HOW AI IS EHNANCING ROUTE OPTIMIZATION IN LOGISTICS TRANSPORTATION

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ABSTRACT

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Route optimization in logistics transportation is a complex effort which requires consistent adjustments to ever changing variables. The demand for timely deliveries, cost effectiveness and fulfilled expectations have been the driving force behind innovation in this area of logistics. Recently, the trajectory of that innovation has increased dramatically as advances in Artificial Intelligence and our interaction with it have fueled the pace of its technological development. In lieu of that, this research begins with organizing and quantifying that trajectory by reviewing route optimization and AI fundamentals, by examining traditional methods for optimizing routes, how AI is currently being used in that process and what literary gaps exist on the topic. It culminates with an examination of how AI as we know it and how the AI of the future can drive further innovation in route optimization. Given that AI advancements currently seem to be fluid and evolving, particular attention has been paid to academic and industry publications that are recent and likely more relevant from both a qualitative and quantitative perspective. Additionally, particular attention has been paid to diversity in logistics transportation use cases so that similarities and differences in route optimization strategies can be examined (i.e. e-bikes and advanced air mobility vs. box trucks and container ships). The result of this research is thus expected to be a comprehensive analysis of where the field has been, where it currently is, and where it is going with respect to route optimization and AI's ability to enhance it.

I dedicate this thesis to my wife and sons who have been so supportive of my academic endeavors through the years.

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INTRODUCTION

Logistics transportation is the physical movement of goods and/or material with the goal of doing so in a timely and cost effective manner that meets stakeholder expectations. Perhaps the single most important factor in achieving and meeting those goals and expectations is determining an optimal route. Route optimization in logistics transportation is thus comprised of a series of complex decisions which can impact something as simple as a bicycle messenger delivering a box in a major city to something as complicated as a humanitarian organization coordinating the delivery of emergency supplies to an isolated area. In these cases, the optimal route can mean the difference in customer satisfaction or refugee survival and this wide spectrum of illustrations is used to underscore the differences and similarities in their common objective. This common objective is the previously referenced "single most important factor" and it is a powerful force driving the adoption of advanced technologies like AI as the quantity and complexity of variables and constraints continues to increase.

The goal of this research is thus to better understand AI's ability to enhance route optimization by examining traditional methods for optimizing routes, how AI is currently being used in that process, and what literary gaps exist on the topic so that we can answer the following research questions:

RQ1: How can traditional AI be further used to optimize routes in logistics transportation?

RQ2: How can non-traditional AI (i.e. generative AI) be further used to optimize routes in logistics transportation?

The way that goal will be achieved will correspond directly with sections of this paper starting first with an examination of where the field has been through the lens of academic textbooks and industry manuals which present the foundations of route optimization and AI. The literature review section represents a comprehensive examination of where the field currently is through the lens of academic articles and publications. Both the research design and findings sections illustrate where the field is going by presenting the steps taken and ultimately the answers to the previously stated research questions. The remainder of this section will examine the foundations of route optimization and AI.

Route optimization in logistics transportation can trace its origins to the various manual methodologies associated with early forms of routing and scheduling. Two of the most well-known are the sweep and savings methods of network modeling. Each is simple enough to calculate by hand and involves manually locating and/or grouping stops on a map and drawing arcs with distances between the various nodes (Sarder, MD, 2019). Because of their simplicity however, neither can guarantee an optimal solution. To achieve an optimal state, operations research (OR) methods developed during WWII must be utilized. Modern day route optimization in logistics transportation relies heavily on OR and has two prevailing goals which are to minimize costs and/or maximize efficiency (Cochran, J., 2019). For this report, cost minimization (efficiency) and asset utilization (opportunity) from an operator's perspective will be the focus, but it could just as easily be associated with performance instead of efficiency subject to space, capacity, financial penalties, driver availability, package types, start/stop locations and/or environmental impact to name a few. Route optimization is therefore a form of combinatorial optimization to be considered either a transportation problem (TP) or vehicle routing problem (VRP) and solved using linear programming. LP (or linear programming) is perhaps the most well-known tool in operations research and management science where optimality is achieved by finding the best mathematical solution or outcome subject to the various constraints that exist. In route optimization, those constraints could be associated with the previously referenced items as well as supply availability, product demand, distance or a combination of those and many others. For static constraints, a spreadsheet program with a solver function can often enable users to find an optimal route. The various constraints are rarely static however, requiring dynamic route optimization which many daily commuters rely on via smartphone navigation apps that route and re-route based on traffic conditions. Route optimization in logistics transportation is often far more complicated than simply using a traffic app requiring calculations to address numerous static and dynamic constraints like multiple stops, returns, and time windows to name just a few. Technological advances in hardware and software are helping to manage this degree of complexity by enabling more efficient and effective use of mathematical tools like linear programming. The most significant of these collective technologies is AI (Sarder, 2019; Cochran, 2019).

The term Artificial Intelligence, or AI, is a broad term that was first used in the mid 1950's to refer to the ability of machines to mimic certain aspects of human intelligence. Today it represents a group of technologies and techniques that perform tasks as well if not better than a human could. Prior to the modern use of machine learning and deep learning, traditional AI techniques used in route optimization included the use things like search algorithms, heuristics/metaheuristics, expert systems, and constraint satisfaction problem (CSP) solvers. Modern AI techniques used include the more familiar machine learning and some deep learning methodologies. Machine learning is a large subset of AI and is perhaps the most common form we utilize today. Historically, machines were trained on structured "labeled" data where they learned in a supervised environment to recognize patterns and relationships so that they could develop models to predict outcomes using regression, clustering, classification, decision trees, and support vector machine algorithms. Today, extraordinary advances in hardware combined with the compounding growth of data have enabled machines to be trained on unstructured and unlabeled "big data" (words, images and sounds) where they learn in a reinforced and unsupervised environment to recognize those same patterns and relationships so that they can develop models to prescribe outcomes using advanced techniques like optimization and simulation. These latest advances in AI have enabled rapid development in ML's subset of deep learning where artificial neural networks utilize natural language processing and computer vision models that have made virtual assistants, chatbots, autonomous vehicles and large language models (LLMs) possible. The latter has ushered in an era of generative and agentic AI where machines cannot only predict and prescribe, they can generate new content (text, images and sounds) and perform specific tasks subject to the data they have been exposed to. The only limitation of both generative and agentic AI is how much data the foundation model has been trained on (Cochran, J., 2019).

CHAPTER I. LITERATURE REVIEW

This section will examine four topics which represent a comprehensive review of academic articles and publications illustrating where the field of route optimization in logistics transportation currently is. Those topics are why this research is needed, traditional/modern methods for optimizing routes, how AI is currently being used in that process, and what literary gaps exist on the topic. Given the rapidly evolving nature of Artificial Intelligence, an effort has been made to review recent articles and publications which will be defined as those articles and publications from 2020 forward. Additionally, an effort has also been made to review a diversity of use cases so that different route optimization strategies can be examined (i.e. e-bikes and advanced air mobility vs. box trucks and container ships). Articles and publications, meeting that criteria, were identified on a shared institutional repository (ScholarWorks@BGSU) by using a combination of the following keywords: logistics, route optimization, transport optimization, transportation optimization, and artificial intelligence. Additionally, multiple academic articles also met that criteria were identified using sources such as MIT Sloan School of Management and Harvard Business Review as well as numerous industry publications. Collectively, those works aided in comprehension and understanding and were cited in answering the following literature review questions:

1.1 Why Is This Research Needed?

Artificial Intelligence and the hardware powering it are advancing at a rate we once thought impossible. Also advancing/evolvling is global commerce and the movement of goods further away from traditional warehousing and storage to even more connected and virtual environments where movement is choreographed across modes. Research into how AI is enhancing route optimization is therefore needed to learn, apply and ultimately leverage the transformative capabilities this technology presents within the field of logistics transportation. It is also needed to provide a framework for continued learning and adoption as capabilities accelerate across industries and functions.

1.2 What Are The Traditional Methods For Optimizing Routes In Logistics Transportation?

A survey of academic publications that did not mention AI revealed various techniques and use cases that relied heavily on OR methods combined with human interaction and decision making throughout the route optimization process. Combinatorial optimization methods like the transportation and vehicle routing problems were subjected to static, dynamic and a combination of static and dynamic constraints. Various forms of software were used to run the algorithms that produced the models that were trained and retrained using various forms of data. The use cases were diverse, but the techniques relied heavily on tools like linear programming (LP).

For this review, the focus remained on cost minimization (efficiency) and asset utilization (opportunity) from an operator's perspective. In general, the techniques observed were mostly variants of previously identified OR methods and some utilized ML techniques without specifically attributing them to or referring to them as AI. The use cases were thought compelling and added dimensionality (fleets, ports, etc.) to the review. In 2020 academic publications presented techniques like reinforcement learning, adaptive vehicle routing and the traveling salesman problem (Cao et al., 2020; Islam, 2020; Ono et al., 2020) with use cases like waste collection processes and cross docking (Kam, 2020; Mavi et al., 2020). In 2021 they presented techniques like workflow/multi-objective optimization, delivery route optimization, enhanced data science and digital transformation (Dacy et al., 2021; Elgharably, 2021; Esasky et al., 2021; Huang et al., 2021; Rici et al. 2021) with use cases like corn co-product logistics, smart city waste collection, identification and sorting technologies for recycling, maritime port of call processes, and supply chain fragility (Adams, D.; Alwabli, 2021; Brooks, 2021; Chen, 2021; Hamilton, 2021). In 2022 academic works presented techniques like multi-criteria modeling, dynamic resource allocation, neutrosophic genetic algorithms, and multi-objective vehicle loading (Alrahahleh, 2022; Chauhan et al., 2022; Heer, 2022; Krairiksh, 2022) with use cases like internet of things, material management, cost estimation, API services, supply chain value supply chain communication and sustainability (Alshehri, 2022; Mabey, 2022; Martin-Jourdenais, 2022; Moller et al., 2022; Oliver, 2022; Olorunfemi, 2022; Peng et al., 2022). In 2023 they presented techniques like log truck route optimization, multi-party vehicle routing, container liner route optimization, healthcare transit optimization, fleet constrained route optimization, and electric vehicle routing problems (Attreya, 2023; Joe et al., 2023; Liu, 2023; Park, 2023; Shamma, 2023; Tahami, 2023) with use cases like electric vehicle discharging strategies, defense and security research, green transport, agricultural transport, reshoring impacts (Fang et al., 2023; Laux et al., 2023; Maudina et al., 2023; Nazemi, 2023; Sarder, 2023). In 2024 academic works presented techniques like minimum spanning tree problem, conditional neural heuristics for multi-objective vehicle routing, service level optimization, algorithm based priority rules, optimization algorithms, hybrid algorithms, harmony search algorithms, cargo consolidation routing and location optimization joint distribution inventory optimization (Dhouib et al., 2024; Fan et al. 2024; Feng et al., 2024; Harrath et al. 2024; Harrath, 2024; Mahmoudinazlou, 2024; Minanda et al., 2024; Monsreal et al., 2024; Wan et al., 2024) with use cases like retail logistics warehouse execution systems, sustainable development, student transportation, food ordering systems, seaborne transport and decarbonization (Broughton, 2024; Guennoun et al., 2024; Harrath, 2024; Kamm, 2024; Liu et al., 2024; World Maritime University, 2024). Overall, the survey of academic publications revealed how the foundational concepts and methodologies associated with optimization can seemingly be combined and applied to a limitless number of route related scenarios.

In addition to academic publications, multiple non-academic web-based articles were reviewed to determine traditional methods for optimizing routes in logistics transportation. As was previously the case, techniques and use cases were determined. While they mostly reinforced what was previously identified, there were a few notable additions. Specifically, techniques like real time data integration, multi-stop sequencing predictive route planning, feedback loops, integration with other systems, Dijkstra's algorithm, ant colony optimization, and simulated annealing were presented with use cases like environmental impact, collaborative route planning, Transportation Management Systems, Geographic Information Systems, Telematic Systems, penalty/delay minimization, driver behavior monitoring, geofencing, vehicle health and maintenance (Choudhary, 2024; Singh, 2024). Overall, the limited survey of non-academic web-based articles reinforced the previous review.

1.3 How Is AI Being Used To Optimize Routes In Logistics Transportation?

A survey of academic publications that mentioned AI revealed various techniques and use cases that intend to mimic human intelligence or minimize human interaction. Collectively the various methods still relied heavily on OR's combinatorial optimization methods like the transportation and vehicle routing problems, and they were still subjected to static, dynamic and a combination of static and dynamic constraints. The introduction of the "intelligence" aspect however was seemingly focused on AI's subset machine learning (primarily supervised) using various forms of software to run advanced algorithms and train models significantly faster than traditional methods. As was the case with the traditional methods in route optimization, the use cases were diverse, but the techniques relied on more than just tools like linear programming.

Again, for this review, the focus remained on cost minimization (efficiency) and asset utilization (opportunity) from an operator's perspective. As was the case previously, the techniques observed were mostly variants of previously stated methods focusing mostly on machine learning. As was also the case previously, the use cases were thought compelling, adding dimensionality (i.e., waste management, electric vehicle recharging strategies, etc.) to the review. From 2020 to 2024 academic publications presented techniques like container tracking optimization, AI adaptation determinates, machine learning, hierarchical optimization, dynamic vehicle distribution path optimization, GRASP solution approach, quantum AI integration, deep reinforcement learning, neural network algorithms, exact model heuristics and supervised learning, deep learning, supply chain dynamics optimization, quadratic unconstrained binary optimization, time dependent shortest path problem, system planning and truck operation optimization (Al-Ali, 2023; Bak et al., 2022; Davis, 2020; Du et al., 2023; Fan et al., 2020; Gunawan et al., 2023; How et al., 2024; Joe et al., 2020; Liu et al., 2021; Lyu, 2023; Shih et al., 2024; Siddiqui, 2024; Suen et al., 2022; Vidhya et al., 2024; Wu, 2023) with use cases like decarbonization, thermal imaging, autonomous vehicles, sales management, sustainable waste management, weather routing, container distribution, multi-party vehicle routing, electronic transportation management, maritime collision prediction, weather routing, carbon footprint mitigation, digital supply chain management, digital technology development, ethical landscapes, multi-modal routing, logistics planning, last mile logistics, sustainable product-service system, complex data driven agriculture, low carbon logistics, and dynamic urban logistics (Arayakee, 2023; Azeem, 2022; Cristancho et al., 2022; Dinana, 2020; El-Sayad et al., 2023; Gong, 2022; Imayanti et al., 2024; Joe et al., 2021; Jovic et al., 2020; Kim et al., 2023; Lou, 2023; Pendyala et al., 2022; Pflaum et al., 2022; Qi, 2021; Ruehle, 2020; Sanga, 2022;

Schmidtke et al., 2021; Shao et al., 2023; Su et al., 2023; Taylor et al., 2021; Xu et al., 2022; Yang, 2023). Additionally, multiple web-based academic articles were surveyed which presented techniques like algorithmic carrier pricing in freight, generative AI trained models that algorithmically design optimal routes, and LLM’s to translate human questions into a mathematical code (Burnham, 2024; Menache et al., 2025). Those techniques were combined with use cases like connecting fragmented supply chains, accurately forecasting demand, return logistics, market volatility, safety, and climate change (Burnham, 2024; Menache et al., 2025). Overall, the survey of academic publications revealed how the foundational concepts and methodologies associated with traditional forms of AI are in use and where new concepts and methodologies associated with non-traditional forms of AI are beginning to be applied.

In addition to academic publications, multiple non-academic web-based articles were reviewed to determine how AI is being used to optimize routes in logistics transportation. As was previously the case, techniques and use cases were determined. While they mostly reinforced what was previously identified, there were a few notable additions. Specifically, techniques like real time vehicle monitoring, stock level optimization, and scalable advanced ML algorithms utilizing neural networks for pattern recognition and prediction were identified. In this latter scenario, scalability powers learning and prediction subject to ingesting more data and larger problems associated with numerous and increasingly stringent constraints. These various techniques were presented with use cases like blockchain and IoT integration, personalized deliveries, warehouse automation, and inventory management (Lakshman, 2024; Unknown, 2024). Overall, the limited survey of non-academic web-based articles reinforced the previous review.

1.4 What Gaps Exist In The Existing Literature?

Earlier, the comment was made that the trajectory of innovation in route optimization seems to have increased dramatically in lieu of the seemingly constant advancements in technologies like AI. Those advancements were earlier referred to as “fluid and evolving” to underscore the pace of its innovation. That innovation can be confirmed through a web search of available software products on the market today. Those products are being offered by some of the most recognizable brands in the world like Google who applies self-described techniques like “optimization AI” to route fleet vehicles (from the cloud) using integrated mapping tools. The literary gap therefore exists because of the rapid development in AI that seems to have outpaced the ability for authors to publish scholarly articles en masse about its application to route optimization. In some cases, these developments were referred to generally as “showing promise” or “early stage” and the intent is clearly there to research and write about these topics.

Previously, AI was defined as a group of technologies and techniques that perform tasks as well if not better than a human could. In conducting the review, the focus remained on cost minimization (efficiency) and asset utilization (opportunity) from an operator’s perspective and while there were compelling use cases, there were noticeably absent techniques and technologies being applied to route optimization that could make them even more compelling. Specifically, traditional and modern forms of AI like supervised machine learning were found in abundance but non-traditional forms of AI (i.e. generative and agentic AI) like the use of advanced forms of deep learning and artificial neural networks enabling foundational LLM’s and computer vision models in route optimization were found to be limited. Those techniques combined with technological advancements in robotics, assisted and autonomous driving and unmanned aerial vehicles (UAV) capable of vertical takeoff and landings (VTOL) will undoubtedly present even more compelling use cases.

CHAPTER II. RESEARCH DESIGN

This section will present the process and steps taken to collect and analyze the data that will enable the previously stated research questions to be answered. That data, analysis, and the research findings will be presented in subsequent sections and the joint goal of each is to illustrate where the field of route optimization in logistics transportation is going with respect to the use of AI. As previously stated, this research is needed to learn, apply and ultimately leverage the transformative capabilities of AI within the field of logistics transportation. It is also needed to provide a framework for continued learning and adoption as capabilities accelerate across industries. This research design aligns with these overarching principles and provides a blueprint for both this and future reports. The remainder of this section will discuss how the blueprint was created.

The formal research process consisted of six steps and was both qualitative and quantitative, involving the collection of both primary and secondary data. The initial secondary data was collected during the literature review and was therefore the first step in the research process. The methodology for primary data collection was also established in the first step and that data was collected directly from industry professionals in two iterations after the initial collection of secondary data. Additional primary data was collected by academic professionals/researchers followed by additional secondary data collected in the form of qualitative and quantitative case studies to validate the primary data. Figure 2.1 below is an illustration of that process:

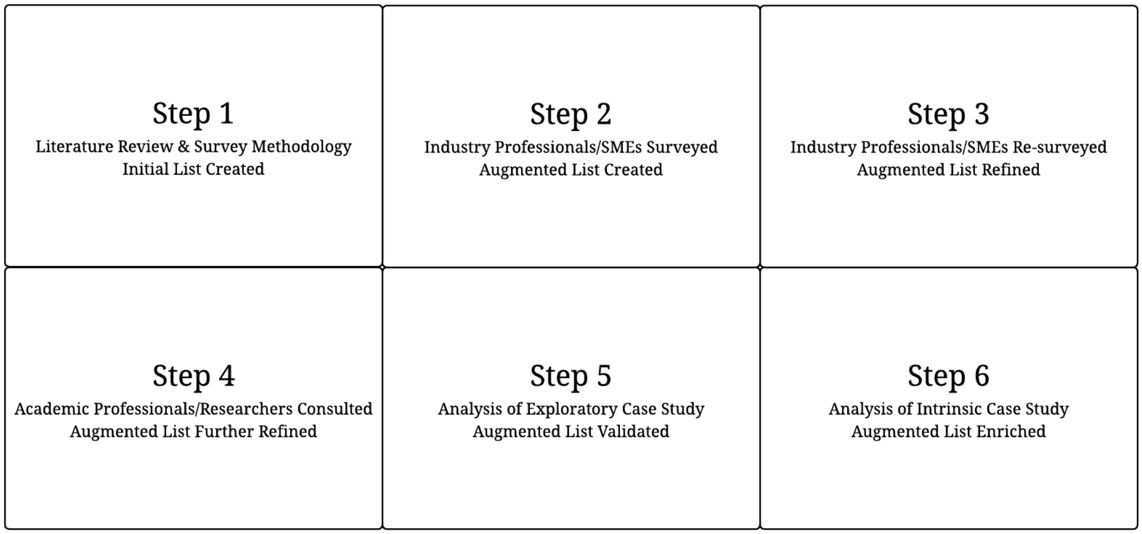

Figure 2.1 Research Design Steps

In step one, a comprehensive literary review of AI techniques applied to route optimization was conducted, and a preliminary list of recent AI advancements was made because their use and/or application were not abundantly found applied to the optimization of routes. Research thus commenced to develop and define a more comprehensive list of recent AI advancements as well as a list of all the components of the routing process in logistics. As previously stated, the focus of this report is cost minimization (efficiency) and asset utilization (opportunity) from an operator's perspective therefore the components listed were associated with the costs that would otherwise impact the operator's profit. Additionally, the methodology and standards were developed for use in the subsequent subject matter expert surveys. Prospective SMEs were identified using a combination of first-hand knowledge and professional networking sites. A threshold of 20 and 10 written/verbal responses was established for data and logistics professionals respectively at an expected response rate of greater than 80% for data professionals and between 20-30% for logistics professionals. Those rates were achieved at 88% (22 of 25) and 33% (10 of 30) respectively. The sample sizes were chosen given the characteristics (i.e. qualifications and experience) of the “expert pool” and the disparity in the response rates was due in large part to active industry affiliation (i.e. currently employed) versus past industry affiliation (i.e. previously employed). As illustrated in Figure 2.2, survey questions were initially broad and open ended while follow-up questions (i.e. re-surveyed) were more precise. Select academic/research professionals were identified by first or second-hand knowledge of their individual expertise in logistics and AI. In each case, the surveyed questions were qualitative and either emailed or discussed over the phone as depicted in the following:

Initial List from Literature Review

Logistics: Completed

AI: Completed

Augmented List Created

Logistics Professionals:
"From an operator's perspective, what do you feel are the components of the logistics routing process?"

Data Professionals:
"Can you provide a list of what you consider to be recent advancements in AI?"

Augmented List Refined

Logistics Professionals:
"From an operator's perspective, what of the identified logistical elements could benefit most from the application of AI?"

Data Professionals:
"What of the identified AI techniques show most promise when applied to route optimization?"

Augmented List Further Refined

Academic Professionals/Researchers:
"Do you agree or disagree with the "consensus" list obtained from logistics and AI practitioners and do you have any additional input?"

Figure 2.2 Research Design Process

In step two, industry professionals that were directly associated with professional associations and/or relevant organizations were used as subject matter experts in augmenting the before mentioned lists. To develop and define a more comprehensive list of recent AI advancements not abundantly found in route optimization, data professionals from both the Association for Advancement of Artificial Intelligence and multiple U.S.-based data technology firms were consulted. To list all components of the logistics routing process from an operator's perspective, senior supply chain executives, Certified Supply Chain Professionals (CSCP), and Certified Logistics, Transportation and Distributions (CLTD) professionals from the Association for Supply Chain Management (ASCM) were independently consulted. The three lists were then prepared for analysis of those same professionals to determine what opportunities exist for AI to further enhance route optimization in logistics transportation.

In step three, the before mentioned logistics professionals were once again surveyed to determine in their expert opinions what of the identified logistical elements could most benefit from the application of artificial intelligence. The AI professionals were likewise surveyed to determine in their expert opinions what of the identified artificial intelligence techniques show most promise when applied to route optimization. The two sets of data were then combined to present a joint "consensus" opinion from the two groups.

In step four, academic professionals/researchers associated with an R1 research institution and with expertise in logistics and AI respectively were asked to review the "consensus" data collected from practitioners. In each case they were provided with the research questions and preliminary data collected and asked if they agreed/disagreed and if they had any additional input. That data was incorporated and augmented the prior lists.

In step five, an analysis of an exploratory case study was conducted to determine if the stated opinions of the subject matter experts could be independently validated or verified via a real world example or examples. In this instance, the before mentioned SMEs agreed that a particular high profile example validated their opinions both qualitatively and quantitatively and an analysis was conducted to determine if those opinions were indeed accurate. This case study focused on measurable data considered "obvious" (i.e. efficiency gains).

In step six, an analysis of an intrinsic case study was conducted that added additional qualitative and quantitative dimensions to the same opinions. In this instance, the focus was on measurable data considered "less obvious" (i.e. opportunity) and incorporated as a baseline from which to present answers to the research questions. I produced the case study research in March of 2020 under the guidance of an Associate Professor of Agricultural Economics. The technical data presents an opportunity to illustrate both how traditional AI could further optimize the routes and how non-traditional AI could likewise be leveraged for additional gains.

Collectively these six steps provide a blueprint from which to evaluate, learn, apply and ultimately leverage the transformative capabilities of AI in route optimization both now and in the future. As previously stated, the goal of the design is to provide a framework for continued learning and adoption as capabilities accelerate across industries. The results of the data collection and analysis are presented in the following section.

CHAPTER III. DATA COLLECTED AND DATA ANALYSIS

This section aligns with the research design section and details the primary and secondary data that was collected as well as the analysis of that data. In step one, the previously noted AI "gap" list was determined and was initially identified as generative and agentic forms of AI. Specifically, in addition to agents they were identified as deep learning and artificial neural networks (ANNs) enabling foundational models like LLM's, computer vision models, etc.

In step two, subject matter experts were consulted in their respective fields of logistics and AI. The operational network components of the logistical routing process (from an operator's perspective) were identified as loading and unloading, line-haul and back haul, local vehicle routing, and sorting and involve all five modes of transportation (truck, rail, air, water, and pipelines). These components may be intramodal, intermodal, unimodal and/or multimodal and may incur special fees like drayage, demurrage, and detention while in transit (Sarder, MD, 2019). Additionally, because the focus remained on cost minimization (efficiency) and asset utilization (opportunity) from an operator's perspective, the import and export processes were explored to see if AI could foreseeably reduce costs associated with those processes. Subject matter experts were also consulted to create an expanded list of recent advancements in AI which included additional forms of ANNs (i.e. GANs, VAEs, DMs, etc.) hybridization, hardware/compute power, model development and scaling, agents and the introduction of new data sources and technology. Collectively, these advancements all present an opportunity for innovation in route optimization and subsequent sections will identify which of those areas hold the most promise and in what form (i.e. robotics, assisted/autonomous driving, unmanned aerial vehicles, etc.).

In step three, additional primary research done on the logistical routing elements determined that given the significant cost and environmental impacts, subject matter experts feel that intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting could benefit most from the use both traditional and non-traditional forms of AI. Additionally, primary research conducted on traditional AI elements determined that subject matter experts feel that hybridization, data/technology integration, and more sophisticated model development (with the assistance of hardware/compute power) could likewise benefit the routing process significantly. These same SME's felt that non-traditional forms of AI like artificial neural networks (ANNs), and the introduction agents could additionally benefit the routing process significantly. This additional primary research therefore concluded that in the traditional sense, by consistently developing more sophisticated models run by highly capable hardware, by integrating disparate data sources and technology types, and by combining several AI techniques (hybridization), an operator's bottom line could be most impacted when those elements are applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting. In a non-traditional sense, the use of artificial neural networks (GANs, VAEs, LLMs, CNNs, DMs), and agentic AI in addition to the previously stated techniques present untapped opportunities when applied to route optimization.

In step four, academic professionals/researchers reviewed the research questions and "consensus" data collected from practitioners. They agreed with the consensus but added Retrieval Augmented Generation (RAG) to the list with an emphasis on graphRAG. Additionally, a Naval Postgraduate Thesis, *Wargaming the Impact of External Risks to the Fuel Supply Chain* (Their, 2023), was provided to illustrate how AI models can be used to simulate and respond to contested logistics events, attacks, natural disasters, and in conflict avoidance along routes. Caution was recommended, however, with respect to the use of generative AI given its infancy. Hallucinations (aka Squirrel results) remain a concern as does data security.

Table 1 below summarizes the operational network components of the logistical routing process (from an operator's perspective) and was generated with the complete list of traditional and recent advancements in AI to aid in additional primary and secondary data collection:

Table 3.1 Operational Network Components of Logistical Routing Process

Logistical Routing Components	**Traditional AI**	**Recent AI Advancements**
Loading/Unloading	Search Algorithms	Artificial Neural Networks: GANs, VAEs, LLMs, CNNs & Diffusion Models (DMs)
Line-haul/Back-haul	Heuristics & Metaheuristics	Hybridization
Local Vehicle Routing & Sorting	Expert Systems	Hardware/Compute Power
Specific Modes (Truck, Rail, Air, Water, & Pipeline)	Constraint Satisfaction Problem (CSP) Solvers	Model Development & Scaling
Mode Combination (Intramodal, Intermodal, & Multi-modal)	Machine Learning	Integration with Other Data & Technology
Special Fee Services	Deep Learning (some)	Retrieval-Augmented Generation (RAG)
Import & Export Services		Introduction of Agents

In steps five and six, research and analysis were then conducted in the form of case studies to determine if the opinions of logistics and AI subject matter experts could be validated by researching both traditional and non-traditional AI examples (applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting). An analysis of the evolution of UPS's On Road Integrated Optimization and Navigations (ORION) system as well as additional UPS technology provided an excellent opportunity to do that very thing. Additionally, an analysis of agricultural company IGI's hypothetical use of route optimization in price promotions also presented an excellent illustration.

3.1 UPS Case Study Analysis:

It is an all too familiar observation around the holidays and one that is often written about on platforms ranging from social media to major news outlets. The "observation" I am referring to is the fact that UPS drivers almost never turn left. Atlanta based UPS has always been known for its industrial engineering prowess presumably influenced by its proximity to elite academic institutions like the Georgia Institute of Technology. It is therefore no surprise that before onboard software, UPS was optimizing routes as far back as the 1970's using a manual technique called "loop dispatch" which prioritized same side street deliveries that followed a right-hand loop (Prisco, 2017). This manual method evolved into the first electronic version of ORION in 2008 which downloaded data to a handheld device called the Delivery Information Acquisition Device. In 2017, UPS shared that ORION had evolved to a connected onboard system analyzing 250 million addresses a day and was optimizing 30,000 routes per minute (Prisco, 2017). This optimization enabled wage, fuel and maintenance savings of $300 to $400 million and removed emissions equivalent to 20,000 passenger cars in 2017 (Prisco, 2017). Fast forward to 2021 when ORION had been upgraded to incorporate dynamic routing which UPS claimed saved an additional 2 to 4 miles per driver in addition to the original savings of 8 miles per driver (Leonard, 2021). This new version was affectionately referred to as "Dynamic Orion" and dynamically optimized routes subject to changing conditions and additional pickup requests. In addition, UPS was looking externally to improve its algorithm by offering a six figure prize like a joint Amazon MIT competition for help capturing knowledge from drivers (i.e. parking and short cuts) that spend significant time in certain neighborhoods. UPS's quest for knowledge and efficiency extends beyond the last mile with multiple data sources powering the UPS Network Planning Tool and Harmonized Enterprise Analytic Tool that enables real time routing decisions based on macro-factors like severe weather conditions. From 2020 to 2023 the firm forecasted that demand for small package deliveries would outpace capacity with a forecasted volume growth of 20% (Leonard, 2021). Route optimization enabled efficiency gains without significant capital investment and the advent of generative AI in 2024 allowed UPS to find additional efficiency gains by generating scenario based data to model alternative routes that take into consideration shifting and volatile demand patterns. This ability to generate scenario based content and model the adaptation to it is just one of many generative AI use cases that UPS is undoubtedly reviewing and the reason the firm is at the forefront for innovation in route optimization (Sharma, 2024).

The UPS analysis seemed to validate the previously stated SME opinions. Although focused on local vehicle routing and sorting, there were implied references to macro components like intermodal and multi-modal line-haul/back-haul activities. Additionally, most if not all the traditional and non-traditional AI methodologies mentioned were present in the analysis.

The final data collected involved an intrinsic case study analysis that added an additional dimension to the same opinions. The following is a quantitative research paper I authored in March of 2020 under the guidance of an Associate Professor with technical assistance from a Professor of Agricultural Economics and a team of freight brokers from an industry recognized

Top 20 Global Logistics firm. This was a hypothetical case study incorporating then current data and its associated linear program model sought to optimize the global sale and transport of grain for a real company whose name has been abbreviated for this report to IGI. This report incorporated real world costs and rates and illustrates how route optimization can create opportunities in addition to creating efficiencies.

3.2 IGI Case Study Analysis:

The purpose of the report is to take an objective look at a hypothetical scenario involving inbound grain, elevator capacity, buyer availably and transport optimization. In doing so I hoped to illustrate how stakeholders in the sale of grain can capitalize on a variety of opportunities. The methodology used began with empirical research. That research was both qualitative and quantitative and its aim was to illustrate the scenario from its origin to its destination. More specifically from its harvest and initial transport to its export and ocean voyage. A Professor of Agricultural Economics served as the technical authority on Agriculture and a team of industry recognized freight brokers served as technical authorities on Transportation. The overall findings conclude that when given short notice of inbound product and when certain marketing levers are utilized, the operators of grain elevators can profitably move product to foreign buyers. The remainder of this section will discuss how these findings were determined. The model began with the formulation of a hypothetical question involving a company called IGI. IGI operates a grain elevator out of St. Louis, MO with a total capacity of 4 million bushels. In the scenario, its facility is at capacity which consists of 3 million bushels of corn and 1 million bushels of soybeans. The elevator expects at least ten 1,500 acre Midwestern farms to deliver their harvest within the week. The harvest of each farm consists of 1,000 acres of corn and 500 acres of soybeans. The farmers traveled no more than 20 miles to deliver their product to IGI.

The company can arrange to export its product to overseas buyers but needs to know (A.) how much product should be sent to each buyer to make room for incoming product (B.) how to satisfy the needs of the expected buyers and (C.) how to maximize its profits. The remaining scenario information is:

- IGI has arranged three buyers in (1.) Mexico, (2.) Japan and (3.) Saudi Arabia.
- To export the grain, it will be transported from St. Louis via multi-mode to the Port of South Louisiana then exported to (1.) Mexico – Port of Altamaria (2.) Japan – Port of Nagoya and (3.) Saudi Arabia – Damman Port.
- The transportation costs per pound and per bushel (from origin to destination) are in Table 2 below:

Table 3.2 IGI Transportation Costs per Pound per Bushel

Transport Costs	Per LB	Per Bu Corn	Per Bu Bean
Mexico	0.10427	5.83912	6.2562
Japan	0.10405	5.8268	6.243
Saudi Arabia	0.10438	5.84528	6.2628

- The minimum quantities demanded by each buyer are in Table 3 below, however they will buy whatever is available:

Table 3.3 IGI Minimum Quantities Demanded

Minimum Bushels Demanded	Corn	Soybeans
Mexico	300,000	70,000
Japan	400,000	60,000
Saudi Arabia	500,000	50,000

- Baseline prices are itemized below however the Saudi Arabian buyer is willing to pay .01 extra per bushel for soybeans, the Japanese buyer is willing to pay .02 extra per bushel for corn and the Mexican buyer will buy both at baseline prices.
- Buyers typically pay transportation charges but as an incentive to free up capacity, IGI is willing to pay 30% per bushel toward the cost to ship corn and 10% per bushel to ship soybeans.

Supplemental information is:

- The yield per acre of corn is 170 bushels for corn and 55 bushels for soybeans.
- Corn weighs 56lbs/bushel and beans weigh 60lbs/bushel.
- Corn is selling for 9.60/bushel and beans are selling for 3.86/bushel.

By standardizing the freight component into a cost per unit metric we can estimate the transport charges. It is important to note that the transport metric does not include duties, taxes, insurance or any other fees associated with customs clearance. It is simply the variable freight component quoted in March of 2020. The model then was built off the following illustrated in Figure 3.1:

Variables

CMX – Corn to Mexico; CJA – Corn to Japan; CSA – Corn to Saudi Arabia; SMX – Soybeans to Mexico; SJA – Soybeans to Japan; SSA – Soybeans to Saudi Arabia

Objective Function

Max Profit = (7.848) CMX + (7.872) CJA + (7.846) CSA + (3.234) SMX + (3.236) SJA + (3.244) SSA

Constraints

Demand: CMX >= 300,000; CJA >= 400,000; CSA >= 500,000; SMX >= 70,000; SJA >= 60,000; SSA >= 50,000

Supply: CMX + CJA + CSA = 1,700,000; SMX + SJA + SSA = 275,000

Non-negativity: Xi >= 0

Figure 3.1 IGI Linear Programming Model

The optimal solution concludes that the minimum amount required by all buyers be met except for corn to Japan and soybeans to Saudi Arabia. In these instances, 900,000 bushels of corn should be exported (as opposed to the minimum of 400,000 demanded) and 145,000 bushels of soybeans be exported (as opposed to the minimum of 50,000 demanded). By doing so, IGI's maximum profit is $14,253,339. A review of the sensitivity report provides some interesting findings. The LP model provides for an infinite decrease in all variables but corn to Japan and soybeans to Saudi Arabia. In these instances, they allow for very limited decreases. Specifically, it allows for a decrease of .024 in corn to Japan and .008 in soybeans to Saudi Arabia. This would imply that for IGI to maximize its profits it must export the minimum value computed in the LP model. They must maintain the schedule specified by the freight brokers, however, to control the cost of transport. From an operational perspective, a failure to export the correct quantities at the correct time may result in higher transportation charges. Transport charges are a component of the time required, and the mode selected. In IGI's case, the transport incentive they are willing to pay is subject to the ordinary pressures that drive freight prices. They are basing their model on an expected freight cost that corresponds to a specific schedule. To maximize the utility of its available product, they must maintain that schedule. The LP model would have to be rerun, and quantities may change if they are unable to meet that schedule. The transport incentive referenced previously is a strategic decision by IGI to control the outbound movement of product. From a marketing perspective, this enabled an order winner for inbound products. By incentivizing its buyers to take the optimal amount of outbound product, IGI has created operational efficiencies that give it an advantage over its competition. This was perhaps the biggest takeaway. A lever such as a transport price promotion in the sale of grain can give an elevator operator a strategic advantage in the marketplace (Tribble, 2020).

The data collected and analyzed in this section represents an initial list of observed literary gaps that was subsequently augmented by logistics and AI subject matter experts. Those respective lists were then scrutinized by those same SMEs to create a “consensus” perspective. That consensus was objectively scrutinized by academic professional/researchers and through the lens of case studies involving observed efficiencies and opportunities related to advancements in traditional and non-traditional technology and techniques. The next section incorporates that data and analysis to answer the previously stated research questions.

CHAPTER IV. FINDINGS

This section answers the previously stated research questions and illustrates where the field of route optimization in logistics transportation is going. The focus remains on cost minimization and asset utilization from an operator's perspective, and an important early distinction relates to the choice of the phrase "further used to optimize" in each research question. That phraseology is intended to explore opportunities for efficiency gains (i.e. UPS) and to differentiate those from opportunities created (i.e. IGI) by route optimization.

4.1 Research Question 1: How Can Traditional AI Be Further Used To Optimize Routes In Logistics Transportation?

As shown in Figure 4.1, research determined that in the traditional sense, by leveraging highly capable hardware, by consistently developing more sophisticated and scalable models, by integrating both disparate data sources and technology types, and by combining several AI techniques (hybridization), an operator's bottom line could be most impacted when those elements are applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting.

Traditional AI

1. by leveraging highly capable hardware and compute power
2. by consistently developing more sophisticated and scalable models
3. by integrating both disparate data sources and technology types
4. by combining several AI techniques (hybridization)

an operator's bottom line could be most impacted when those elements are applied to

1. intermodal and multi-modal
2. line-haul/back-haul
3. local vehicle routing and sorting

Figure 4.1 Traditional AI Findings

Here is what the surveyed experts meant by each of these individually and how collectively they can be used to create both efficiencies and opportunities via route optimization:

4.1.1 Hardware/Compute Power

Perhaps the single most important development driving innovation in Artificial Intelligence is the storage capabilities and computational ability of hardware that process data and perform calculations at increasingly rapid rates. NVIDIA and Google are perhaps the firms best known for the specialized hardware driving this innovation through their Graphic Processing Units (GPUs) and Tensor Processing Units (TPUs) which run the algorithms we marvel at today. Most data professionals will agree that the math and models at the core of many of these advancements are not new. What is new, however, is the ability to analyze large amounts of complicated data while running increasingly sophisticated algorithms that take into consideration real time constraints at speeds once thought impossible. Without these developments in hardware/compute power, AI's ability to influence route optimization in both traditional and non-traditional forms would not be where it is today (Slattery et. al., 2025). Here are the reasons the surveyed experts felt hardware/compute power is important for traditional AI to further optimize routes:

1. Advancements in memory capabilities (i.e. RAM, VRAM, etc.) enable access to more data and more sophisticated models. This makes it feasible to deploy advanced AI models like deep reinforcement learning, large scale graph neural networks, and complex predictive models (Zavadko, V., 2025 & Bali, S., 2025).
2. Parallel processing capabilities (i.e. multi-core CUPs, GPUs, TPUs, etc.) and the ability to manage vast memory enable simultaneous evaluation, the handling of more complex

models and the solving of larger problems and allow for the optimization of logistics at a scale previously impossible (Pykes, K., 2024).

3. High throughput processing (i.e. faster storage I/O, bus speeds, etc.) combined with large memory capacities allow for the ingestion and analysis of new data types (i.e. video feeds, IoT sensor data, real time weather data, etc.) beyond just GPS and traffic feeds (Relo, D., 2024 & Isarsoft Blog, 2025).
4. Specialized AI accelerators (i.e. TPUs, NPUs, customer ASICs, etc.) enable optimized AI workloads, energy efficiency, and faster inference for real time decisions. Faster processing speeds enable quicker execution and real time recalculations enabling customized routes subject to criteria for individual deliveries, customers, or even driver preferences (i.e. minimizing left turns, prioritizing certain routes, precise delivery windows, etc.) (Armoni, M., 2024).
5. Powerful computing allows for the creation of "digital twins" of entire logistics networks. Businesses can run extensive what-if scenarios and simulations to test new business models, network designs, or responses to hypothetical large scale disruptions (Bansal, A., 2024).
6. While still emerging, advancements in quantum computing can be used specifically to target optimization problems (SPINQ Blog, 2025).

4.1.2 Model Development and Scaling

Model development and scaling refer to increasing the sophistication of the algorithms and logic used then applying them to increasingly larger and more complex use cases. It is directly tied to quality of data and the storage/computational resources available. Traditional forms of AI have the advantage of transparency and explainability. When coupled with the advancements in hardware/compute power, models can adaptively solve increasingly complex routing scenarios that are subject dynamic multi-objective constraints and do so in a way that is not considered to be a “black box” technology. Additionally, models inherently become smarter and faster as they are exposed to increasingly vast amounts of data therefore model development could also be thought of model training in the traditional sense (Puri, 2025). Here are the reasons the surveyed experts felt model development and scaling is important for traditional AI to further optimize routes.

4.1.2.1 Model Development

1. Sophisticated algorithms are key to ongoing model development and involve:
    a. Hybrid approaches that combine the capabilities of several algorithms to compensate for the deficiencies that one may have (Rota, E., 2022).
    b. Parameter tuning that enables the development of more advanced machine learning methods to automatically and dynamically tune algorithm parameters for optimal performance (Tomar, V. et. al., 2024).
    c. Constraint handling that improves the ability of algorithms to efficiently manage a wider array of complex constraints, such as time windows, vehicle capacities, driver work rules, varying road restrictions, and customer specific requirements (Luhhu Blog, 2025).
2. Advanced feature engineering is also key to ongoing model development and involves:
    a. Richer data integration that incorporates data sources like real time traffic data, weather forecasts, road closures, historical delivery data, vehicle telematics, fuel prices and/or toll costs (Lakshman, R., 2024).

b. Predictive capabilities that predict likely traffic congestion at specific times or potential delays due to recurring events. While still within the realm of traditional AI (i.e. time series analysis, regression models for prediction, etc.), these predictive elements feed more accurate information into the optimization algorithms (Descartes Blog, 2025).

c. Dynamic recalibration models that can quickly re-optimize routes in response to real time events and new information, rather than relying solely on static pre-planned routes (Puri, K., 2025).

4.1.2.2 Scaling

3. Computational power and efficiency are key to scaling and involves (Brickclay Blog, 2023):
    a. Parallel and distributed computing which break down large optimization problems into smaller sub-problems that can be solved simultaneously across multiple processors or machines. This drastically reduces computation time for complex routing scenarios.
    b. Cloud computing platforms utilize scalable infrastructure to access vast computational resources allowing companies to tackle large scale optimization without significant upfront investment in hardware.
    c. Optimized data structures and algorithms that reduce the computational burden associated with large datasets.
4. Handling increased complexity and scope is key to scaling and involves (Puri, K., 2025):

a. Network wide optimization that moves beyond optimizing routes for individual locations by optimizing entire logistics networks which take into consideration global constraints.
b. Multi-objective optimization that efficiently balances multiple, often conflicting, objectives (i.e. minimizing cost, reducing delivery time, lowering carbon emissions, balancing driver workload, etc.) across large fleets and numerous deliveries.
c. Real time fleet management that applies dynamic routing and re-routing decision making capabilities to assets operating in complex environments.

4.1.3 Data and Technology Integration

The integration of different data and technologies is having and will continue to have a profound impact on both route optimization and decision making with respect to transport and logistics. Advancements in hardware/compute power and the sophistication and scalability of the models being run have set the stage to integrate data and technology such as autonomously driving vehicles, drones, robotics, IoT, real time weather data, customer connected market data, blockchain applications, etc. This holistic view of a supply chain presents enormous potential in developing risk resistant and resilient global networks (Adeoye, et. al. 2024). Here are the reasons the surveyed experts felt data and technology integration is important for traditional AI to further optimize routes.

4.1.3.1 Data Integration

1. Incorporating real time traffic data feeds (i.e. traffic cameras) enables AI algorithms to dynamically re-route to avoid congestion. Traditional AI that is consistently

exposed to large amounts of data can learn traffic patterns at different times/days which improves overall predictive accuracy (Gangil, A., 2025).

2. Incorporating real time and forecasted weather data helps AI anticipate disruptions caused by extreme weather (Lakshman, R., 2024).
3. Access to data from vehicle sensors (i.e. fuel consumption, engine status, weight, tire pressure, etc.) enables AI to optimize routes for fuel efficiency, vehicle wear, and vehicle specific constraints (i.e. weight limits on bridges) (Lakshman, R., 2024).
4. Integrating historical route data, delivery times, and past disruptions allows traditional AI to identify patterns and make more accurate predictions about future conditions (Descartes Blog, 2025).
5. Information like delivery windows, customer preferences, and location specific details (i.e. loading dock availability, specific entry points, etc.) can be fed into an AI model. This ensures routes are not just optimal in terms of distance/time but also in meeting location requirements and customer expectations (Wispelaere, A., 2023).
6. Advanced and real time mapping data, including road gradients, speed limits, turn restrictions, and scheduled events (i.e. sporting events) provide greater detail for the AI model to use in predicting (Aptean Blog, 2024).
7. Integrating in house data like driver hours, service schedules and a WMS allows the AI model to synchronize delivery requirements and personnel availability (Puri, K., 2025).

4.1.3.2 Technology Integration

8. Robotics are used extensively in warehouses where they form an operational backbone enabling advanced distribution mechanisms like cross docking and capturing incredible amounts of data that can be used by AI (Zewe, A., 2024).
9. Internet of Things (IoT) enabled equipment (i.e. sensors on vehicles, infrastructure, in cargo, etc.) capture significant amounts of data. Integrating this data provides AI models with visibility into the current state of the entire logistics network (ScyllaDB Blog., 2025).
10. Autonomous Vehicles (AVs) are equipped with sensory devices like lidar, radar, and cameras that not only aid, guide and direct drivers, but capture incredible amounts of information about routes for use in AI models (DPV Transportation Blog., 2025).
11. Unmanned Aerial Vehicles (UAVs) or drones are being used extensively in contested/austere environments. They are also being used in select urban settings for law enforcement/medical response and show similar promise for last mile and/or difficult deliveries in urban environments (Ochmanek, D., et. al., 2023).
12. Cloud platforms offer the scalability and processing power to analyze massive datasets in real time. This enables more complex AI algorithms to run efficiently for route optimization (Intellias Blog., 2024).
13. Advanced analytics platforms can process and find insights within the vast amounts of data collected. These insights (i.e. identifying hidden correlations between weather and delivery delays) can further fine tune the AI models (Rapidops Blog., 2025).

14. Digital twins of a logistics network allow AI to both simulate and test different routing scenarios under various conditions to identify an optimal route (Anglen, J., 2024).
15. Mobile apps integrate with a central AI system and allow for real time communication, route updates, proof of delivery, and feedback collection (Western Systems Blog., 2025).

4.1.4 Hybridization

A late 2024 Forbes article described Hybrid AI as "the next big thing in tech" and the increasingly common talk of AI tech stacks refers to a sub-specialty within an organization's traditional technology stack. In conjunction, some organizations have established AI "teams" whose charter is to stay abreast of accelerating developments to incorporate best practices and products. Hybridization is therefore "the art of blending various AI techniques and models to achieve outcomes that surpass what any single AI approach could accomplish alone (Marr 2024)." Here are the reasons the surveyed experts felt hybridization is important for traditional AI to further optimize routes:

1. Improved solution quality and global optimization through (Shahbazian, R., et. al., 2024):
    a. Combining metaheuristics with exact methods.
    b. Integrating machine learning for heuristic selection or improvement (i.e. learn from past routing problems and solutions).
2. Enhanced adaptability/responsiveness by (Esmaeili, H., et. al., 2022):
    a. Pairing predictive analytics and ML with optimization algorithms.
    b. Combining differing metaheuristics (i.e. hybrid metaheuristics for dynamic re-routing).

3. Better handling of uncertainty through: (Ochoa, P., et. al., 2025):
    a. The use of fuzzy logic with traditional optimizers for uncertain or vague information.
    b. Optimization algorithms that generate routes scenarios, and then simulation models to evaluate the routes under various conditions.
4. Increased scalability/efficiency through (Lee, S., 2025):
    a. Decomposition techniques to break routing problems into smaller manageable problems.
    b. Learning augmented optimization to learn patterns in large datasets.
5. Less development time and better tuning through (Black, T., et. al., 2023):
    a. Bayesian optimization and evolutionary algorithms to discover parameter settings for traditional AI optimization algorithms.

4.1.5 Efficiencies Gained

In the context of the efficiencies presented in the UPS case analysis, here are the benefits the surveyed experts felt can be realized by using traditional AI to further optimize routes:

1. Lower fuel consumption: Optimized routes mean less distance traveled and less idling which translates to lower fuel costs.
2. Decreased mileage/maintenance: Shorter routes lead to less use of vehicles translating to lower repair and maintenance costs.
3. Optimized labor costs: Efficient routes mean drivers spend less time on the road translating to less overtime paid.

4. Faster delivery/service times: AI enhanced systems can calculate the quickest routes by factoring in current traffic, road closures, and other dynamic variables like weather that can lead to reliable delivery and service times improving overall customer satisfaction.
5. Reduced planning time: Manually planning routes for large fleets and/or complex multi-stop trips, can be time consuming. AI algorithms can generate optimized routes in a fraction of the time and adjust them as factors change.
6. Increased throughput of product: More efficient and effective routes means that businesses can handle higher volumes of deliveries and/or service appointments.
7. Better resource allocation/utilization: Enhanced AI systems can optimize fleet management by assigning the right vehicle to the right route subject to capacity, type of goods, delivery requirements, etc.
8. Improved constraint handling: Traditional AI systems can effectively manage numerous constraints like time slots, vehicle capacities, driver regulations, priority stops and road restrictions (i.e. height and weight limits).
9. Dynamic re-routing: AI enhances systems can enable quicker recalculation of routes when accidents or road closures occur thus minimizing disruptions.
10. Scalability: AI enhanced systems can optimize routes for a growing number of vehicles and destinations far more effectively than traditional methods or basic software.
11. More accurate ETAs: Route optimization and dynamic rerouting lead to more reliable estimates of arrival times.
12. Fewer delays: Reduced chances of getting caught in traffic jams means fewer late deliveries or missed time windows.

4.1.6 Opportunities Created

In the context of the opportunities presented in the IGI case analysis, here are the benefits the surveyed experts felt can be realized by using traditional AI to further optimize routes:

1. More prospect meetings: By utilizing route optimization, sales representatives spend less time driving and more time with customers, which leads to more meetings and more opportunities for sales.
2. More follow-up opportunities: Optimized routes enable frequent follow-up visits with existing clients or promising leads which can translate to faster sales due to relationship enhancement.
3. Strategic prospecting: AI enhanced systems enable complete coverage of a sales territory which minimizes the chances of missed opportunities and helps identify clusters of potential clients that can be visited efficiently.
4. Targeted campaigns: Optimized routing enables targeted sales campaigns to target specific demographics or business types within a geographic area.
5. Quick on-site demonstrations/consultations: When a hot lead emerges, AI enhanced systems can alert/direct the nearest available salesperson to respond before competitors arrive.
6. Reliable delivery and service times: Customer satisfaction can be influenced by product delivery and/or on-site service reliability therefore optimized routes can lead to more accurate and reliable arrival times and happier customers.
7. Improved service levels: For businesses where service calls are a part of the sales offering (i.e. field service, maintenance contracts, etc.), efficient routing allows technicians and/or service personnel to respond quickly thus leading to higher satisfaction and more sales.

8. Offering faster and more reliable service: It is a strong selling point to be able to consistently deliver products and/or services faster and more reliably than competitors.
9. Demonstrating efficiency and professionalism: Smooth and consistent operations reflect well on the entire business (at all levels) which increases a customer's confidence in their choice of carrier
10. Increased sales budget: The fuel, maintenance, and labor savings achieved through route optimization can be redirected/redeployed to expand the sales team, invest in sales training, and/or boost spending on marketing efforts that ultimately drive sales growth.
11. Identifying profitable routes/customers: Mining and analyzing data from optimized routes can reveal which types of customers and/or geographic areas are most profitable to serve which allows the sales teams to focus on the best yield to effort ratios they can achieve.
12. Optimizing sales territories: Data from routing optimization efforts enables the design of more balanced and efficient sales territories.

4.1.7 Research Question 1 Summary

Traditional AI can be further used to optimize routes in logistics transportation by leveraging highly capable hardware, by consistently developing more sophisticated and scalable models, by integrating both disparate data sources and technology types, and by combining several AI techniques (hybridization). An operator's bottom line could be most impacted when those elements are applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting. In the context of the UPS and IGI case analyses, specific areas were identified for efficiency gains and opportunities created by using traditional AI in route optimization.

4.2 Research Question 2: How Can Non-Traditional AI (i.e. Generative and Agentic AI) Be Used To Optimize Routes In Logistics Transportation?

As shown in Figure 4.2, primary research determined that in a non-traditional sense, the use of artificial neural networks (GANs, VAEs, LLMs, CNNs, DMs), retrieval-augmented generation (RAG) and agentic AI in addition to the previously stated traditional techniques present enormous opportunities when applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting. Here is what the surveyed experts meant by each of these individually and how collectively they can be used to create both efficiencies and opportunities via route optimization:

Traditional AI

1. by leveraging highly capable hardware and compute power
2. by consistently developing more sophisticated and scalable models
3. by integrating both disparate data sources and technology types
4. by combining several AI techniques (hybridization)

Non-traditional AI

5. through the use of artificial neural networs (ANNs) like GANS, VAEs, LLMs, CNNs and Diffusion Models
6. through the use of retrieval augmented generation (RAG)
7. through the use of agentic AI

an operator's bottom line could be most impacted when those elements are applied to

1. intermodal and multi-modal
2. line-haul/back-haul
3. local vehicle routing and sorting

Figure 4.2 Non-Traditional AI Findings

4.2.1 Artificial Neural Networks (GANs, VAEs, LLMs, CNNs and DMs)

Artificial Neural Networks (ANNs) are associated with ML's subset Deep Learning and mimic the way the human brain operates. Contrary to traditional forms of AI, ANNs are a "black box" technology that is not easily understood and nor explained given its multiple layers and how its connections are made within an unstructured database. The most well-known ANN is arguably a Large Language Model (LLM) which many consumers have interacted with via text and language products like ChatGPT. Lesser known ANN's are Generative Adversarial Networks (GANs) that learn by seeking to distinguish right from wrong data through an iterative back and forth adversarial process. Also less known, Variable Autoencoders (VAEs) learn from compressed representations of data and are useful in scenario simulation. Convolutional Neural Networks (CNNs) may not be widely known by name but their use in image processing, particularly self-driving cars, is familiar to most consumers. Lastly, Diffusion Models (DMs) are a form of Artificial Neural Network whose popularity in the world of generative AI is increasing given their ability to generate and refine both realistic and highly complex datasets. (Databricks 2025).

Here are the reasons the surveyed experts felt ANNs are important for non-traditional AI to further optimize routes

1. Unlike traditional systems that rely on simpler algorithms for fixed routes, ANNs can process and learn from numerous complex, dynamic variables in real-time and at the same time. These include (Karkouri, N., et. al., 2025):
    a. Adapting routes based on current congestion, accidents, or closures.
    b. Proactively altering routes to avoid delays caused by weather or threat of weather.
    c. Ensuring compliance with customer required delivery times.
    d. Optimizing load distribution/design and vehicle selection/assignment.
    e. Factoring in driver availability/schedules and regulatory constraints (i.e. ELD).

   f. Identifying patterns in past delivery data, past traffic trends, and small correlations often overlooked by human planners allow for more accurate predictions of travel time and potential disruptions.

2. ANNs can dynamically adjust routes in response to unforeseen events like unexpected delays. If a delivery vehicle encounters an unexpected delay, the ANN can quickly recalculate the optimal path for the remaining deliveries. This is a stark contrast to traditional systems that require manual intervention or operate on pre-planned routes with little flexibility (Mahmud, D., 2025).
3. ANNs can be trained to simultaneously optimize and balance multiple often competing/conflicting objectives such as (Berg, E., 2024):
   a. Minimizing total travel distance and time.
   b. Reducing fuel consumption and carbon emissions.
   c. Maximizing vehicle utilization.
   d. Improving customer satisfaction through on-time deliveries.
   e. Balancing workload among drivers.
4. ANNs are also designed to learn and improve over time. As they process more data, their predictive accuracy and routing efficiency improve. This continuous learning cycle means that the logistics network becomes progressively more optimized with each delivery cycle (Weiss, A., 2023).

4.2.2 Retrieval-Augmented Generation

RAG or Retrieval Augmented Generation are typically associated with LLMs and represent the ability for a Large Language Mode to retrieve external information to augment a deficiency in its response. That deficiency is typically associated with its training data and can close a gap between an LLM's knowledge cutoff and the current date (by going out to the web or another data source). RAG can often be described as giving an already knowledgeable person access to a library. More precisely, RAG makes an LLM both more powerful and reliable. Here are the reasons the surveyed experts felt RAG is important for non-traditional AI to further optimize routes

1. Dynamic routing and adaptability: RAG can retrieve real-time data on live events like traffic conditions, weather forecasts, road closures, accidents, and even port congestion allowing the system to dynamically adjust routes, suggest alternatives, while minimizing delays and optimizing fuel consumption (Omnitrac Blog, 2024).
2. Incorporating numerous complex constraints: RAG can access and process information from various internal and external databases to include vehicle specifications, driver availability, hours of service regulations (i.e. ELD), specific customer delivery windows/preferences, and real time order updates that the system can use generate optimized routes that adhere to these constraints (Confluent Ebook, 2025).
3. Improved decision support for dispatchers and planners: When disruptions occur (i.e. vehicle breakdown, urgent new order, etc.), dispatchers can utilize RAG to retrieve information like the location of other available vehicles, proximity to service centers, and status of other deliveries to help system suggest the most optimal re-routing strategy (Ratzki, A., 2024).
4. Enhanced last mile delivery efficiency: RAG can help improve on time driver performance by retrieving local information which may not be available in standard mapping data like building entry points, parking availability, and/or local delivery restrictions (McDonald, N., et. al., 2022).

5. Personalized customer communication: By retrieving real time shipment status and dynamically adjusted ETAs, RAG can help generate accurate updates for customers which may improve overall customer satisfaction (ExpressIt Blog, 2025).
6. Optimized resource allocation: RAG can pull data on historical delivery times, driver performance in certain areas, and vehicle efficiency to enable the system to best match both drivers and vehicles to routes (Hernandez-Salinas, L., 2024).
7. Integration of external knowledge for strategic planning: RAG can assist companies in making more informed decisions by retrieving broader external datasets like economic indicators, fuel price trends, upcoming local events, and/or sustainability suggestions that can help achieve certain goals and objectives (Bradley, C., et. al., 2024).
8. Handling unforeseen events and queries: RAG can retrieve a significant up to date knowledge base to provide external relevant information and/or suggestions that cater to the unique and often unscripted nature of logistics (Confluent eBook, 2025).

4.2.3 Introduction of Agents

Agentic AI, or simply Agents, are specialized systems or actions that work independent of human oversight and perform a defined set of tasks often utilizing other forms of AI like LLM's. A characteristic of Agents is that they learn and get better at performing their defined specialty beyond the rules based systems of the past. An important distinction between generative AI and agentic AI is the focus on decisions (agentic) versus content generation (generative). Agents have historically been associated with chatbots in sales and customer service but use cases are evolving rapidly as systems of agents utilizing LLM's interact to accomplish a complex objective (Purdy, 2024). Here are the reasons the surveyed experts felt agents are important for non-traditional AI to further optimize routes.

1. AI agents can take over decision making processes currently requiring human interaction and/or intervention including among other things dynamically rerouting vehicles in response to actual events impacting the route (Malec, M., 2025).
2. Agentic systems can both predict issues and act on them by learning from historical data and current trends. Agents can predict and adjust routes, schedules, or allocate resources to mitigate the impact of things like last minute order changes and/or urgent deliveries (Malhotra, G., & Abielmona, A., 2025).
3. Agents can monitor countless internal and external variables (from different datasets) and iteratively adjust routes subject to changing conditions. This means that the optimal route is constantly changing as conditions change with respect to the route and the delivery itself (Kardinal Blog, 2021).
4. Agents can analyze, balance and act on competing factors like fuel costs, delivery windows, driver regulations, vehicle load capacities and environmental impact to quickly identify optimal solutions that a human planner might need to consider (Sifted Blog, 2024).
5. Agentic systems can incorporate data from numerous sources like GPS, IoT sensors, weather services, traffic APIs, and ERP systems, etc. that enable coordination and optimization of various aspects of the supply chain like warehousing, dispatch, and customer communication (Lee, S., 2025).
6. A key element of agentic AI is the ability to learn from each delivery, delay, and/or successful reroute which provides data that the system can use to refine its models and improve future decision making (Chia, A., 2025).

7. Agentic AI can provide a logistics manager with enhanced operational visibility and offer insights into inefficiencies through simulation optimization (Malhotra, G., & Abielmona, A., 2025).
8. Agents can automate complex planning and decision making tasks designed help companies make more efficient use of their existing logistics workforce and/or resources (O'Neal, W., 2025).

4.2.4 Efficiencies Gained

In the context of the efficiencies presented in the UPS case analysis, here are the benefits the surveyed experts felt can be realized by using AI to further optimize routes:

1. Less fuel consumption, lower labor costs, faster delivery times, and faster responses to disruptions.
2. Reduced travel times and fuel costs through both dynamic rerouting and simulation of potential disruptions.
3. Increased operational efficiency by predicting unrealized events and optimizing resource use.
4. Improved delivery accuracy and customer satisfaction because of reliable and timely deliveries.
5. Better utilization of assets and human resources like vehicle capacity and driver hours.
6. More accurate and reliable route planning through incorporation of external data.
7. Faster decision making when disruptions occur.
8. Reduced errors by having access to better information.
9. Streamlined communication between drivers, dispatchers, and the routing system.
10. An overall reduction in delays through autonomous and proactive rerouting.

11. Optimization through enhanced resource utilization and workload balancing.
12. Increased resilience to disruptions and unexpected events through iterative learning.
13. An overall reduced need for manual work which frees up human dispatchers for complex tasks.
14. Improved monitoring and adherence to agreements that influence customer satisfaction.

4.2.5 Opportunities Created

In the context of the opportunities presented in the IGI case analysis, here are the benefits the surveyed experts felt can be realized by using AI to further optimize routes:

1. Generative AI can design routes based on preferred delivery windows, vehicle specific constraints (i.e. EV range and charging), driver preferences, and environmental factors. This level of personalization can be a strong selling point.
2. Sales teams can showcase generative AI tools that allow clients to simulate various scenarios (i.e. demand surges, road network changes, regulatory landscapes, etc.). This planning ability is a valuable offering that enables customers to build more resilient and adaptive logistics operations.
3. Generative AI can suggest new optimized routes in real time as unforeseen disruptions occur. Selling this capability equates to hard dollar savings through reduced delays, lower fuel consumption from idling, and higher customer satisfaction.
4. For businesses looking to expand or restructure their logistics networks, generative AI can design optimal warehouse and distribution hub locations. This type of service offers a high value and distinct sales advantage.
5. RAG powered systems can provide dispatchers and drivers with real time information beyond simple navigation including customer specific delivery instructions, historical

data on access issues, real time local advisories (i.e. temporary road closures not yet in standard map data), or company specific operations procedures. This type of decision support is a marketable feature.

6. By accessing and processing real time data (i.e. weather, traffic, vehicle telematics, historical delivery times for specific routes/customers, etc.), RAG can help generate more accurate and reliable ETAs. Sales teams can highlight this improved reliability as a key benefit for both their clients and their clients' customers.
7. RAG can retrieve and integrate the latest regulatory information, safety protocols, and location specific risk assessments into the route planning process. Offering route optimization solutions that proactively flag potential compliance issues and/or high risk zones is a very marketable feature.
8. Sales can offer services where RAG analyzes completed routes to generate reports against a backdrop of data (i.e. driver notes, customer feedback, unforeseen event logs, etc.). These reports can identify recurring issues, suggest improvements, and demonstrate the value delivered by the optimization service.
9. The ability for an AI agent to autonomously manage and dynamically adjust entire fleets in real time is a powerful selling point for sophisticated clients. This includes not just optimizing routes but also making decisions about resource allocation (i.e. assigning the right vehicle/driver to the right job based on complex criteria).
10. Agentic AI can identify potential issues (i.e. a vehicle breakdown, a sudden road closure affecting multiple deliveries, etc.) and autonomously initiate solutions to include rerouting other vehicles, rescheduling deliveries, and notifying relevant stakeholders.

Incorporating these proactive capabilities into the sales process may prove valuable to certain clients.

11. A key sales advantage of agentic AI is its ability to learn from every delivery, delay, and piece of feedback to continuously improve routing strategies. This means the system becomes more efficient and effective the longer it's in use.
12. Agentic AI can extend beyond route optimization to influence broader supply chain decisions such as inventory management within smart warehouses. Selling an integrated solution where AI agents optimize various logistics nodes presents a highly sophisticated suite of capabilities to potential new customers.

4.2.6 Research Question 2 Summary

Non-traditional AI can be further used to optimize routes in logistics transportation using artificial neural networks (GANs, VAEs, LLMs, CNNs, DMs), retrieval augmented generation and agentic AI in addition to the previously stated traditional techniques. An operator's bottom line could be most impacted when those elements are applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting. In the context of the UPS and IGI case analyses, specific areas were identified for efficiency gains and opportunities created using non-traditional AI in route optimization.

4.3 Demonstration of Findings

Previously, an analysis was conducted in the form of case studies to determine if the opinions of logistics and AI subject matter experts could be validated by researching both traditional and non-traditional AI examples (applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting). This section will go beyond general validation by demonstrating how the details of the before mentioned findings can further enhance route optimization. The demonstration will include elements of the previously referenced traditional aspects that leverage highly capable hardware, sophisticated and scalable models, disparate data sources and technology types, and that combine several AI techniques (hybridization). Additionally, the demonstration will include elements of the previously referenced non-traditional aspects that leverage the use of artificial neural networks (GANs, VAEs, LLMs, CNNs, DMs), retrieval augmented generation (RAG) and agentic AI.

The prior IGI case study presents an excellent opportunity to illustrate the findings beyond the opportunistic perspective in which it was presented. As a reminder, the original purpose of the research was to determine if profits could be maximized by incentivizing foreign buyers to take product (and create space for incoming product) through a transportation price promotion. The LP model used was static and the variables, objective function and constraints were previously shown in Figure 3.1. What wasn't illustrated previously were the sub-components of the profit margin variable in the objective function. Steps five and six in Figure 4.3 below illustrate the calculation details of those sub-components which include the quantity of products sold subject to the sales price and the transportation cost subject to the price promotion:

Step #1									
Number of Farms	**Acres**	**Total Acres**							
10	1,000	10,000	**Corn**						
10	500	5,000	**Soybeans**						
Step #2									
Yield/Farm - Total Weght	**Bu/Acre**	**Bu / Farm**	**Total Weight**	**Weight/bu**					
Corn	170	1,700,000	95,200,000	**56**	**Corn/Bu**				
Soy	55	275,000	16,500,000	**60**	**Beans/Bu**				
Step #3									
Demand	**Mexico**	**Japan**	**Saudi**		**Bu Demand**	**Remaining**			
Corn	300,000	400,000	500,000		1,200,000	-500,000			
Soy	70,000	60,000	50,000		180,000	-95,000			
Step #4									
Transport Costs			**Leg 1**	**Leg 2**	**Total**	**$/lb**			
St. Louis	Port of South LA		3,500				**50,000**	**lb/Container**	
Port of South LA	Mexico - Port of Altamaria			1,713.50	5,213.50	$0.10427	per/lb		
Port of South LA	Japan - Port of Nagoya			1,702.50	5,202.50	$0.10405	per/lb		
Port of South LA	Saudi Arabia - Port of Damman			1,719	5,219	$0.10438	per/lb		
Step #5									
Minimum Bushels Demanded				**Transport Costs/lb**		**Bu/Corn**	**Bu/Beans**	**Seller Paid - Beans**	**Seller Paid - Corn**
	Corn	**Soybeans**						**0.3**	**0.1**
Mexcio	300,000	70,000		Mexcio	$0.10427	$5.8391	$6.2562	$1.7517	$0.6256
Japan	400,000	60,000		Japan	$0.10405	$5.8268	$6.2430	$1.7480	$0.6243
Saudi Arabia	500,000	50,000		Saudi Arabia	$0.10438	$5.8453	$6.2628	$1.7536	$0.6263
Step #6									
	X11	**X12**	**X13**	**X21**	**X22**	**X23**			
Sales Price/bu (Corn and Soybeans)	9.6	9.62	9.6	3.86	3.86	3.87			
Transport Price/bu (I26-28)	1.752	1.748	1.754	0.626	0.624	0.626			
Net Profit/bu	7.848	7.872	7.846	3.234	3.236	3.244			

Figure 4.3 IGI LP Model Steps and Data

In keeping with the intent of the original IGI research, this research and its findings will be applied to the model and its sub-components to demonstrate how traditional and non-traditional forms of AI can enhance route optimization. An important assumption in this demonstration is that the price of the transportation sub-component is likely obtained by an in-house logistics team working in conjunction with external logistics professionals and/or freight brokers. It is also important to emphasize that the prior research applied to a single location in the U.S. and the before mentioned professionals are likely responsible for similar activities at multiple locations simultaneously around the world. As a reminder the earlier research findings are illustrated in Figure 4.2.

4.3.1 The Scenario:

An AI enhanced platform at IGI is not static like the earlier model and can best be demonstrated through the lens of a global event that impacted freight transport prices. In this scenario, the "event" is the March 2021 Suez Canal blockage which was sudden, severe, and injected both uncertainty and a cascading ripple effect into the global economy causing transportation expenditures to immediately increase by approximately 4-5% (Lee et al., 2021). IGI can control the transportation price incentive, the quoted transportation choice and its corresponding schedule but it cannot control global commodity prices and the quantity demanded by foreign buyers. The stated goal of this report remains cost minimization and asset utilization from an operator's perspective. In this scenario, the in-house team is the "operator" and their job is to minimize the cost of transportation subject to the before mentioned schedule while maximizing the utilization of the assets under their control (i.e. grain silos). Perhaps better said, despite the "event" IGI must still make room for the inbound product.

4.3.2 The Research Applied:

In lieu of the canal blockage and corresponding rate increases, the IGI bottom line can be most impacted when the following techniques are applied to the multi-modal transportation costs and the incentives offered in the model:

4.3.2.1 Leveraging Highly Capable Hardware and Compute Power

High-performance hardware and computing allow for near real-time large scale optimization and re-optimization of complex computational scenarios. As previously pointed out, the model presented is for a single St. Louis, Missouri grain elevator servicing two products from 10 farms. At any given time however, IGI may operate 200 grain elevators servicing 500 farms and 300 international buyers via 50 ports around the world. The "event" would trigger a re-evaluation of all scenarios and require running tens of thousands of variations that would only be possible using massive parallel processing (CPUs and GPUs).

4.3.2.2 Developing More Sophisticated and Scalable Models

As previously discussed, hardware and compute power allow for more sophisticated and scalable models to be efficiently applied to large-scale scenarios and incorporate among other things predictive techniques like AI/ML, Monte Carlo Simulation, Integer Programming, Stochastic and Robust Optimization, etc. The nature of a model is to be trained and to iteratively learn so that its accuracy improves over time and its performance is tolerable when subjected to unforeseen data like the "event".

ANNs are critical to the process of enhanced sophistication and scalability because they can be trained on significant amounts of unstructured historical data to find non-linear patterns that enable further development and scaling of models. In certain scenarios, APIs would enable the ingestion of actual rates but ANNs could predict the rate based on historical market fluctuations as well as predict the performance of certain multi-mode carriers under certain conditions. That same prediction capability can be applied to market prices and demand by foreign buyers. The result is an assessment of supply chain risk and viability that could occur months in advance of an event. While predicting the actual event may be difficult, there may be certain months in a year when similar occurrences are more likely based on weather patterns, geography, or geopolitics and a hybrid model incorporating these techniques can alert stakeholders to the increased possibility.

4.3.2.3 Integrating Disparate Data Sources and Technology Types

Integrating external data sources into IGI's AI enhanced platform would be done using a combination of API's and IoT data that ingest real-time transport costs, commodity prices, and operational data like GPS sensors, weather, etc. and allow for near real time decision making relative to the transport incentive and scheduling. In Figure 4.4 below, the circled sales prices and transport prices would update automatically, and the discount would move based on the desired total margin:

Step #1									
Number of Farms	**Acres**	**Total Acres**							
10	1,000	10,000	**Corn**						
10	500	5,000	**Soybeans**						
Step #2									
Yield/Farm - Total Weght	**Bu/Acre**	**Bu / Farm**	**Total Weight**	**Weight/bu**					
Corn	170	1,700,000	95,200,000	**56**	**Corn/Bu**				
Soy	55	275,000	16,500,000	**60**	**Beans/Bu**				
Step #3									
Demand	**Mexico**	**Japan**	**Saudi**		**Bu Demand**	**Remaining**			
Corn	300,000	400,000	500,000		1,200,000	-500,000			
Soy	70,000	60,000	50,000		180,000	-95,000			
Step #4									
Transport Costs			**Leg 1**	**Leg 2**	**Total**	**$/lb**			
St. Louis	Port of South LA		3,500				**50,000**	**lb/Container**	
Port of South LA	Mexico - Port of Altamaria			1,713.50	5,213.50	$0.10427	per/lb		
Port of South LA	Japan - Port of Nagoya			1,702.50	5,202.50	$0.10405	per/lb		
Port of South LA	Saudi Arabia - Port of Damman			1,719	5,219	$0.10438	per/lb		
Step #5									
Minimum Bushels Demanded				**Transport Costs/lb**		**Bu/Corn**	**Bu/Beans**	**Seller Paid - Beans**	**Seller Paid - Corn**
	Corn	**Soybeans**						**0.3**	**0.1**
Mexcio	300,000	70,000		Mexcio	$0.10427	$5.8391	$6.2562	$1.7517	$0.6256
Japan	400,000	60,000		Japan	$0.10405	$5.8268	$6.2430	$1.7480	$0.6243
Saudi Arabia	500,000	50,000		Saudi Arabia	$0.10438	$5.8453	$6.2628	$1.7536	$0.6263
Step #6									
	X11	**X12**	**X13**	**X21**	**X22**	**X23**			
Sales Price/bu (Corn and Soybeans)	9.6	9.62	9.6	3.86	3.86	3.87			
Transport Price/bu (I26-28)	1.752	1.748	1.754	0.626	0.624	0.626			
Net Profit/bu	7.848	7.872	7.846	3.234	3.236	3.244			

Figure 4.4 IGI LP Model Variables Influenced

Additionally, both weather and GPS sensory data would be incorporated to determine if there was any jeopardy in the product missing the scheduled voyage to the foreign buyer. If either occurred, it would require alternate arrangements in the multi-modal scenario and likely result in higher transport prices and lower profit margins. With respect to the event, the sales price and transport cost would react in real time, and a corresponding transport incentive would be available that would result in a desired profit margin range.

4.3.2.4 Retrieval Augmented Generation (RAG) and Agentic AI

In this scenario, the Retrieval Augmented Agent would work as an autonomous system that monitors on its own the IGI external environment and ecosystem and acts when necessary to achieve its goal of maximum profits. The RAG element acts as an external conduit connecting and augmenting the LP model and its constraints via a live external knowledge base that is both structured and unstructured. Structured data can be real time transportation costs and commodity prices via an API. Unstructured data could be a news report about the "event" obtained via web scraping and a buyer email with order changes from an CRM. The agent continuously monitors and dynamically incorporates the data from all the platform resources and iteratively runs and re-runs the LP model while keeping its human operator in the loop. The Agent would be given parameters under which it can act on its own versus those that require human intervention.

4.3.3 The Results

As the 2021 Suez Canal blockage unfolds, IGI's AI enhanced platform is hosted in an environment with exceptional hardware and compute power. Its model has been trained and is iteratively re-trained on structured and unstructured data incorporating ANNs. External data is connected via API and IoT and is augmented via RAG. An Agent incorporates all data sources and acts within its limits to dynamically re-run the LP model and calculate the new profitability across the entire scope of IGI's operations. More specifically, with respect to this one grain elevator an increase of 4.5% in transport prices would trigger an immediate reduction in the transportation incentive for beans from 30% seller paid to 28.6%. In doing so profits remained steady with a slight increase to $14,256,804 from $14,253,359 while all quantities remained unchanged. If the AI enhanced platform had not been in place, IGI risked providing an incentive that would cause its profits to drop to $14,111,697. The same response would occur across the entire spectrum of IGE's operations and Figure 4.5 below illustrates the changes in the variables for the St. Louis, Missouri elevator.

Step #1										
Number of Farms	**Acres**	**Total Acres**								
10	1,000	10,000	**Corn**							
10	500	5,000	**Soybeans**							
Step #2										
Yield/Farm - Total Weght	**Bu/Acre**	**Bu / Farm**	**Total Weight**	**Weight/bu**						
Corn	170	1,700,000	95,200,000	**56**	**Corn/Bu**					
Soy	55	275,000	16,500,000	**60**	**Beans/Bu**					
Step #3										
Demand	**Mexico**	**Japan**	**Saudi**		**Bu Demand**	**Remaining**				
Corn	300,000	400,000	500,000		1,200,000	-500,000				
Soy	70,000	60,000	50,000		180,000	-95,000				
Step #4										
Transport Costs			**Leg 1**	**Leg 2**	**Total**	**$/lb**			**Suez Canal Increase**	
St. Louis	Port of South LA		3,500				**50,000**	**lb/Container**	1.045	
Port of South LA	Mexico - Port of Altamaria			1,713.50	5,448.11	$0.10896	per/lb			
Port of South LA	Japan - Port of Nagoya			1,702.50	5,436.61	$0.10873	per/lb			
Port of South LA	Saudi Arabia - Port of Damman			1,719	5,454	$0.10908	per/lb			
Step #5										
Minimum Bushels Demanded				**Transport Costs/lb**		**Bu/Corn**	**Bu/Beans**	**Seller Paid - Beans**	**Seller Paid - Corn**	
	Corn	**Soybeans**						**0.286**	**0.1**	
Mexcio	300,000	70,000		Mexcio	$0.10896	$6.1019	$6.5377	$1.7451	$0.6538	
Japan	400,000	60,000		Japan	$0.10873	$6.0890	$6.5239	$1.7415	$0.6524	
Saudi Arabia	500,000	50,000		Saudi Arabia	$0.10908	$6.1083	$6.5446	$1.7470	$0.6545	
Step #6										
	X11	**X12**	**X13**	**X21**	**X22**	**X23**				
Sales Price/bu (Corn and Soybeans)	9.6	9.62	9.6	3.86	3.86	3.87				
Transport Price/bu (I26-28)	$1.7451	$1.7415	$1.7470	$0.6538	$0.6524	$0.6545				
Net Profit/bu	7.8548622	7.8785443	7.85302117	3.2062271	3.2076065	3.2155374				

Figure 4.5 IGI LP Model Variables Changed

CONCLUSION

Research has determined that in the traditional sense, by consistently developing more sophisticated models run by highly capable hardware, by integrating disparate data sources and technology types, and by combining several AI techniques (hybridization), an operator's bottom line could be most impacted when those elements are applied to intermodal and multi-modal line-haul/back-haul as well as local vehicle routing and sorting. In a non-traditional sense, the use of artificial neural networks (GANs, VAEs, LLMs, CNNs, DMs), retrieval augmented generation (RAG) and agentic AI in addition to the previously stated techniques present untapped opportunities when applied to route optimization. That is true not only the focus of this report (logistics transportation operators) but also the previously referenced vehicle modes (i.e. e-bikes and advanced air mobility vs. box trucks and container ships) and use cases (i.e. bicycle messenger delivering a box in a major city and a humanitarian organization coordinating the delivery of emergency supplies to an isolated area). In all cases, stakeholders can look at AI's role to create both efficiencies and opportunities in route optimization as a strategic initiative that will become increasingly critical across all industries/domains. This report presents a framework from which to evaluate the value of that initiative as the pace of AI innovation continues to accelerate.

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APPENDIX A. SURVEY STEPS AND QUESTIONS

Prospective SMEs were identified using a combination of first-hand knowledge and professional networking sites. A threshold of 20 and 10 written/verbal responses was established for data and logistics professionals respectively at an expected response rate of greater than 80% for data professionals and between 20-30% for logistics professionals. Those rates were achieved at 88% (22 of 25) and 33% (10 of 30) respectively. The sample sizes were chosen given the characteristics (i.e. qualifications and experience) of the "expert pool" and the disparity in the response rates was due in large part to active industry affiliation (i.e. currently employed) versus past industry affiliation (i.e. previously employed). As illustrated in Figure 2.2, survey questions were initially broad and open ended while follow-up questions (i.e. re-surveyed) were more precise. Select academic/research professionals were identified by firsthand knowledge of their individual expertise in logistics and AI. In each case, the surveyed questions were qualitative and either emailed or discussed over the phone as depicted below:

Step 2: Industry Professionals/SMEs Surveyed, and an Augmented List Created

- Logistics SME Question: From an operator's perspective, what do you feel are the components of the logistics routing process?
- Data SME Question: Can you provide a list of what you consider to be recent advancements in AI?

Step 3: Industry Professionals/SMEs Re-surveyed, and an Augmented List Refined

- Logistics SME Question: From an operator's perspective, what of the identified logistics elements could benefit most from the application of AI?
- Data SME Question: What of the identified AI techniques show most promise when applied to route optimization?

Step 4: Academic Professionals/Researchers Consulted and Augmented List Further Refined

- Logistics and Data SME Question: Do you agree with the “consensus” list obtained from logistics and AI practitioners and do you have any additional input?