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Optimal Route Planning Using Computer Simulation In The Context Of Distributor-To-Consumer Supply Network

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OPTIMAL ROUTE PLANNING USING COMPUTER SIMULATION IN THE CONTEXT OF DISTRIBUTOR-TO-CONSUMER SUPPLY NETWORK

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by

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ABSTRACT

Effective route planning for distribution centers is a multifaceted challenge crucial to business success, as it directly impacts time and cost savings while enhancing overall delivery efficiency. Oversight of proper planning can lead to problems and inefficiencies in the distribution process. Hence, this work undertakes a comparative experiment of two delivery strategies in a distributor-to-consumer supply network. While the first strategy investigates the delivery process by zip area, the second strategy considers the clustering of the areas for more streamlined delivery fulfillment. The effectiveness of the delivery process is gauged based on a set of metrics, including total distance traveled, average delivery time, missed target deliveries, and resource utilization. The study specifically addresses five distribution centers in the El Paso, Texas, USA, area and the delivery addresses across various zip codes in El Paso. The delivery network was simulated using the AnyLogic software, with results analyzed on both daily and weekly timelines. Simulation data were systematically logged into the AnyLogic database for subsequent analysis. In doing so, this paper presents a comprehensive analysis derived from observed data, offering a comparative assessment of the two delivery strategies. The findings provide a quantitative evaluation of the effectiveness of route planning within diverse scenarios in end-user supply networks.

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SECTION 1: BACKGROUND

The challenges associated with route planning within the supply chain context have earned heightened attention. Several factors have contributed to this attention, particularly the emergence of additional relationships between the operational landscape. The intricate nature of the fundamental procurement, production, and distribution processes, coupled with the growing number of involved parties, highlights the need for efficient support systems [1]. In addition to the previously mentioned parties, route planning within the supply chain confronts further challenges, specifically those linked with the physical aspects of deliveries. Establishment of planning objectives is a task undertaken by decision-makers, who consider various criteria. These criteria include minimizing, fixed and variable cost, fleet size, total transport times, and total distance travel, along with reducing waiting times [2].

Delving into a more specific aspect of route planning involves examining a localized system, that routes from a distribution center to individual residences or retail stores. In a broader context, focusing on localized routes naturally prompts a discussion on factors such as traffic volumes and time constraints. The exponential growth in the number of vehicles over time is anticipated to result in a disorderly impact on road infrastructure, intensifying traffic conditions to an unprecedented level [3]. Furthermore, a system involving multiple deliveries within a city may pose a more excellent logistical context. The package delivery system evolves into an increasingly intricate process with the augmentation of data volume. Navigating multiple road networks options to determine the shortest path is an even more demanding task [4]. Challenges arise due to output variability in every instance. Customers have expectations involving the delivery of their product, particularly on high-interest deliveries [5]. The quantity of deliveries may fluctuate, with variations in the destinations occurring on a case-by-case basis. Hence, it is essential to account for these unpredictable variables during the planning and execution of the delivery process.

Moreover, the duration required for a delivery plays a pivotal role in defining the business's sucess [6]. As diverse industries undergo evolution and advancement, it is necessary to establish a system geared toward mitigating the avoidable costs associated with inefficient routing. Illustratively, contemplate the food industry where food manufacturers handling refrigerated or frozen products rely on dedicated resources to uphold the quality of the food throughout its transit. The duration of travel assumes significance to anticipate customer complaints, and the presence of multiple drop points can significantly impact the product's condition, particularly upon reaching its destination. Although carrier and truck operation are essential components for the efficacy of route planning, it is also crucial to underscore that the critical factor in this study is the directionality of the route.

Strategizing route planning entails a heightened awareness of the prevailing road conditions, adhering to speed limits, and accounting for time constraints. Several critical challenges associated with route planning encompass the environmental characteristics of the region through which the delivery will be conducted, and the subsequent steps. Given the inherent unpredictability, it is impossible to ascertain and forecast occurrences such as nearby accidents or instances where traffic is redirected to alternative routes potentially leading to further delays. Anticipating and accounting for these aspects in advance is inherently challenging. Additional challenges may encompass adverse weather conditions, poorly maintained infrastructure, and parades of other events that can significantly impact the normal flow of vehicles.

In any comprehensive study, consideration should consistently be accorded to the potential occurrence of unexpected outcomes in route planning. Diving into route planning with an informed and receptive mindset regarding possible outcomes is critical for research. As previously emphasized, certain aspects within this context cannot be quantified. Nevertheless, the quantifiable elements necessitate meticulous consideration to target and attain an optimal route plan. Engaging in the exploitation and exploration of the data constitute pivotal phases that transpire to the initiation of experimentation [7].

Moreover, the strategic planning of optimal routes within the delivery management systems is integral in delineating the success of a business. The management systems, algorithms, or approaches exhibit variability across various parameters. Furthermore, the attributes associated with the delivery system play a key role in determining the correct method to employ. Numerous approaches undergo scrutiny within supply chain context, spanning industries such as pharmaceutical, food, automotive, and various other sectors. There is no one-size-fits-all solution.

Consequently, the pursuit of optimized planning requires multiple experiments and studies. Diverse factors contribute to a scenario where identifying a method for optimized planning becomes unattainable [8]. Similarly, there may be instances when a study may prove detrimental to the route system, often attributable to the oversight of certain factors.

Moreover, in route planning, critical factors include speed, traffic conditions, and distance, aiming to align with a predetermined schedule upon departure from a distribution center. In the given context, strategically, delivering to a location a mile from the distribution center appears more appropriate than prioritizing deliveries over a greater distance. Various techniques can be employed to ascertain the quickest route considering the distance between consecutive deliveries. Considering these factors offers several advantages, including time savings, enhanced operational efficiency, and cost-effectiveness. A beneficial method for analyzing these factors and their corresponding benefits is through cross-referencing. The primary objective is to facilitate a thorough analysis to guide the selection of the most suitable method for achieving optimized route planning. Subsequent subsections will delve into the implementation of cross-referencing for this purpose.

Subsection 1: Leveraging speed for time savings in operational processes

Speed plays a pivotal role in quantifying the temporal demands of package delivery. This phenomenon is notably influenced by speed regulations. The imposition of a reduced speed limit within a given area impacts the temporal efficiency of the delivery process. Considering the extent determined by companies for their operational shifts shapes the regions to be serviced and the corresponding time frames allocated. Moreover, due to the pervasive speed limits across the urban landscape, resources can be either saved or expended. In situations of this nature, the pivotal factor is not strictly the spatial distance, but rather the temporal investment necessary to traverse from a designated point to a predetermined area. For example, the duration to cover a downtown area may exceed that an interstate-covered segment of city; this is attributed to the prevailing speed limits in the respective region. Such intricacies are focal part in discerning the nuanced difference between time conservation and defining the region for efficient delivery operations.

Subsection 2. Traffic dynamics for enhanced operational efficiency

Industries have encountered technological advancements while recognizing that performance entails an enhancement not only in temporal and qualitative aspects but also in other contributing factors [9]. Certain routes exhibit amplified congestion in comparison to others. This may result in a delay in the delivery timeline, consequently impacting overall operational efficiency. Route planning is a complex undertaking influenced by numerous variables, including traffic patterns and road conditions [10]. While two deliveries can be at an equivalent distance, the temporal requirements for arrival can be impacted by factors such as traffic congestion and road closures. The repercussions of delays and imprecise calculations extend to the business, given that customers hold specific expectations of their order's arrival. Hence, it is imperative not to overlook the significance of this information. The area in which the addresses are situated must be considered during the delivery process.

Subsection 3. Distance-driven cost-effective in logistics optimization

The capability to effectuate deliveries to diverse locations within the city is paramount for the operational efficacy of a business. Irrespective of proximity or distance, this location represents an opportunity for revenue generation. While the correlation between distance and delivery fees may not be the primary focus in the delivery system, services may nevertheless utilize these data points as contributing factors in determining the fee structure. The significant aspects lie in providing a growing business with the means to ensure coverage, thereby addressing customer needs with the assurance that packages can be ordered and delivered to any address, irrespective of the distance, while prioritizing satisfaction and safety.

Therefore, it is to assert that an efficient delivery method constitutes a critical component for a delivery system. This is accomplished through consideration of the abovementioned factors and their interrelationships. The strategic planning for the high-volume delivery of products to an end-user network is a challenging endeavor that warrants comprehensive examination.

SECTION 2: LITERATURE REVIEW

Numerous scholarly articles scrutinize algorithm methodologies for addressing and resolving route planning fixes. Also, various papers delve into the exploration of algorithmic frameworks and methodologies dedicated to the resolution of route planning complexities. Certain studies employ fuzzy approaches, while others opt for the utilization of fusion algorithms. A substantial portion also consider technological advancements, notably Geographic Information Systems (GIS). Moreover, certain studies incorporate simulation methodologies, whereas others rely on real-time data for their analysis. Furthermore, there are unconventional factors, including environmental considerations, among other variables, that may take time to be intuitive. Critical elements within the realm of supply chain management undergo evaluation and quantification as they pertain to travel across a road transport network. These encompass energy utilization, time efficiency, waste generation concerning products, traffic safety, the well-being of goods and individuals, accessibility, and economic prosperity [11].

Delving deeply into the specific methodologies identified across the research, the review of selections and inquiry of various methods are systematically examined. Irrespective of the chosen method, it is important to acknowledge that additional methods demanding consideration within the supply chain. It is imperative to note that there has been an increased interest in modeling scenarios that encompass multiple elements within the supply chain [12]. The selection of an appropriate method poses a non-trivial challenge. The supply chain industry has devised multiple algorithms and methodologies aimed at optimizing the route planning process. Logistics planning constitutes a field employed for resolving a myriad of shortest path simulations within the domain of transportation [13]. Regarding the delivery of products to customers, certain algorithms consider the distance travelled between individual addresses. Such is exemplified in the Traveling Salesman Method, which employs the nearest neighboring system. This algorithm determines the most concise itinerary among a defined set of "places," addressing them sequentially one at a time [14]. Additional methods used for calculating these distances include the Haversine formula, which leverages the longitude and latitude coordinates of the addresses to determine the shortest distance. The Haversine formula constitutes an equation occupied in navigation that accommodates the shape of the earth [15].

Conversely, linear programming seeks to optimize the ideal outcome by using mathematical models. This model is fashioned by establishing linear relationships with the respective addresses. Upon scrutinizing all conceivable options, this model will attempt to ascertain the optimal outcome [16]. Additional tools facilitating the development of the delivery system include applications employed in conjunction with complementary methodologies. The area of route planning needs more information on real-time decision-making when drivers must decide. Accurately capturing drivers' partialities towards potential routes is typically challenging due to the influence of past experiences, subjective interpretations of provided traffic information, and dynamically changing personal attitudes in response to evolving traffic conditions [17].

This study diverges from most of the existing research literature by assuming a comparative analysis of two scenarios, employing a synthesis of functions, algorithms, and simulation software tools. The objective is to maximize the value derived from the study. Furthermore, its distinctive characteristics lie in being a localized experiment simulated with actual geographical locations.

SECTION 3: METHODOLOGY

Subsection 1: Case Study

The principal objective of this study is to conduct a comparative analysis between two simulation scenarios, juxtaposing their respective outcomes. This multifaceted evaluation aims to discern and comprehend the variable contributing to inefficiencies to provide a comprehensive understanding of the comparative performance of the two scenarios.

To begin with the study, a specific area was delineated, accompanied by a series of distribution centers dispersed across the designated region, to investigate a delivery system and route planning.

The chosen region was El Paso, TX, which is located on the west side of Texas. The El Paso area compromises multiples zip codes and neighboring towns that belong to the county of El Paso. The region was stratified into five sectors: the West, East, Far East, North and Central Areas. These designations are colloquially recognized, and the present paper must acknowledge them explicitly in relation to both methods. Key points aid in the identification of these areas. Another method for easy identification is the zip codes, which can aid in pinpointing the outline for these areas. This recognition will be utilized in the study throughout this paper. Furthermore, it is anticipated that each area has a distribution center. The process of selecting delivery locations emerged through the identification of all pertinent Zip codes within El Paso, TX region.

Illustration 3.1: Zip Code Designation.

From this, the Zip codes were allocated to their geographical areas on the map. The following table illustrates the alignment of zip codes with their corresponding area.

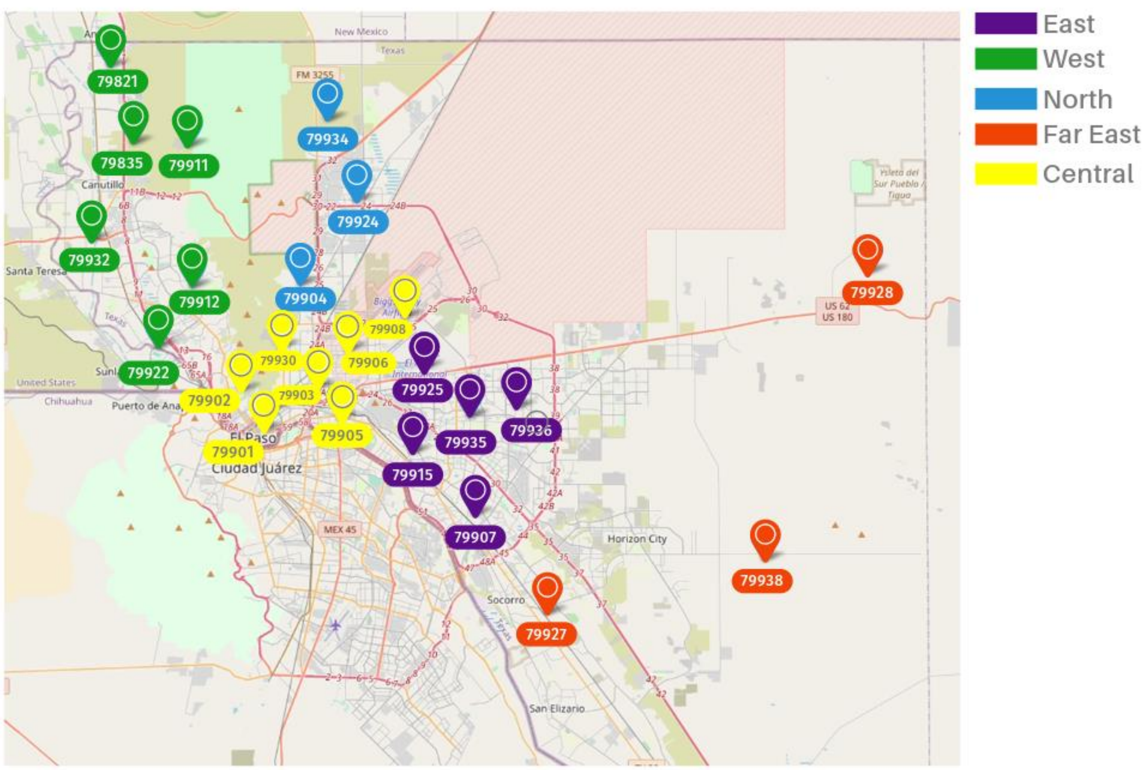

Illustration 3.2: Map for Zip Code Designation.

Following the acquisition of data, a sample of 30 deliveries was randomly selected from the identified zip codes. Five distribution centers were situated for each designated area. Utilizing the Geographic Information System (GIS) Map feature from AnyLogic program, 150 addresses were inputted and pinned along with the distribution centers.

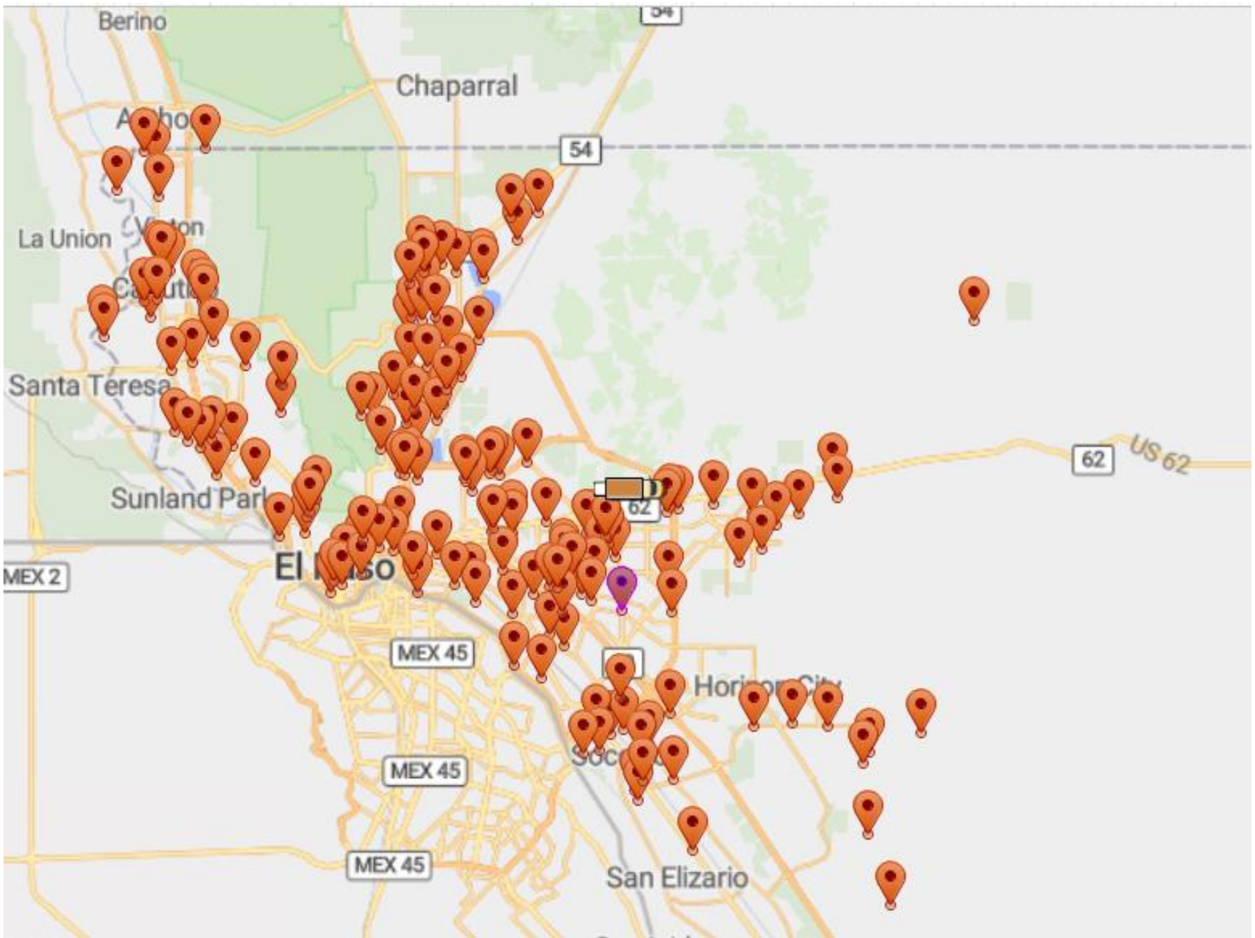

Illustration 3.3: AnyLogic GIS Map with 150 target addresses

Subsection 2: Solution Approach

AnyLogic is a simulation program predicated on the involvement of agents while incorporating events, variables, and collections to facilitate its functionality. In the context of this research, the simulation of agent movement, specifically the trajectory of the truck from the distribution center to the selected addresses and subsequently back to the distribution center, it achieved by creating a streetchart with AnyLogic. A flowchart was generated to streamline the input of parameters, including the speed of the truck, delivery delays, and the details pertaining to the final stages of the delivery processes. The flowchart serves as a guide for configuring and managing information within the simulation model.

Subsequently, an order was established to disseminate instructions to the agents regarding their designated routes. This implementation necessitated the utilization of variables and collections to store and manage the information. Individualized collections and variables were assigned to each district area. It is important to note that the delivery process transpired without randomness. The deliberate exclusion of randomization in the order event aligns with the simulation’s objective of determining the most optimized route. This intentional approach emphasizes the precision and methodical nature of the simulation. The optimization strategy will be further revealed in subsequent sections through the application of the haversine formula within the software tools. In the event sequence, each delivery was invoked through a specified sequence. The order of delivery was orchestrated through the implementation of a “Foor loop” facilitating the processing of the 30 addresses.

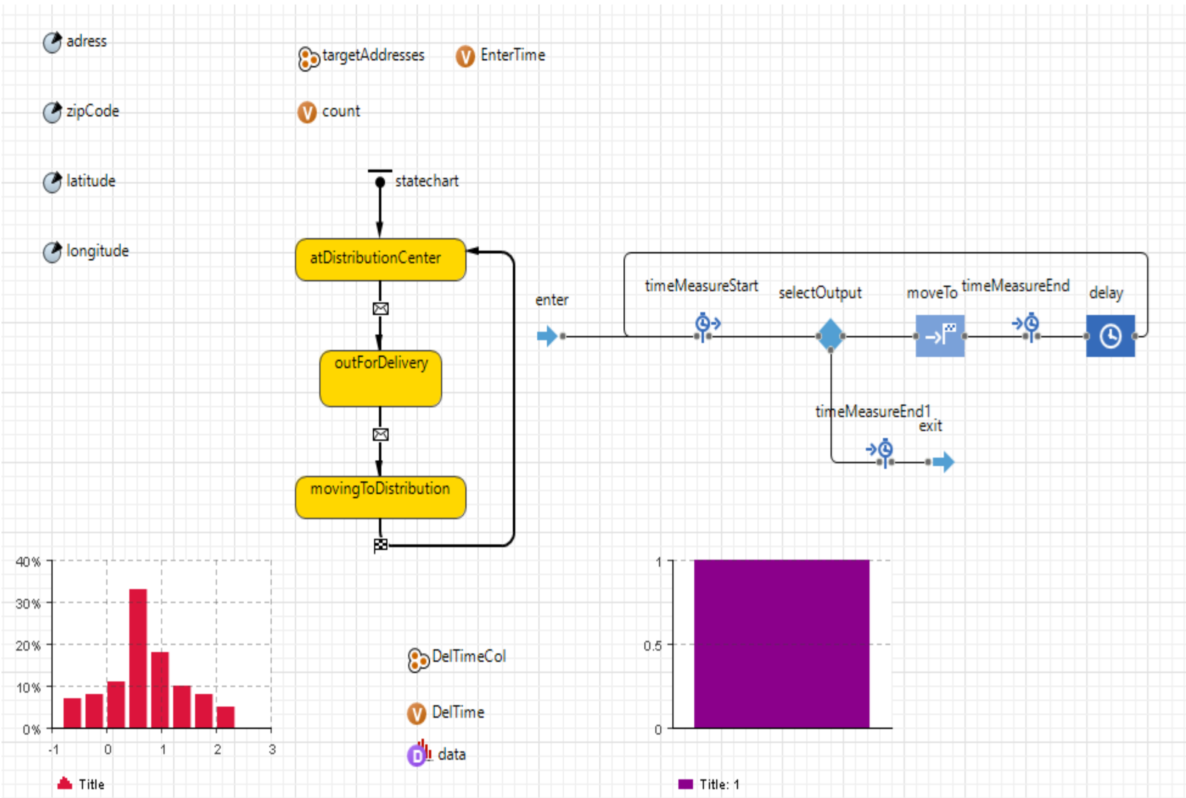

Illustration 3.5: Truck agent with flowchart and blocks

Subsection 3: Software and tools used.

One of the features within AnyLogic is the GIS map, a global map that can be utilized as the simulation domain for a process. This map, along with agents, can simulate deliveries for an area. This can be accomplished through the aid of streetcharts and blocks within AnyLogic that illustrate the procedural flow of the process. More tools include order events, collections, and variables. This software application also collects data in tables after a simulation has been run. A distinctive home icon was employed to represent delivery addresses, a warehouse icon denoting the distribution centers, and for the representation of the delivery trucks, colored icon trailers were assigned.

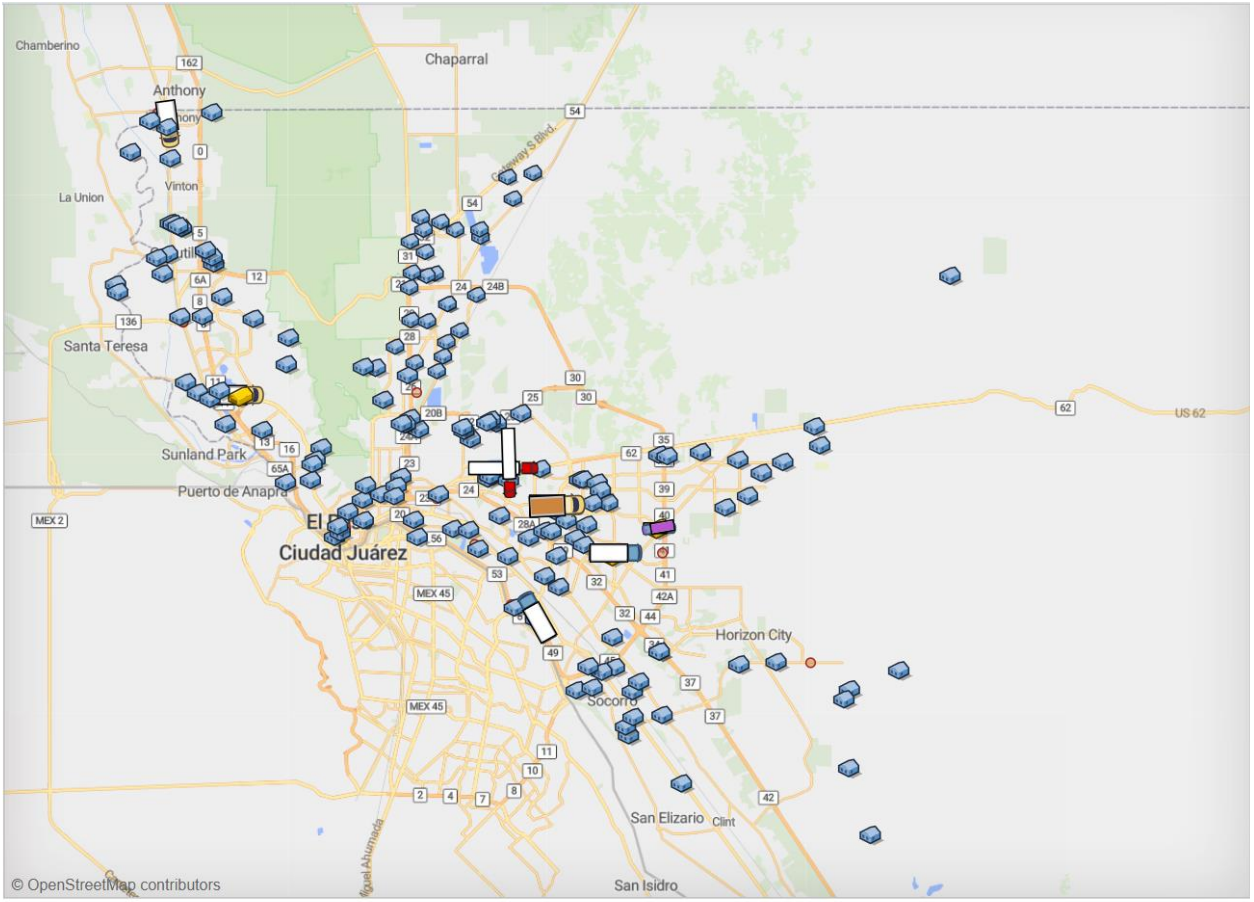

Illustration 3.6: Truck agent with flowchart and blocks

As the second software tool in the study, a VBA code was used along with a Haversine formula. These were employed to optimize address ordering, using the distribution center as the starting point. This allows for the determination of the shortest path within the deliveries.

The formation of clusters sought to aim at an alternative to the delivery system. In lieu of relying solely on zip codes and predefined areas to determine the distribution centers, a novel approach was adopted. Clustering was executed based on longitude and latitude coordinates, thereby grouping sets of addresses that exhibited spatial proximity. The capability was achieved through the employment of Python and Jupyter lab extension. Numpy, matplotlib, sklearn.cluster using Kmeans was imported into Jupyterlab. Python is a language program software with a variety of features. In data analysis, the program can present the information in a structured and manageable manner, eliminating the need to review large pieces of data. This program also has the capability to use extensions that can provide graphics and clustering of data appropriate to the packages called within the coding. Such is the case as the Jupyterlab. Python with Jupyterlab extensions is employed to facilitate a clustering method. Clustering methods handle deliveries comprehensively and place them in groups as an efficient means to reduce the distance.

Python with Jupyter lab extension was employed to cluster the second part of the study. As coordinates were incorporated into the programming code, and a clustering algorithm was executed, the delineation of the data into five distinct sections followed. The program generated cluster centers as part of the clustering process. Subsequently, a new model was instantiated in AnyLogic, maintaining the same information for the first scenario. The pivotal modifications transpired within the delivery order event, wherein a reconfiguration of the address sequence occurred. Once again simulation was executed for both time frames and comprehensive data was collected.

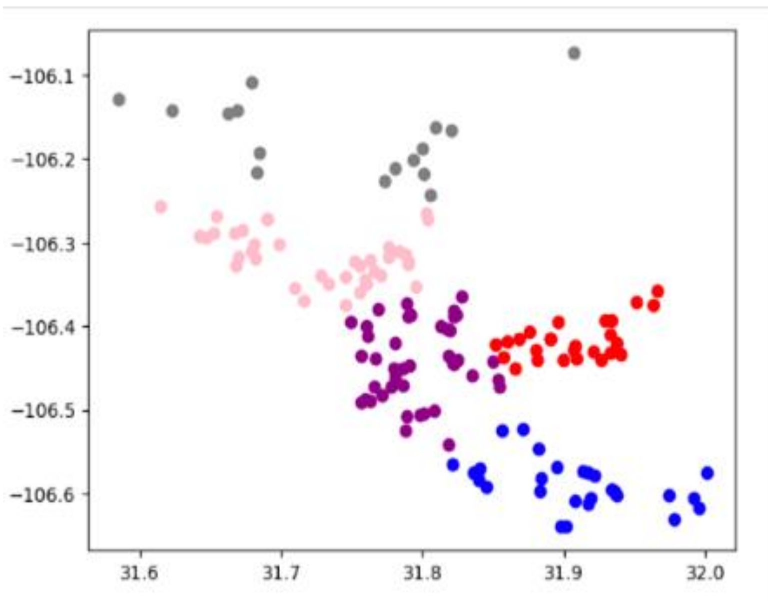

Illustration 3.7: Truck agent with flowchart and blocks

Section 4: Experimental Setup

Two major scenarios were considered, a zip code area and a clustering system. These two runs for the same time period and will have the nearest address as the next delivery stop. The simulation runs multiple times in both scenarios for comprehensive analysis and robust evaluation. One is an 8-hour shift and the next is a 56-hour shift, simulating a 7-day week. AnyLogic incorporates a log feature that once a simulation is run, it will generate statistics of this run. However, other details were considered such as histogram data and bar charts.

The presentation of the distribution of addresses within sip code areas is depicted below. As can be observed, these areas appear to be evenly distributed.

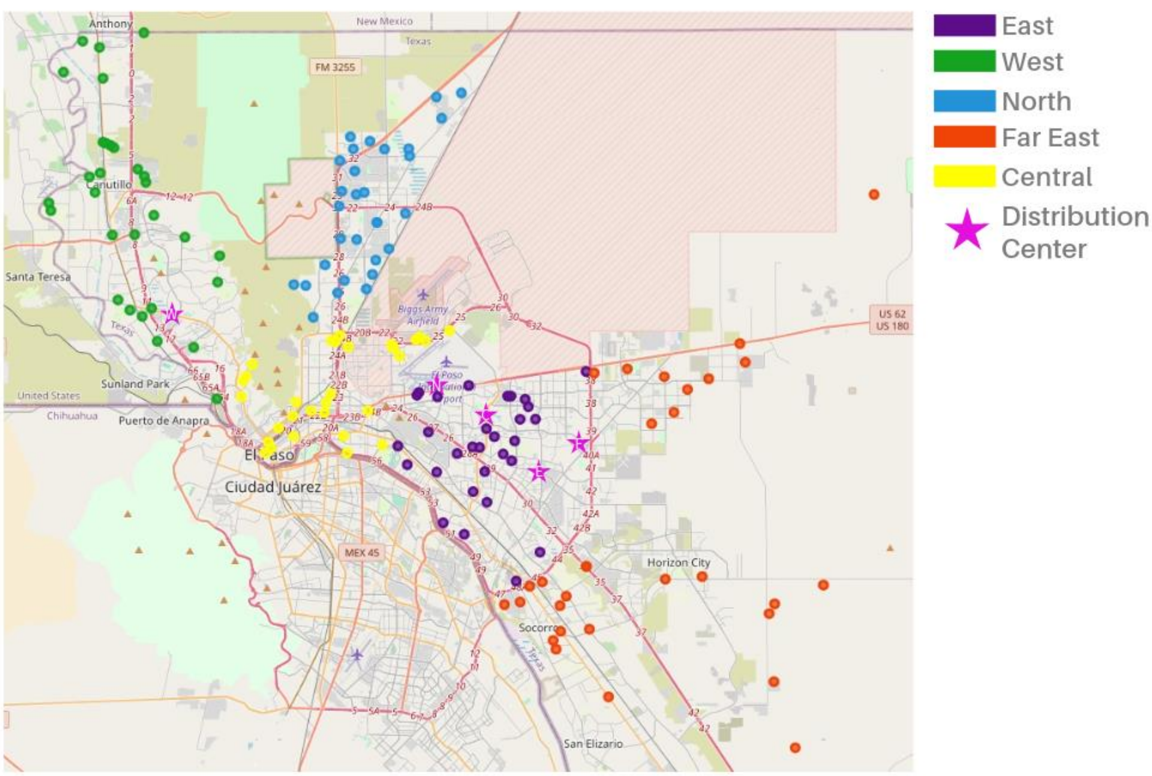

Illustration 3.7: Zip Code Delivery Addresses with Distribution Centers.

The illustration below displays the distribution of addresses area after the execution of the clustering system.

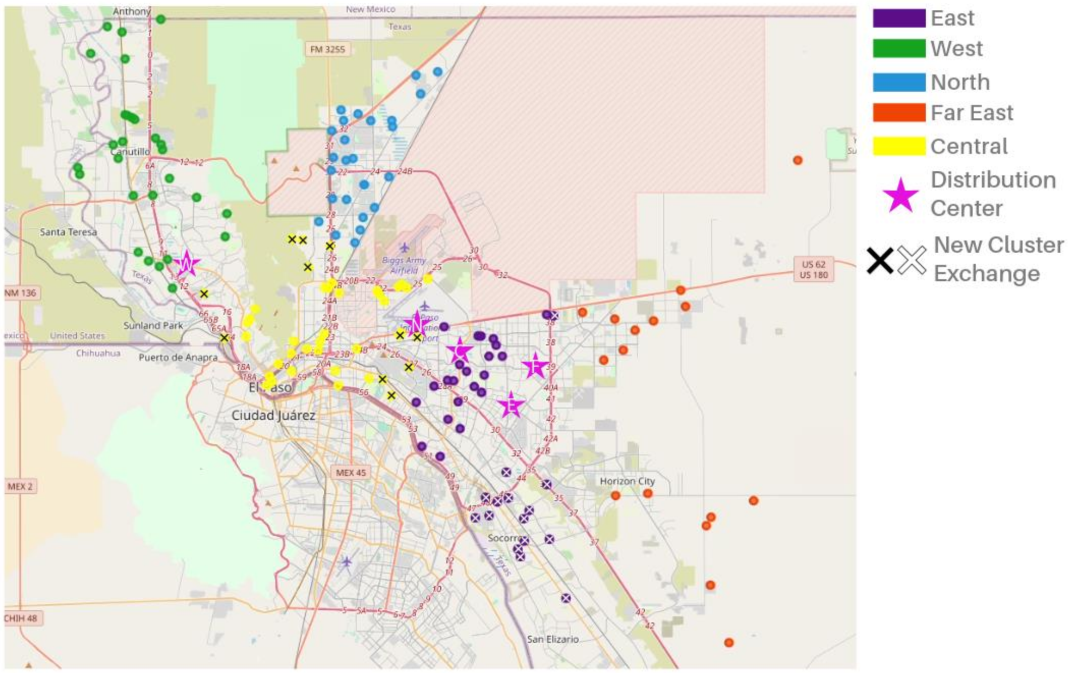

Illustration 3.8: Clustering Delivery Addresses with Distribution Centers.

SECTION 4: RESULTS AND FINDINGS

Subsection 1: Evaluation Metrics

In order to facilitate the comparison and analysis of results, a set of key metrics needs to be acquired from the simulation. In this analysis, the evaluation metrics include the distance travelled, representing the distance covered by the truck agent from the distribution and through the deliveries until the end of the time stipulated. Additionally, a metric for deliveries completed is considered, indicating the number of deliveries successfully covered during the simulation time. Furthermore, an indicator for missing deliveries is included, representing the disparity between the total number of deliveries and those successfully completed during the simulation. Moreover, the number of target addresses is defined as the address set per area. While this quantity varies in the clustering system, it remains constant within each zip code area replicate. Finally, the maximum delivery time indicator is considered, representing the time taken to complete the last delivery within the specified time, while the mean time to deliver is derived from histogram data, reflecting the average time for all deliveries within the simulation run.

Subsection 1: Observed simulation results by Zip code for 8HRS.

From the presented results, the east side simulation achieved a completion rate of 24 deliveries out of 30, with a mean of 0.293 hours. The west area completed 22 deliveries, with a mean delivery time of 0.289 hours. The north area successfully completed all 30 deliveries, boasting a mean delivery time of 0.103 hours. Similarly, the far east area accomplished all 30 deliveries with a mean delivery time of 0.161 hours, while the central area completed all 30 deliveries with a mean delivery time of 0.038 hours.

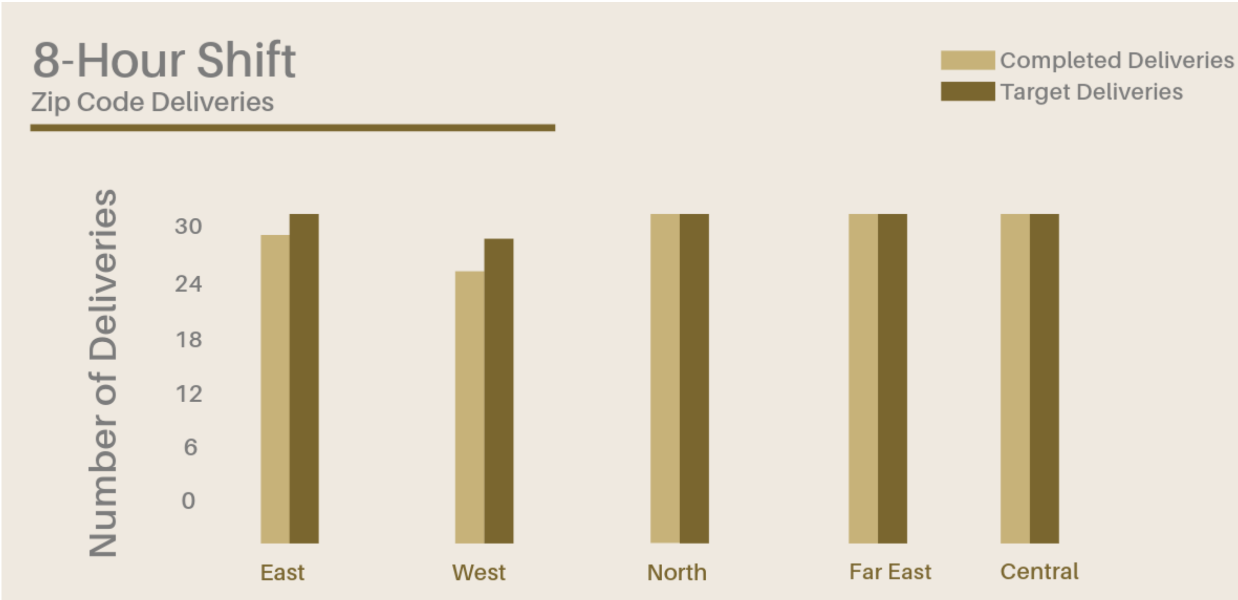

Figure 3.1: Zip Code Deliveries for 8-hr shift

Overall, three areas demonstrated a successful delivery rate, encompassing a total of 136 deliveries in all areas per this simulation.

Subsection 2: Observed simulation results by Zip code for 7 days

In the second time frame in the zip code area simulation, observations indicate that the east area completed 114 deliveries out of 210, with a mean delivery time of 0.301 hours. The west area accomplished all 113 deliveries, reporting a mean delivery time of 0.291 hours. The north area successfully completed all 210 deliveries, exhibiting a mean delivery time of 0.114 hours. Similarly, the far east area completed all 210 deliveries, with a mean delivery time of 0.178, while the central area completed all 210 deliveries with a mean delivery time of 0.042 hours.

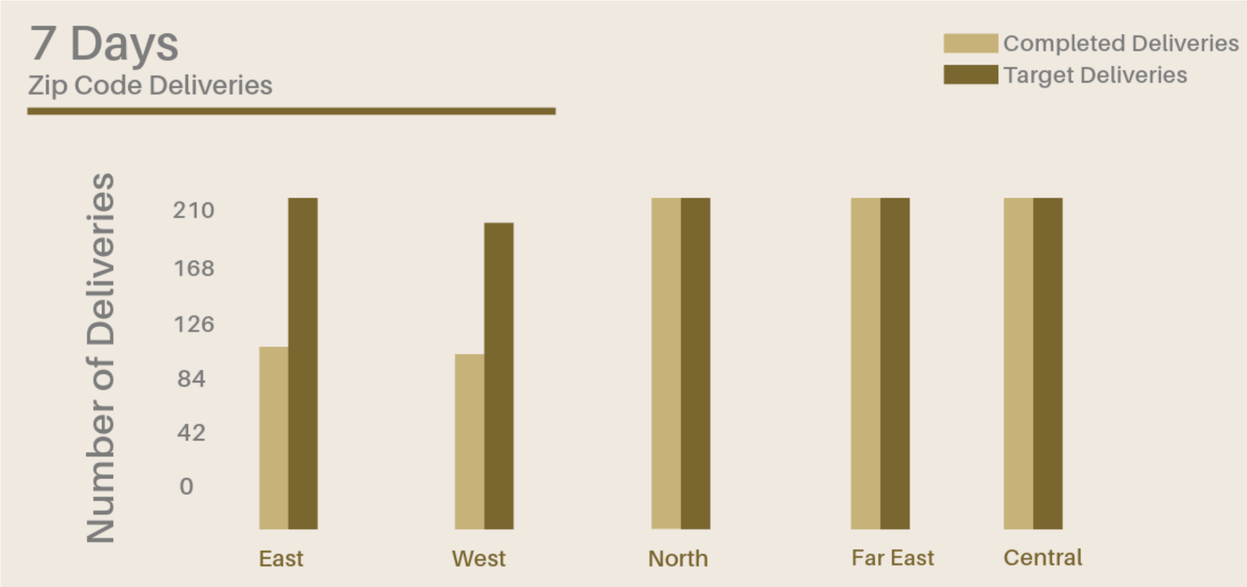

Figure 3.2: Zip Code Deliveries for 7-day

The observed proportional consistency between the first and second set of data is notable, particularly with the last three areas covering all deliveries. Upon closer examination, it is discerned that the west and east area contain addresses located on the outskirts of the city. This geographical factor may contribute to the occurrence of unfinished tasks in these areas.

Subsection 3: Observed simulation results by clustering for 8HR.

As previously recalled, the clustering system does not generate areas with precisely 30 addresses; rather, it forms clusters based on distances between each address using latitude and longitude coordinates. However, it is important to note that the total number of addresses remained consistent at 150 addresses. This implies that certain areas may have more or fewer than 30 addresses, a characteristic influenced by the proximity of the addresses. The following provides a breakdown of the clusters.

For the initial segment of the simulation for the clustering system for 8 hours, the results were collected as follows. The East area achieved 24 deliveries out of 38, with a mean delivery time of 0.305 hours. The west area completed 22 deliveries out of 28, with a mean delivery time of 0.308 hours. The north area successfully completed 26 deliveries out of 26, with a mean delivery time of 0.056 hours. The far east area accomplished 16 deliveries out of 16, with a mean delivery time of 0.282 hours. Lastly, the central area achieved 42 deliveries out of 42, with a mean delivery time of 0.081hr.

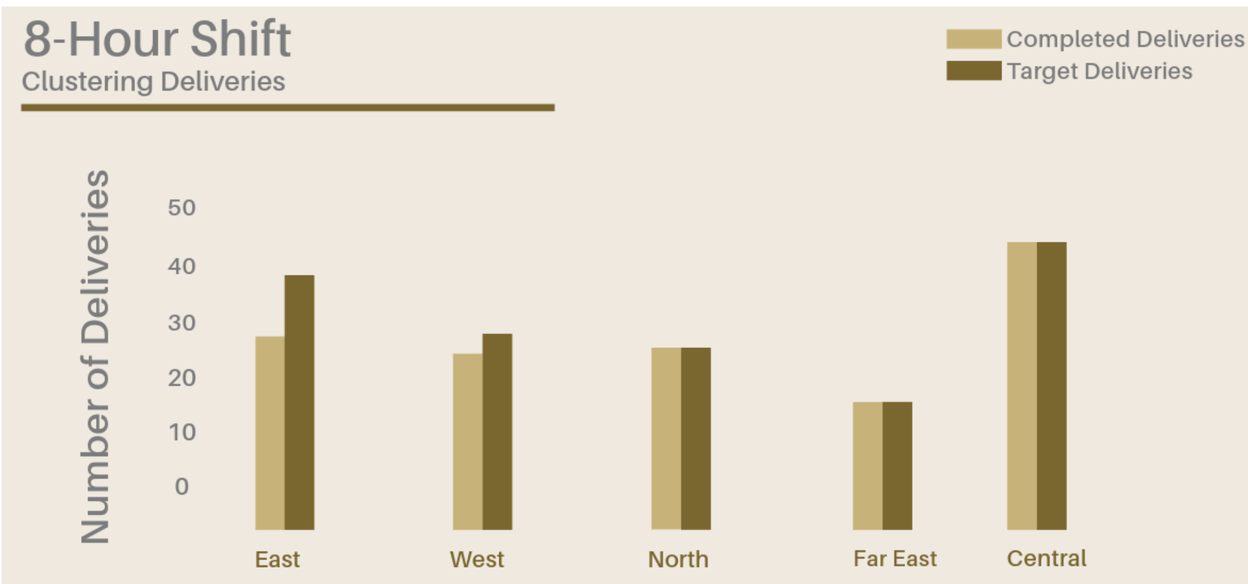

Figure 3.3: Clustering Deliveries for 8-hr shift

The 8hr simulation clustering across all areas yielded a total coverage total of 131 deliveries, indicating a lower delivery count compared to the zip code area simulation.

Subsection 4: Observed simulation results by clustering for 7 days.

In the 7-day simulation with clustering across all areas, the results are as follows. The east area completed 138 deliveries out of 226, with a mean delivery time of 0.338 hours. The west area achieved 107 out of 196 deliveries, with a mean delivery time of 0.313 hours. The north area achieved 182 out of 182 deliveries, with a mean delivery time of 0.062 hours. The far east area accomplished 112 out of 112 deliveries, with a mean delivery time of 0.313 hours. Lastly, the central area completed 294 out of 296 deliveries, with a mean delivery time of 0.089 hours. Total deliveries across all areas amounted to 833.

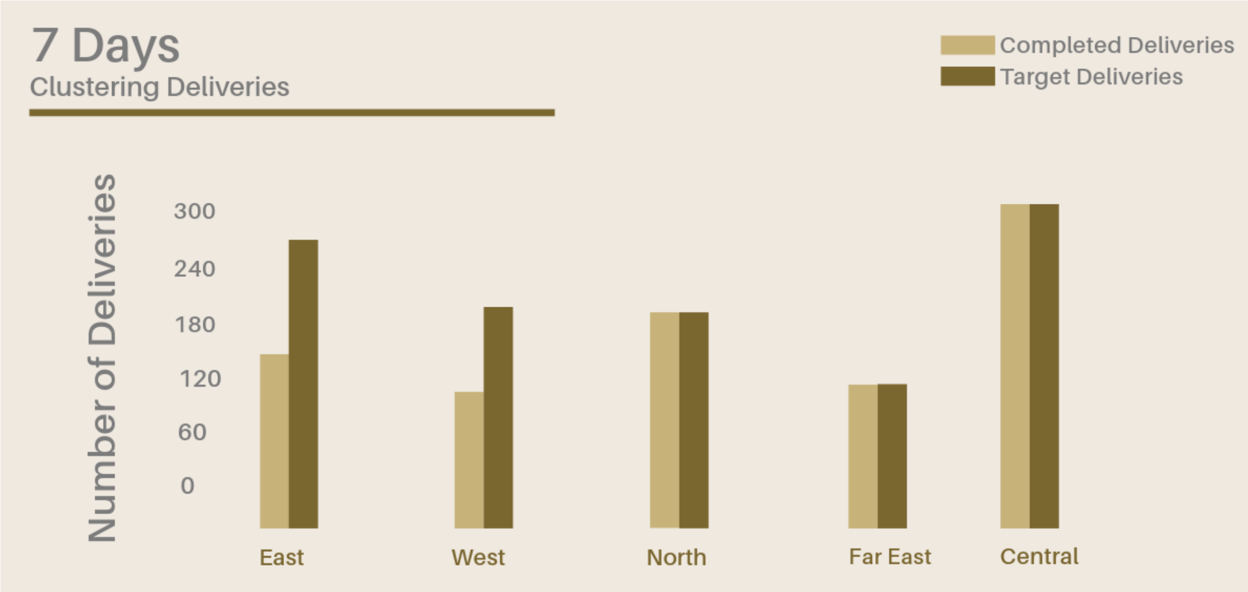

Figure 3.4: Clustering Deliveries for 7-day

SECTION 5: DISCUSSION AND EVALUATION

After evaluating all testing scenarios, it is evident that the zip code-based simulations yielded superior results compared to the clustering approach. This is attributable to a higher number of completed addresses, and a decrease in the overall traveled distance in the zip code-based simulations. However, a crucial consideration must be made; the clustering performed on Jupyter lab did not allow an evenly distribution of addresses. While certain areas remained unaffected by an increase in delivery addresses, others experienced a substantial impact because of the clustering approach. As an example, the east area witnessed a decline in success rate from 93.33% to 71.05% for completed deliveries because of the clustering approach. It experiences an increase in the number of deliveries by 8 when transitioning from the zip code-based approach to the clustering method. In contrast, the central area demonstrated benefits from the clustering approach, experiencing positive outcomes in terms of delivery efficiency. The addresses added to the clustering for the central area were 12 more than the zip code set of 30. Also, an increase in total distance and the maximum delivery time was observed. The table below shows the key metrics measured during the data collection for the 8-hour shift for both simulation types.

Table 6.1: 8-hr Shift Data for Zip Code vs Clustering System

Delivery method	Shipping area	Number of targeted addresses to delivery	Total distance travelled	Total delivery time	Max delivery time	Number of completed delivery	Number of missing deliveries
Delivery by area	Area 1 (East)	30	48.46097368	8 hr	7.926	28	2
	Area 2 (West)	30	54.26121811	8 hr	7.837	25	5
	Area 3 (North)	30	68.79890133	8 hr	1.379	30	0
	Area 4 (Far East)	30	134.7897969	8 hr	2.301	30	0
	Area 5 (Central)	30	53.61816379	8 hr	1.267	30	0
Delivery by clustering	Cluster 1 (East)	38	48.82443965	8 hr	7.693	27	11
	Cluster 2 (West)	28	53.46999741	8 hr	7.827	25	3
	Cluster 3 (North)	26	60.68498356	8 hr	1.164	26	0
	Cluster 4 (Far East)	16	116.8639535	8 hr	1.478	16	0
	Cluster 5 (Central)	42	99.16910976	8 hr	2.168	42	0

The table below shows the results for the time frame corresponding to the 7-day simulation types.

Table 6.2: 7-Day Data for Zip Code vs Clustering System

Delivery method	Shipping area	Number of targeted addresses to delivery	Total distance travelled	Total delivery time	Max delivery time	Number of completed delivery	Number of missing deliveries
Delivery by area	Area 1 (East)	210	244.1824759	55.96	56	118	32
	Area 2 (West)	210	410.6611454	55.801	56	115	35
	Area 3 (North)	210	481.4973317	56	56	210	0
	Area 4 (Far East)	210	943.2671679	56	56	210	0
	Area 5 (Central)	210	375.3289687	56	56	210	0
Delivery by clustering	Cluster 1 (East)	266	393.1744901	55.782	56	141	125
	Cluster 2 (West)	196	269.8611155	55.845	56	110	86
	Cluster 3 (North)	182	424.7980738	56	56	182	0
	Cluster 4 (Far East)	112	818.0479193	56	56	112	0
	Cluster 5 (Central)	294	694.1859347	56	56	294	0

In conclusion, this comparative analysis revealed varied outcomes favoring one simulation over the other in different instances. Nonetheless, certain nuances and details must be carefully considered in the assessment of these results.

SECTION 6: CONCLUSION

Route planning in the supply chain industry is a challenge contributed to various factors. In this study, a comparative analysis seeks to understand the multiple factors involving a shortest path approach. The inefficiencies found include the layout of a region that showed to benefit a simulation over another. This allows for the examination of attributes per area to determine what is the best outcome. Future work includes a more precise delineation of distribution centers. Additionally, exploring the impact of varying batch quantities for the zip-code addresses could provide more valuable insight. Furthermore, considering an even distribution of areas in multiple simulations may enhance overall efficiency and merit future investigations.

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