Enhancing Cost Efficiency in Cold Chain Logistics Services: A Performance Comparison between Experience-Based Routing and Excel Solver Optimization

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Abstract

In the cold chain logistics industry, maintaining product integrity through precise temperature control and timely delivery is paramount. However, many Small and Medium Enterprises (SMEs) continue to rely on subjective, experience-based routing—a heuristic approach that often leads to sub-optimal paths and inflated operational costs. The objectives of this study were: 1) to analyze and document empirical experience-based routes used by drivers; 2) to develop a mathematical optimization model specifically for cold chain logistics using Excel Solver; and 3) to evaluate the performance gap between manual intuition and algorithmic solutions to quantify potential efficiency gains. The research utilized purposive sampling of five empirical delivery routes as the primary sample from a distribution plant in Pathum Thani. The research tools included manual driver logs and Microsoft Excel Solver utilizing the Simplex LP algorithm. Data were collected by documenting distances from experienced drivers to establish a baseline, which were then analyzed through a comparative performance gap analysis against the mathematical model to identify efficiency improvements. The research results are as follows: 1) Algorithmic optimization consistently outperformed human heuristic decision-making in 80% of the tested cases (Routes 1, 3, 4, and 5); 2) The most significant efficiency gain was recorded in Route 1, where the total distance was reduced by 9.5%, decreasing from 95 to 86 units; and 3) While driver intuition reached the mathematical optimum in one instance (Route 2), the overall findings indicate that human experience is inconsistent across complex scenarios compared to systematic optimization. The study concludes that integrating a systematic routing tool like Excel Solver enables measurable reductions in mileage and fuel

consumption. For SMEs, this represents a viable, low-cost digital transformation strategy that strengthens both cost-efficiency and product quality retention in cold chain operations.

Keywords: Cold Chain Logistics, Vehicle Routing Problem (VRP), Excel Solver, Experience-Based Routing, Cost Efficiency

Background and Statement of the problem

In the modern food industry, the demand for fresh and frozen products has led to the rapid growth of Cold Chain Logistics. Unlike standard delivery services, cold chain logistics requires maintaining a specific temperature range throughout the entire transportation process to ensure food safety and quality. Any delay in the delivery schedule directly impacts on the perishability of the products, leading to financial losses and potential health risks for consumers.

Efficient Vehicle Routing Problem (VRP) management is the backbone of cold chain operations. In many small to medium-sized enterprises (SMEs), route planning is still conducted through Manual Experience (Experience-Based Routing). While this method relies on the local knowledge of drivers, it often lacks the precision needed to handle complex variables such as traffic fluctuations, multiple delivery windows, and fuel consumption optimization.

The primary challenge in cold chain delivery is the high operational cost associated with specialized refrigerated vehicles and the strict time constraints required to prevent spoilage. Relying on human intuition for route planning often results in sub-optimal paths, leading to unnecessary mileage, higher fuel expenses, and increased "open-door" frequency, which compromises temperature integrity.

There is a critical need for an accessible, cost-effective computational tool that can assist businesses in optimizing their routes without the need for expensive, high-end logistics software. Microsoft Excel Solver (in brief Excel Solver), a powerful optimization add-in, offers a potential solution by using mathematical algorithms to find the most efficient routes. However, its effectiveness compared to traditional manual methods—specifically within the rigorous demands of cold chain services—remains a subject that requires empirical validation.

This research aims to bridge the gap between traditional delivery practices and mathematical optimization. By conducting a performance comparison, this study evaluates whether Excel Solver can significantly enhance cost efficiency and reduce delivery times in cold chain logistics. The findings will provide local food delivery businesses with a data-driven framework to minimize operational costs while maintaining the high standards of the cold chain.

Objective

1. To analyze and document current experience-based routing: To investigate the existing delivery paths chosen by drivers in a cold chain logistics service, identifying the patterns and distances resulting from manual, experience-based decision-making.
2. To develop an optimization model using Excel Solver: To design a mathematical model specifically for cold chain logistics that minimizes transportation costs and distances while adhering to strict delivery time-windows.
3. To evaluate the performance gap between manual and optimized routing: To conduct a comparative analysis of the results from Step 1 and Step 2, quantifying the potential for cost reduction and efficiency gains through the use of Excel Solver.

Expected benefits

1. For the Logistics Service Provider
   - Operational Cost Reduction: The company can identify specific opportunities to reduce fuel consumption and vehicle wear-and-tear by adopting mathematically optimized routes.
   - Enhanced Time Management: By minimizing travel time, the company can improve its "on-time delivery" rate, which is a critical performance metric in cold chain services.
   - Improved Resource Utilization: The study will demonstrate how to better allocate drivers and vehicles, potentially allowing the company to handle more deliveries with the same fleet size.
2. For Cold Chain Integrity and Quality Control

• Minimized Spoilage Risk: Efficient routing reduces the time products spend in transit, thereby maintaining the "thermal envelope" and ensuring that perishable goods reach customers in optimal condition.

• Consistency in Service: Shifting from subjective driver intuition to an algorithmic model ensures a more predictable and standardized delivery schedule, regardless of which driver is assigned to the route.

3. Academic and Practical Contributions

• Validation of Low-Cost Tools: This study will prove that SMEs (Small and Medium Enterprises) do not need expensive, specialized software to optimize their logistics; a standard tool like Excel Solver can provide significant value.

• Baseline for Future Research: The comparative data between manual and optimized routing can serve as a foundation for more complex studies involving real-time GPS tracking or multi-depot cold chain problems.

Conceptual Framework

1. Vehicle routing problem (VRP)

The Vehicle Routing Problem (VRP) is a well-established optimization challenge with a 40-year history (Pitakaso, 2017). Its enduring relevance stems from the ability to incorporate complex, real-world variables into the model. Key research includes the management of logistics for multi-terminal pickup and delivery (Nagy & Salhi, 2005), and the implementation of time-window constraints within multi-trip transportation frameworks (Nueangnitnaraporn & Karoonsoontawong, 2018). Additionally, the inclusion of stochastic demands (Dror et al., 1989) and time-restricted freight pickups (Solomon, 1983) further complicates the model, requiring more sophisticated decision-making tools to find efficient solutions.

2. Transportation cost

According to established logistics principles, transportation expenditures are primarily driven by four key determinants: density, distance, storage, and volume (Bowersox & Closs, 1886). As illustrated in Figure 1, there is a direct correlation between distance and total logistics costs, where increasing travel spans lead to a proportional rise in transportation outlays.

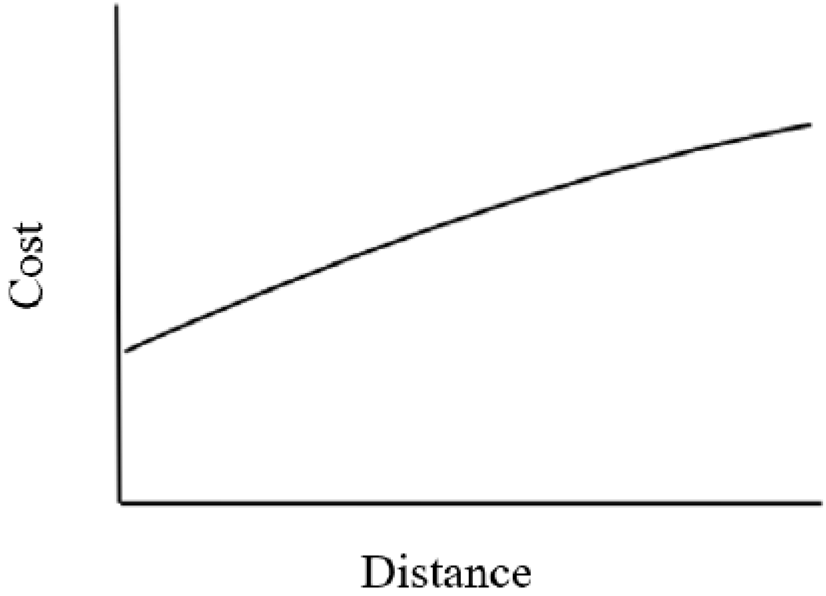

Figure 1 The relationship between distance and transportation cost

3. Microsoft Excel Solver

Linear Programming (LP) serves as a fundamental technique within operations research, widely adopted by scientists, engineers, and decision-makers for resolving resource allocation challenges. These challenges typically involve managing finite assets—such as capital, time, labor, and raw materials—under specific constraints of scale or volume. The primary objective of LP is to achieve an optimal outcome, such as maximizing profits or minimizing operational expenditures, under the assumption of linear relationships between variables (Srinual,2016). Within the scope of this study, LP is utilized via Excel Solver, a versatile optimization tool integrated into Microsoft Excel.

The management of cold chain logistics is significantly more complex than standard dry cargo logistics due to the sensitivity of the products involved. According to Smith (2021), the primary objective of a cold chain is to preserve the physical and chemical properties of perishable goods from the point of origin to the final consumer. However, several critical challenges hinder the efficiency of this process.

4. Challenges in Cold Chain Logistics

Perishability and Product Integrity: The most fundamental challenge is the inherent perishability of the goods, such as fresh produce, dairy, and pharmaceuticals.

Unlike general commodities, these products have a limited shelf life that is directly affected by environmental conditions. Gupta and Kerr (2020) emphasize that any delay in the transportation cycle accelerates the rate of spoilage, leading to significant "food loss" and financial deficits. In a study by Rong et al. (2011), it was noted that the quality of food products degrades exponentially relative to the duration of exposure to sub-optimal temperatures, making "time-efficiency" the most critical factor in route planning.

Temperature Fluctuations and Technical Barriers: Maintaining a "constant temperature environment" is a significant technical hurdle. Rodrigue (2020) argues that the "last mile" of delivery is the most vulnerable segment of the cold chain. Frequent door openings during multiple delivery stops lead to temperature fluctuations inside the refrigerated container, which can compromise the entire batch of products. Furthermore, James and James (2010) highlight that equipment failure or poor insulation in older vehicle fleets—often found in SMEs—increases the risk of "thermal shocks," where products are exposed to ambient air, leading to bacteria growth and safety hazards.

High Operational and Energy Costs: Cold chain operations are energy-intensive and costly. Tassou et al. (2012) found that refrigerated transport can consume up to 20% more fuel than standard transport due to the power required to run the Transport Refrigeration Unit (TRU). This creates a conflict between maintaining high-quality service and achieving cost efficiency. Consequently, as noted by Bogataj et al. (2005), optimization of the Vehicle Routing Problem (VRP) is not merely a logistical preference but a financial necessity for cold chain providers to remain competitive in a low-margin market.

5. Related work

Extensive research has been conducted to optimize vehicle routing across various industries (Komutpun, 2013). For instance, Excel Solver was successfully implemented to enhance the efficiency of waste management logistics. In terms of construction materials, Chaiwongsakda et al., (1989) applied the Savings Algorithm to optimize brick delivery routes within the Bangkok Metropolitan Region. More advanced approaches, such as Evolutionary Algorithms, were utilized in (Maneengam et al.,1989) and Wajanawichakon & Srisurin (2019) to address complex garbage collection scenarios under varying conditions. Furthermore, comparative studies have been used to validate optimization tools; for example, Sawangyat (2018) evaluated Excel Solver against the Greedy Algorithm and traditional experience-based methods for tourism routing. Other methodologies, such as the Clarke-Wright Savings method for national freight (Pichpubul & KaewThumchai, 2012) and a comparison between the Clustering-Locating-Routing technique and the Sweep Algorithm for medical device maintenance (Supakdee et al.,1989), further demonstrate the diverse landscape of VRP optimization.

The existing body of literature demonstrates that VRP research is highly contextual, with constraints and conditions tailored to specific operational scenarios. These problems are typically addressed using either bespoke algorithms or accessible commercial tools such as Excel Solver. Consequently, this study employs both a Greedy Algorithm and the Linear Programming (LP) capabilities of Excel Solver to address an identical VRP case, providing a rigorous comparison of their respective performances.

Conceptual Framework

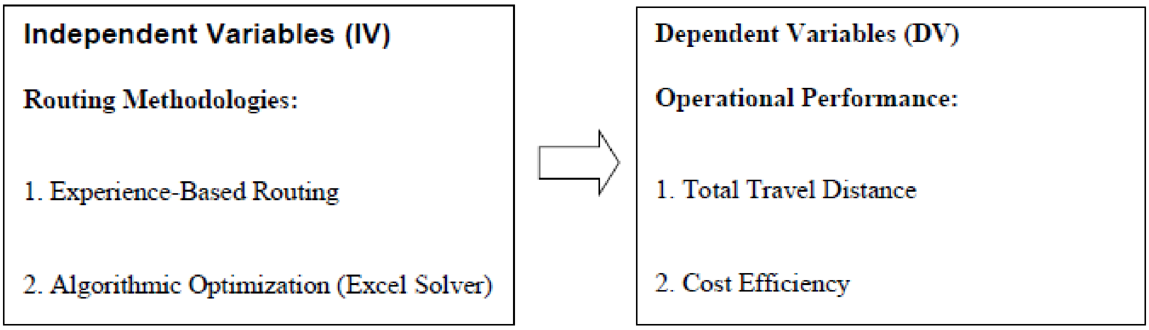

Figure 2 Conceptual Framework of the Study

As illustrated in Figure 2, the conceptual framework of this research is structured to evaluate the causal relationship between routing methodologies and operational outcomes. The Independent Variables consist of two distinct approaches: 1) Experience-Based Routing, which relies on subjective human intuition and historical familiarity; and 2) Algorithmic Optimization via Excel Solver, which utilizes the Simplex LP engine for mathematical precision. The framework posits that the choice of methodology directly impacts the Dependent Variables, specifically the Total Travel Distance (spatial efficiency) and Cost Efficiency (financial impact). This is particularly critical in Cold Chain

Logistics, where reduced distance leads to shorter transit times, thereby maintaining product integrity and reducing fuel consumption associated with refrigerated transport.

Research Methodology

1. Research Design

This study employs a quantitative research design, specifically a comparative experimental approach to evaluate logistical efficiency. This framework allows for a precise measurement of the performance gap between manual intuition and algorithmic solutions by converting empirical delivery operations into measurable datasets.

2. Population and Sample

The population of this study encompasses the total network of temperature-controlled delivery routes managed by a specialized cold chain logistics provider in Pathum Thani, Thailand. Given the resource-intensive nature of cold chain operations and the need for high-precision data, a purposive sampling technique was strategically employed to select the research sample.

The study focused on five primary delivery routes that were selected based on a rigorous set of criteria to ensure they represent the core operational challenges of the firm:

- **High Operational Frequency:** These routes are executed daily or on a consistent weekly basis, ensuring that any identified efficiencies would have a significant cumulative impact on annual operational costs.
- **Structural Complexity**: Each selected route involves multiple delivery nodes (destinations), providing a sufficient level of complexity to test the limitations of human heuristic decision-making against mathematical algorithms.
- **SME Operational Context:** The routes mirror the typical constraints of Small and Medium Enterprises, such as limited fleet size and strict customer time-windows, making the findings highly applicable to the industry.

This sampling strategy ensures that the collected data is both representative of daily operations and sufficiently complex to test the optimization model's limits. Consequently, these five routes provide a robust and representative dataset for a meaningful quantitative comparison between traditional experience-based paths and the proposed optimized solutions.

3. Research Tool

The tools utilized in this quantitative research consist of both empirical data collection instruments and mathematical software:

- **Manual Route Logs:** Historical data and GPS records from experienced drivers were used to document the "Experience-Based Routing" baseline. This represents the heuristic decision-making process currently used by the firm.
- **Microsoft Excel Solver:** The primary optimization engine used to develop the Linear Programming (LP) model. This study specifically utilizes the **Simplex LP algorithm** to find the global optimum for distance minimization.
- **Conceptual Framework:** A systematic model (Independent vs. Dependent variables) used to guide the analysis and ensure all operational constraints, such as time-windows and set-point temperatures, are accounted for.

4. Data Collection and Analysis

Data were collected and analyzed through a systematic four-step process:

- **Data Acquisition:** Documenting the actual distances traveled by drivers for the five selected routes over a one-month period to establish a baseline.
- **Distance Matrix Construction:** Building a comprehensive matrix of all possible distances between the distribution plant and the target delivery nodes using digital mapping tools such as Google Maps Distance Matrix API to ensure accuracy.
- **Optimization Simulation:** Inputting the matrix data into the Excel Solver LP model to generate the mathematically shortest possible routes while adhering to delivery constraints.
- **Performance Gap Analysis:** Using descriptive statistics to compare the results from the manual and optimized methods. The analysis focuses on calculating the percentage of distance reduction and the potential fuel cost savings, providing a clear quantitative measure of the Solver's effectiveness.

The research framework is structured into three primary phases to systematically evaluate the efficiency of cold chain routing, as illustrated in the procedural flow in Figure 3.

First Step, Data Acquisition and Manual Route Documentation: The initial phase involves conducting structured inquiries with the logistics drivers. This step captures the actual routes utilized during daily operations, which are formulated based on Experience-Based Routing (human intuition and local knowledge).

Step 2, computational optimization via Excel Solver: In the second phase, the same delivery parameters—including origin points, destinations, and specific cold chain constraints—are modeled within Excel Solver. The Linear Programming (LP) engine is employed to determine the mathematically optimal routes aimed at minimizing total distance or cost.

Next step, comparative Performance Analysis: The final phase involves a rigorous comparison between the results obtained from manual planning and the algorithmic output of Excel Solver. The comparison focuses on key performance indicators (KPIs) such as total mileage, travel time, and estimated fuel consumption to quantify the optimization gap.

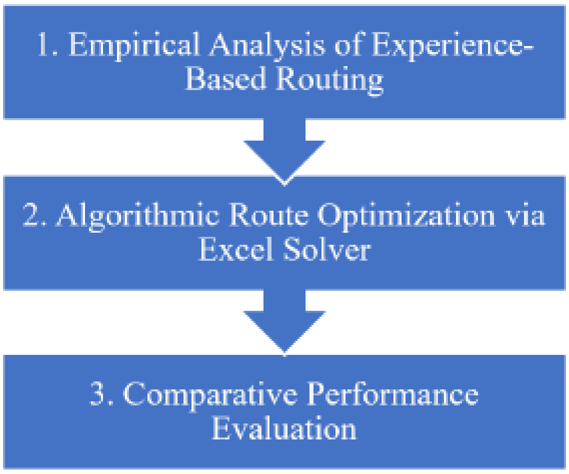

Figure 3 The Methodology of this research

The preliminary stage of this research involved documenting five unique delivery routes executed by five different drivers. These transit paths were determined by the drivers' professional intuition and heuristic judgment, lacking any formal algorithmic optimization. A representative example of such a route is illustrated in Figure 4, where Node A serves as the original plant and Node D as the customer destination. Intermediate waypoints, such as intersections or bridges, are denoted as Nodes B and C. The values assigned to the arcs between these nodes represent the physical distance of each segment. In this manual model, drivers navigate the network autonomously, relying exclusively on their field experience to select their path.

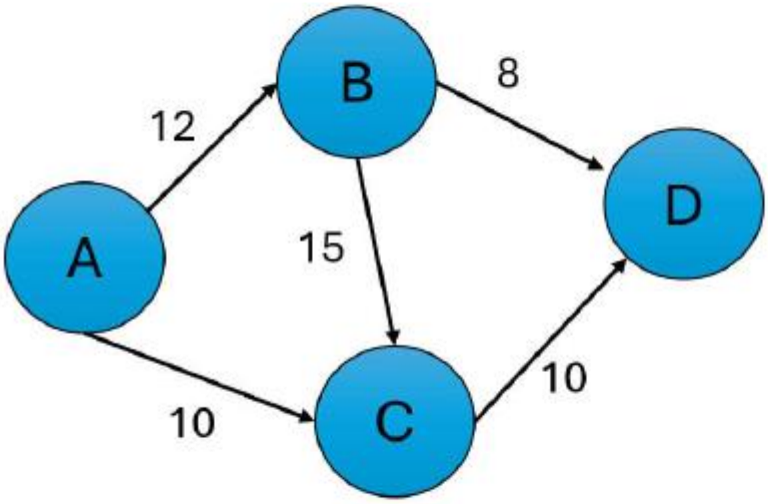

Figure 4 One of the delivery cases

The second phase of the methodology involves solving the routing problem identified in the previous step using the Excel Solver optimization engine. To execute this, it is necessary to establish a system of linear equations that represent the network flow—specifically the 'inflow' and 'outflow' of each node.

The following variables were defined to construct the mathematical model:

- Xi,j is the distance between town i and j.
- Flow_in and Flow_out are the distance between the in- and out-road.
- For the start and destination towns, Flow_in – Flow_out = 1.

For the other towns, Flow_in – Flow_out = 0.

	A	B	C	D	E	F	G
1	**Point**	**Equation**	**From**	**To**	**Distance**	**Symbol**	**Result**
2	A	=G2+G3	1	2	12	X12	
3	B	=G5+G4-G3	1	3	10	X13	
4	C	=G6-G3-G5	2	4	8	X24	
5	D	=G4+G6	2	3	15	X23	
6			3	4	10	X34	
7							

Figure 5 Example of the equations created for the route case

Following the model setup, the Excel Solver parameters were configured as follows: The Objective Function was set to 'Minimize' to identify the shortest possible transit distance. The operational constraints were then integrated into the system as illustrated in Figure 6. Finally, the Simplex LP engine was selected as the optimization algorithm, rendering the model ready for execution.

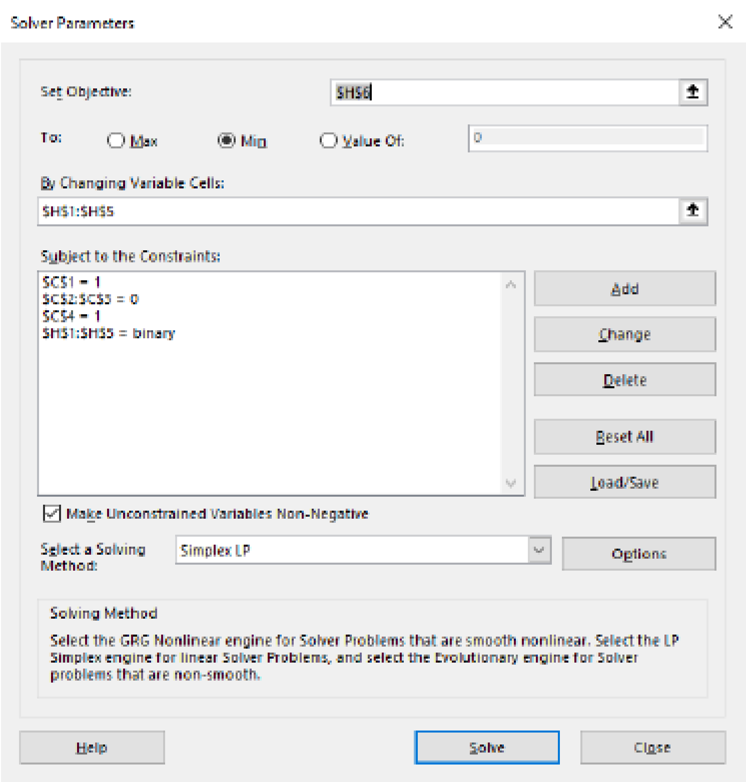

Figure 6 Solver Parameter Settings for Linear Programming Optimization

The final phase of the methodology involves a comparative performance analysis between the heuristic routes derived from driver experience and the optimal solutions generated by Excel Solver. By evaluating these two approaches across all case studies, the research quantifies the efficiency gap and identifies the superior routing strategy. A comprehensive analysis and interpretation of these findings are presented in the subsequent Results and Discussion section.

Research Results

The results of this study are presented in accordance with the three research objectives to demonstrate the transition from manual heuristics to mathematical optimization.

1. Results of Current Experience-Based Routing Analysis

The initial phase of the study documented the baseline performance of the logistics provider's current operations. Based on historical driver logs for the five selected routes, it was found that routing decisions were primarily driven by individual driver intuition. The total distances recorded for these empirical routes were used as the benchmark for comparison. The data revealed that while drivers could navigate effectively, their paths often lacked geographical efficiency, particularly in routes with more than four delivery nodes.

2. Development of the Excel Solver Optimization Model

Following the documentation of manual routes, a mathematical model was successfully developed using Microsoft Excel Solver. By inputting the distance matrix obtained from the Google Maps Distance Matrix API and applying the Simplex LP algorithm, the model generated optimized delivery sequences. The model adhered to all operational constraints, including the distribution plant's location and specific customer delivery windows, proving that a low-cost, standard software tool can effectively solve complex cold chain routing problems.

3. Comparative Performance and Efficiency Gains

The final objective was met by comparing the manual distances against the optimized distances generated in Step 2. The comparative results are summarized in Table 1 below:

Table 1 Comparative Analysis of Total Distances: Empirical Driver Routes vs. Excel Solver Optimization and Resulting Variance.

Route	Driver's experience	Excel Solver	Difference	%
1	95	86	9	9.49
2	115	115	0	0.00
3	80	76	4	5.00
4	102	99	3	2.94
5	65	64	1	1.54

As indicated in Table 1, the Excel Solver successfully optimized the trajectories for Routes 1, 3, 4, and 5, yielding shorter distances than those determined by driver experience. The most significant improvement was observed in Route 1, which achieved a 9.47% reduction in total mileage. For Route 2, the solver matched the driver's performance, indicating that human intuition can occasionally reach the global optimum in simpler or highly repetitive paths. Overall, these reductions in mileage directly correlate with decreased fuel consumption and lower operational expenses, offering the logistics provider a clear pathway toward enhanced cost-efficiency and accelerated delivery lead times.

Summary of the Study

This research evaluated the efficiency of cold chain logistics by comparing experience-based driver routing with mathematical optimization using Excel Solver. The study analyzed five distinct delivery routes originating from a distribution plant in Pathum Thani.

The results, consolidated in Table 1, demonstrate that algorithmic optimization consistently outperformed human intuition. Specifically, the Excel Solver identified shorter trajectories in 80% of the cases (Routes 1, 3, 4, and 5). While Route 2 showed that driver experience can occasionally reach the mathematical optimum, the overall data reveals a significant "optimization gap." For instance, in Route 1, the Solver reduced the distance from 95 to 86 units, representing a substantial improvement in spatial efficiency.

The study concludes that integrating a systematic routing tool allows for a measurable reduction in mileage, which directly supports the primary goals of cold chain management: minimizing transportation costs and ensuring product freshness through reduced transit times.

Discussions

The findings of this research provide a clear roadmap for practical application within the logistics sector. Following the research objectives, the results can be discussed as follows:

1. Analysis of Current Experience-Based Routing

   The investigation into existing delivery paths (Step 1) revealed that drivers rely heavily on "Heuristic" or intuitive decision-making. While this experience-based approach is often perceived as reliable, the data showed that it lead to sub-optimal paths in 80% of the studied cases. This suggests that "subjective" routing is limited by human cognitive capacity when dealing with multiple nodes. By documenting these empirical routes, the study establishes a baseline that highlights the inconsistency of performance across different drivers, regardless of their individual seniority or familiarity with the area.

2. Development and Utility of the Excel Solver Optimization Model

   The successful design of a mathematical model specifically for cold chain logistics (Step 2) proves that complex Vehicle Routing Problems (VRP) can be addressed using accessible technology. A critical point for discussion is that Microsoft Excel Solver—a standard office application—is a powerful enough engine to minimize transportation distances while adhering to strict constraints. For Small and Medium Enterprises (SMEs) in Thailand, this demonstrates that digital transformation in logistics does not require a large capital investment in expensive, specialized software, making high-level optimization reachable for smaller firms.

3. Evaluation of the Performance Gap and Efficiency Gains

   The comparative analysis (Step 3) between manual and optimized routing quantified a significant performance gap, most notably the 9.5% distance reduction in Route 1. This "multiplier effect" translates into two major impacts:

• Economic Impact: Lower mileage directly results in lower fuel costs and reduced vehicle maintenance, which are vital for the survival of SMEs.

• Cold Chain Quality Impact: In cold chain logistics, "time is the greatest enemy." The shorter routes generated by the model decrease the window of risk for temperature fluctuations. According to the results, systematic optimization not only protects the quality of perishable goods but also minimizes carbon footprints through reduced fuel consumption, strengthening both cost-efficiency and product integrity.

Recommendations

1. Implementation of Standardized Routing

   The company should move away from relying solely on driver intuition for route selection. It is recommended that management provides pre-calculated, optimized route maps generated via Excel Solver to all drivers to ensure consistent fuel efficiency and timing.

2. Investment in Low-Cost Digital Tools

   Since the study proves the effectiveness of MS Excel Solver, the company does not need to invest in expensive proprietary software immediately. Instead, they should train logistics staff in basic Linear Programming and solver tools to handle changing delivery locations dynamically.

3. Fuel and Maintenance Monitoring

   The company should conduct a three-month pilot program using the optimized routes from this study to track the actual reduction in fuel consumption and vehicle wear-and-tear. This data would provide a clear Return on Investment (ROI) for optimization efforts.

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