operational cost and delivery duration in this case would not be surprising because the production demand (an output) is more demanding than the need for utilization and operation effort. Despite these, those changes were small by the extent of the demand rise, indicating that the proposed framework has operational advantages in an environment with moderate uncertainty of demand. The combination of neural-network demand prediction and optimization-based demand allocation, as mentioned by the previous paper, produces a more flexible solution than traditional deterministic optimization techniques. At the decision-support level, our findings indicate that the proposed Neuro-OR framework has not rapidly degraded with increased load. Instead, system performance suffers slowly and predictably with increasing demand. This is very helpful for operational-level planning and expected behavior, and it is much more effective in a scenario when decision makers would be using the information in the analysis to look for possible future results in preparation for changing demand, determining accordingly how future resources ought to be distributed at the time. The interaction of prediction and optimization of the proposed framework can also be helpful in linking the robustness of the proposed framework. The demand projections generated by the neural network are based on the non-linearities and hidden correlations in the operational data and the optimization module converts this to actionable resource allocation decisions. It removes the reliance on deterministic commitments and enables the system to adapt to the new dynamic of the operation. However, there are a few caveats that should be noted. The robustness of the method is evaluated in a case study environment only for one demand-growth scenario. So, at the end of the day the results should have been considered as preliminary evidence of the resilience of the framework not robustness. Further research may focus on the uncertainty due to random demand distributions, weather disturbances, battery degradation, and real-time operating limits. Second, real datasets are needed to provide additional credibility of the proposed framework. However, the sensitivity analysis shows that the Neuro-OR framework has already reached the robustness and reasonable performance with the load increasing. We believe that integrating neural prediction with mathematical optimization for these unpredictable demand fluctuations can help to improve decision-making stability and decision-making flexibility in these complex urban logistics systems and their changing demand environment.

7- Results and Discussion

The Neuro-OR (Neuro Operations Research) methodology was tested on simulated data of a drone parcel delivery operation with five operational zones in a larger urban setting. Specifically, in the first stage, demand levels were predicted using a neural network among all zones, and these predictions were then embedded into an optimization model for allocation decisions. Based on allocation outcomes shown in Table 1, zones with anticipated high demand were able to be selected from the available resources through prioritization to minimize the excess operational resources over those of zones C and A in accordance with drone utilization constraints. This shows how the model systematically manages to use the prediction output to drive decision-making. A comparison between the proposed Neuro-OR framework and a standard operations research model is shown in Table 2 and Figure 1. The outcome shows that by adopting demand prediction, the performance level of operation reached a higher level of operation by improving delivery times down by 14.3%, while the overall operating costs reduced by 17.3% compared with the conventional model. These enhancements are said to be due to the ability of artificial neural networks to capture nonlinear demand, which can be excluded by deterministic optimization models. Including expected demand allows the optimization model to make decisions that change over time based on how the demand will evolve, which in turn facilitates optimum solutions. In this study, a sensitivity analysis was performed on the model under a 20% load increase to validate its durability. The model demonstrated steady performance despite higher operating cost and time of delivery (9.3% and 13.9%, respectively). This suggests that the Neuro-OR framework is moderately resilient against variations of demand. Moreover, the assumptions taken by traditional operations research models may not work best in uncertainty situations because it depends on the fixed demand assumption. The proposed approach solves this problem by employing neural network-based prediction and optimization to improve decision quality and flexibility.

8- Conclusion

From the practical application, it is seen that indeed the Neuro-OR framework is capable of optimizing urban drone delivery successfully. This is made possible by combining the use of prediction analytics with optimization.

The proposed results analysis shows that the Neuro-OR approach is capable of assigning drones to zones with high demands and satisfying time constraints.

This result thus underlines the capability of the proposed model to strike a balance between creative potential and possible risks connected with such potential, as well as its capability to allocate these resources in the most optimal way possible. This result also underlies the adaptability of the proposed Neuro-OR approach within the context of decision-making under uncertainty.

9- Future Research Directions

Such work may be extended in the future with adaptive learning mechanisms, which will update the demand estimates continuously with new data. Moreover, in more uncertain environments, flexible and randomized optimization techniques will help to improve the capability of the model in operating in these environments. Moreover, the ability of this framework to be generalizable can be tested in other operational domains (e.g., smart energy management and distribution systems and self-maintenance infrastructure systems).

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