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# A Sustainable Performance Analysis Of Logistic And Route Planning Based On Machine Learning Algorithms

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***Abstract***
*Urban logistics is central to 21st-century supply chains because it promotes efficiency and care for the environment. The presented work provides a brief literature review on the subject and presents an integrated data approach based on the methodology of clustering and evolutionary algorithms to contribute to the enhancement of route planning and logistics location in the metropolis. This research uses geolocation data from 8,079 customer delivery points in Salvador, Brazil, the study aims to make a comparison of K-Means and Mean-Shift clustering techniques in defining service zones performance. Within clusters, intra-cluster routing is improved by shortest path algorithm that is Dijkstra and the GA. As indicated by the survey, integrating mean shift clustering and genetic algorithm provides the best solution for delivery, which reduces travel distance by 2-3 times (operational costs and $CO_2$ emissions by more than 40%). Similarly, the conclusion section reveals the potential of integrating different combined learning techniques to scale up the last-mile delivery solutions into more flexible and sustainable models.*
***Keywords***: *Artificial Intelligence, Dijkstra Algorithm, Genetic Algorithm, Route Optimization and $CO_2$ Emission Minimization, K Means Clustering, Mean Shift Clustering, Urban Delivery.*

## 1. INTRODUCTION

Proper transport network is still central to economic and urban growth as well as convenience to the consumer. Dynamic routing with time windows has been addressed in literature [1] and predictions of ETA techniques for urban logistics have been discussed earlier [2] which was especially in the context of the predictions of ETA in city logistics. The existence of the digital platform in the business environment causes the different need of a complex, accurate, and eco-friendly supply method to emerge. Unfortunately, traditional approaches for logistics planning is not adequately effective for changing urban networks when the traffic flow, levels of delivery, as well as the physical oddments themselves, fluctuate as demonstrated in the detailed review of routing software systems [3] in their analysis in regards to the need for routing software [3]. This paper shows how machine learning (ML) is able to supplement the collection of classical operation's research algorithms to overcome these challenges. Local colleges and universities have put in a lot of effort to connect machine learning with logistics optimization. To enhance time performance in IoT-based intrusion detection, Dhyaa and Essa [4]. introduced a hybrid SVM-RF model and proved how useful intelligent algorithms can be in decision systems. Likewise, Farah and Essa [5] created a combined clustering-routing system for urban delivery, fitting with the integrated ML approach presented here. These studies from the University of Kirkuk give fundamental understanding that is in line with the overall method described in our paper. The literature we considered has pointed out the benefits of density-based clustering [6], and reported that logistics routing issues can be resolved more efficiently with machine learning[7]. The rest section of this paper are organize as. Section 2-Related Work: we review earlier studies focused on logistics optimization and applications of machine learning. Section 3 – Methodology: explains how the experiments are done, using the dataset, clustering algorithms, routing approaches and evaluation tools. Section 4 – Experimental Results: This section of the study tests combinations of the given algorithms. Section 5 – Discussion: covers the outcomes of this study when compared to prior findings and explores what it means in practice, and finally, Section 6 – Future Work: of this paper discusses future research that should be conducted.

## 2. Research Objectives

This study aims to:

1- Create an scalable logistics framework based on real GPS data.
2- Evaluate K-Means and Mean-Shift clustering on effectiveness.
3- Determine the difference between deterministic (Dijkstra) and evolutionary (GA) routing.
4- Track performance through performance metrics to assess cost saving and environmental benefits.
5- Optimize green urban logistics by applying intelligent methods.

## 3. Contributions

This paper makes the following contributions:

1. Suggests a hybrid clustering-routing structure for urban logistics.
2. Shows the effects of Mean-Shift + GA combination.
3. Considers more than one combination using real-life data.
4. Offers performance benchmarking on important logistics indicators.
5. Supplies a repeatable methodology for future smart city applications.

## 4. Related Work

Thus, machine learning has contributed to the development of the field of optimization of urban logistics. It has been ascertained in many studies that such clustering techniques as K-Means and density-based methods enhance the optimality of delivery zone[8], [6]. Several vehicle routing problems with constraints have been solved using genetic algorithms mostly providing better solutions than heuristics techniques [9],[10]. Other approaches which are a combination of clusterization and evolutionary algorithm have also been proposed as a solution recently in the literature[11],[12]. Subsequent studies have focused on specific areas like path planning for Underwater path planning for autonomous vehicle using machine learning techniques has also helped in improving the accuracy of vehicle navigation and flexibility in features of the ocean [13] and Machine learning has been also applied to agricultural supply chain, for example, recognizing and managing the mango supply chain network[14].

The iterative approach of ACO and the extension of the algorithm as a metaheuristic technique in the solution of routing problems has also been discussed in the recent literature [15]. For example, recent developments have been made in dynamics scenarios of logistical requirements and trading effectiveness with utilization of the ML[16]. The current study extends these works by welding Mean-Shift clustering together with GA in real-geographical space routing system.

The most significant developmental in AI in the ML domain, which has made it possible to analyze large depot of geospatial data. Other methods like K-Mean and Mean Shift help in clustering the delivery concentration zones [8], who used K-Meain routing of urban logistics and [13] for the study on machine learning techniques in the vehicle path planning., while metaheuristic optimizers like GA can able to refine the route sequences and minimize the cost time and also lessen the environmental costs [17] who applied GA combined with K-Mean for time-window routing problems and [15] for the study of Ant Colony Optimization (ACO) evolution. While the previous approaches serve as the basis for this work, this paper offers a different approach that aspires to use a combination of unsupervised learning methods for zone definition and routing algorithms for optimization within the zones.

## 5. METHODOLOGY

This study employs a combination of clustering and a heuristic search technique with a view of gaining insights into the research problem. Firstly, the coordinates of 8,079 delivery points in Salvador, Brazil, were obtained [18]. The pre-processing steps carried out on the coordinate data involved checking for the actual physical coordinates, deleting wrong coordinates and normalizing them. Two clustering techniques were used: K-Means which presupposes the number of clusters to be formed and Mean-Shift in which number of clusters is automatically determined on the basis of density. In delivery routes of each cluster, Dijkstra's Algorithm and Genetic Algorithm were used.. The comparisons of various concerns such as the total distance covered, time, cost, $CO_2$ emissions, and cluster accuracy were also computed for each of the permutations. A diagram of the entire research workflow is provided in Figure 1 and shows the process from data preprocessing through clustering and routing until evaluation of performance. It shows two planning paths based on Dijkstra's algorithm and Genetic Algorithm after classifying the logistics centers with clustering.

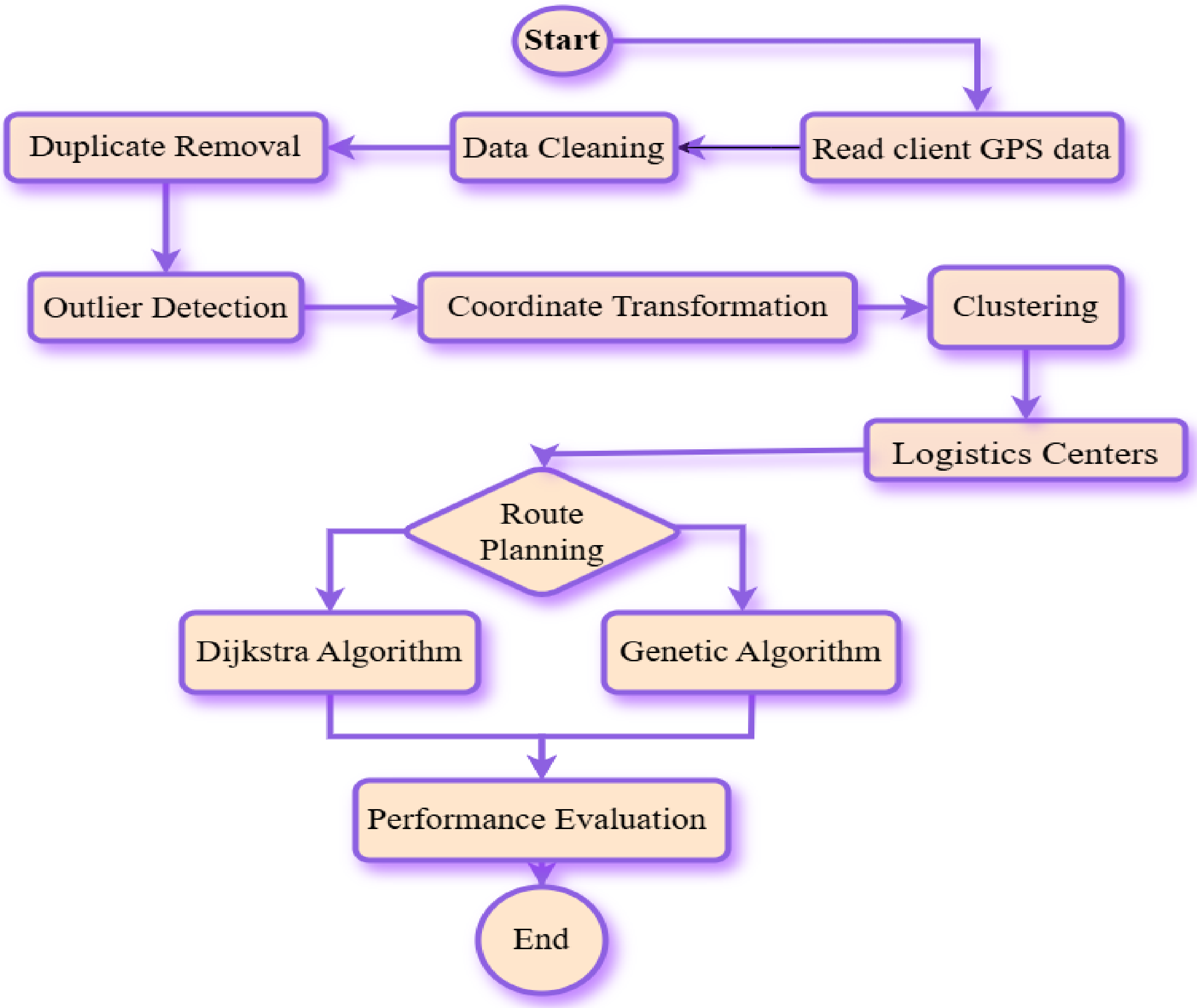


Figure 1. Workflow of the proposed logistics optimization model

## 6. Experimental Results

The quantitative results of all four routing strategies implemented in this study are shown in the Table 1 in terms of total distance traveled, delivery time, operational cost, and $CO_2$ emissions in addition to, clustering precision, recall, and F1 score.

Table 1. Comparative Performance of Routing Strategies

| Method | Distance (km) | Time (min) | Cost (USD) | $CO_2$ (kg) | Precision | Recall | F1-score |
|---|---|---|---|---|---|---|---|
| K-Means + Dijkstra | 40,513.59 | 49,273 | 16,205.52 | 8,508.29 | 0.9946 | 0.9957 | 0.9951 |
| K-Means + GA | 39,288.95 | 52,492.3 | 15,715.24 | 8,250.52 | 0.9946 | 0.9957 | 0.9951 |
| Mean-Shift + Dijkstra | 49,741.12 | 62,245.71 | 24,869.66 | 9,549.68 | 0.9892 | 0.9744 | 0.9815 |
| Mean-Shift + GA | 27,601.68 | 41,402.19 | 13,800.70 | 5,299.65 | 0.9892 | 0.9744 | 0.9815 |

## 7. Algorithm Characteristics Comparison

To gain a clearer perspective on the significance of every algorithm in the direction research, Table 2 synthesizes their computational type (theoretically and observed), strengths, and shortcomings in both theoretical properties and observed results.

Table 2. Characteristics of Algorithms Used in Urban Logistics Optimization

| **Algorithm** | **Type** | **Strengths** | **Limitations** |
|---|---|---|---|
| K-Means | Clustering | Fast, easy to implement, scalable | Sensitive to initial centroids, fixed k |
| Mean-Shift | Clustering | No need to predefine clusters, adapts to density | High memory cost, slower with large data |
| Dijkstra | Deterministic | Guaranteed shortest path, simple to apply | Ignores route order and multi-stop logic |
| Genetic Algorithm | Evolutionary | Handles complex constraints, global optimization | Slower convergence, parameter sensitivity |

Figure 2 shows the comparative performance of the four routing strategies that have been implemented in this study. These include the combinations of K-Means, Mean-Shift clustering techniques, Dijkstra's Algorithm, and the Genetic Algorithm. The figure reveals differences in total distance, delivery time, operational cost, and CO 2 emissions for the configs.

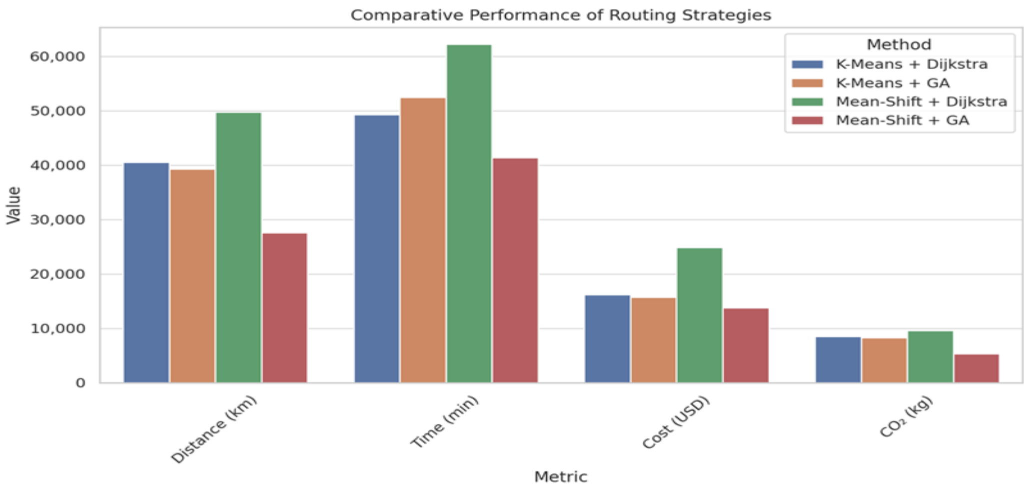


Figure 2. Comparative performance of routing methods across distance, time, cost, and $CO_2$ metrics

As illustrated in figure.2, a combination of Mean-Shift clustering with Genetic Algorithm clearly dominates in minimization of distance traveled, delivery time, fuel cost and carbon emission. This proves the power of density-based clustering when taken as supplementary to global optimization methods in dealing with complicated urban delivery networks.

## 8. DISCUSSION

The experimental results make the deterministic algorithms, such as Dijkstra, limitations in multi-stop logistics contexts clear. Although quicker, they reliably fail to find globally optimised routes. Although GA is more computationally expensive, it consistently outstripped Dijkstra in terms of cutting down on operational cost and emissions. Previous studies had shown that hybrid models relying on a combination of GA and clustering for routing optimization for electric vehicles were effective[10], and studies on robustness in ML-based logistics systems for application in constantly changing urban environments have also been conducted[16]. Additionally, the nature of Mean-Shift as being density-aware can lead to realistic clustering in non-homogeneous cities, hence, oversimplification by traditional methods such as K-Means could be of less value [19] when using matheuristics to increase the accuracy of clustering in logistics routing.

These results are consistent with previous literature supporting hybrid approaches in dynamic logistics environments. During various studies, unified machine learning frameworks aimed at logistics planning have been tried out and authors stated that performance has been enhanced [8], [9], [11]. The application of ML for path planning of vehicles in Smart cities as well as multimodal routing in smart cities add to the agenda of flexibility of these model[20], discussed ML's on vehicle path planning, and[18] looked into the multimodal routing in smart cities. This study builds on those enumerations by providing a scalable model that can be used in a smart city context, which can easily interface with real-time APIs and IoT-based demand-sensing A comprehensive review of the vehicle routing algorithms was provided by [21] out of which key advances in algorithm was outlined, whereas logistics strategies for e-commerce environments were brainstormed in[22].

## 9. CONCLUSION

This study put forward an integrated machine learning-based strategy for optimizing urban logistics by clustering and route planning. Combining K-Means and Mean-Shift for customer segmentation used Dijkstra and GA for intra-cluster routing, the framework that was suggested showed a marked improvement in efficiency and the environmental effects. The Mean-Shift + GA is the best since it achieved the values of more than 40% reduction in distance, cost, and emissions. This approach has the potential for scalable, sustainable, and intelligent urban planning of logistics.

## 10. Future Work

Future studies can develop the current hybrid logistics optimization framework by connecting with actual real-time information from traffic, weather and demand for on-demand deliveries. If the model is improved by reinforcement learning or deep learning, it can update and optimize itself as it receives both old and current performance data. Additionally, if the methodology is adapted to cover mixed transport systems, including combinations of trucks and drones or energy-restricted electric vehicles, it becomes more useful for smart city programs. Testing the framework in cities with different natural and social features would help verify its strength and allow its use in handling many urban logistics problems.

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