

AI in the Supply Chain: Where Are We Now?

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Supply chain management (SCM) is an ideal sector for [AI software development](#), since the supply chain processes are usually distinct and relatively easy to break down. At the same time, the growth of automated transit and logistics reporting technologies over the last thirty years¹ provides a wealth of clean and classifiable data for machine learning systems.

SCM has proved to be a fruitful adoption sector for automated systems, with AI-enhanced supply chain management forecast to grow at a CAGR of 45.3% from the 2019 levels, reaching US\$21.8 billion by 2027².

Areas where algorithms can improve logistics and management in the supply chain include:

- **Risk assessment:** identifying possible threats to an organization's business model and taking steps to mitigate them.
- **Order fulfilment:** ensuring adequate stock to meet demand over the course of a year, based on historic and seasonal demand patterns.
- **Inventory management:** the logging and monitoring of inbound materials, available stock and outbound orders.
- **Fleet management:** including the procurement and maintenance of delivery vehicles covering land, air and sea, as well as monitoring their disposition, availability and TCO.
- **Procurement:** balancing the logistics of inbound materials against delivery dates and fulfilment targets.
- **Last mile delivery:** the optimization of consignment strategies between fulfilment centers and final destination of the product.
- **Capacity planning:** the creation of flexible provisioning for peak stock levels while avoiding long-term over-commitment of storage capacity.
- **Shopping cart diagnostics:** using shopping cart behavior to inform after-market marketing, and analyzing new approaches to retention where stocking or consignment problems occur after a customer has placed an order.
- **Demand forecasting:** AI-enabled analytics helped food producer Danone to achieve a 20% drop in forecast error and 30% reduction in lost sales by adopting machine learning analysis for product demand³.

Let's take a look at perhaps the most obvious challenge for AI in the supply chain: creating the most economical and effective supply routes for delivery of goods.

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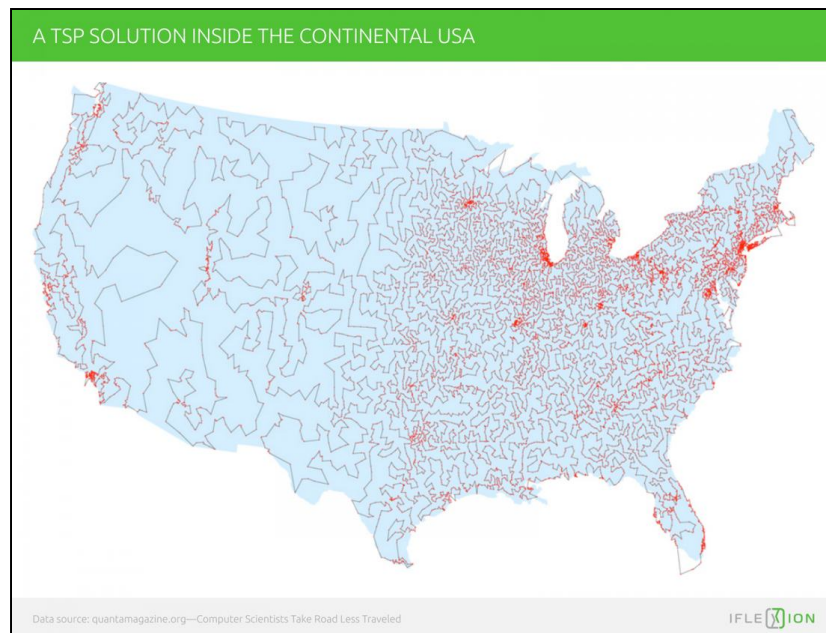
Using AI to Create Optimal Delivery Routes

The 'travelling salesman problem' (TSP) hails back to the early 19th century. It has since become a minor obsession in computer science and, more recently, in machine learning research⁴ aimed at improved route design.

The theoretical challenge is to find the optimum route for a series of stops over a wide geographical area, conserving time and resources where possible. The best solution is surprisingly elusive, and is susceptible to a wide range of mathematical approaches:



Although routes can be optimized on a case-by-case basis, there is an existing general algorithm that's able to predict the best possible way from point A to point B.



Developed in 1976, the 'universal' algorithm's best route is still 50% longer than the most efficient route for any specific case⁵. It took the scientific community more than 35 years⁶ to find ways to improve this generalized algorithm even by 10%.

Over the last decade, however, the combination of big data and GPU-accelerated machine learning has made new inroads on route optimization.

Optimizing Land Delivery Routes

UPS's On-Road Integrated Optimization and Navigation (ORION) framework currently spares the logistics company 100 million miles of travel per year over 55,000 routes in the US, saving ten million gallons of consumed fuel and 100,000 metric tons of carbon emissions⁷. The system now constantly analyzes vehicle feedback in a centralized machine learning framework⁸ based in New Jersey.

Other AI-based initiatives for optimizing supply chain routing include:

- **Amazon Prime**, which leverages Amazon research into artificial intelligence, machine learning, and predictive statistics to calculate total deliveries and allocate vehicle space based on weight, volume, driver workload, traffic, and even the type of building that deliveries are destined for⁹.
- **LaMP**, an AI-powered regional logistics platform covering Southeast Asia that uses machine learning to consolidate deliveries from multiple companies into the most convenient vehicle available to deliver all of the items¹⁰.
- **Uber Eats**, which addresses the logistical complexity of hot food delivery by feeding GPS and motion data into a machine learning system that's capable of calculating the many variables that make efficient takeout logistics harder than transporting passengers¹¹. The system uses conditional random field (CRF) to model the 'trip state' and generate predictions for delivery times, as well as to calculate optimal routes.

In Southeast Asia, the growing demand for deliveries in densely-populated cities is leading to further innovation from the scientific community. Research out of the Singapore Institute of Manufacturing Technology¹² proposes a new method to overcome the logistics issues that arise when suppliers have incomplete information about peak demand times, the actual volume of customer packages (rather than the registered weights), and whether or not their delivery requirements will need to be redirected to third-party companies.

A study from Thailand uses artificial neural networks (ANNs) to generate a new guidance system for automated vehicles and robots that must traverse vast factory floors and navigate novel obstacles that may or may not be permanent.

Finally, a collaboration between industry and academia in China recently published details of a smart tour route-planning algorithm for popular Chinese cities¹³. The system mines historical data and is powered by a Naïve Bayes classifier. It can develop unique routes based on the interests of particular assemblies of tourists (rather than identifying and touring the 'most popular' locations).

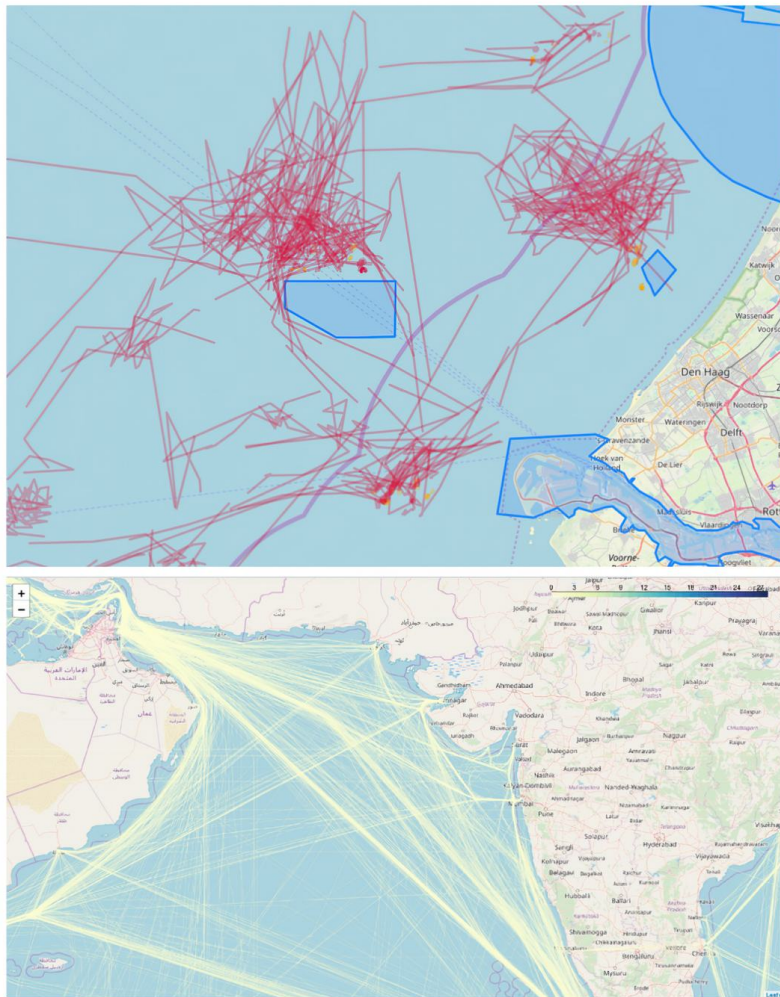
Calculating Shipping Routes and Port Navigation with Machine Learning

Maritime transport represents around 90% of global trade¹⁴, as it remains the most economical method of delivering goods. Since it also represents 2.5% of global greenhouse gas emissions¹⁵ and was estimated in 2017 to lose US\$18 billion annually to 'wait times'¹⁶, the shipping sector is motivated to achieve more optimized ocean journeys and make shorter and more productive stops at busy ports.

It's possible to incorporate historical data of the behavior of commercial ships near busy ports¹⁷ in order to assess the risks of being delayed there in a variety of possible circumstances. One marine information services provider uses¹⁸ the Random Forest Classifier in scikit-learn on such data to analyze historical patterns of 'loitering' and 'anchoring' near busy ports, in order to determine optimal routes and schedules.

ML-OPTIMIZED SHIPPING ROUTES

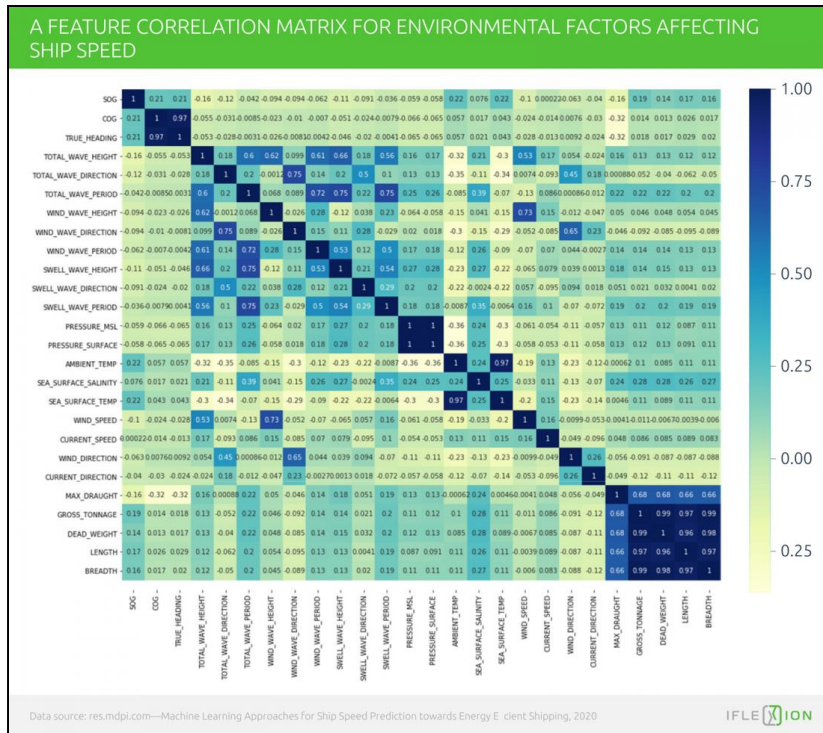
AIS data regarding anchoring and loitering near ports in Belgium and the Netherlands (above), and a calculation of optimal routes arrived at with Random Forest classifier via scikit-learn.



Data source: towardsdatascience.com—Creating sea routes from the sea of AIS data, 2019

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Late-arriving ships have an impact on the tight schedules of ports and can compromise delivery targets. A proposal from Korea¹⁹ uses historical AIS transponder data to develop a more accurate model of the water-resistance for generalized shipping traffic — a critical factor in determining a vessel's actual running speed and estimating a more precise arrival time.



The system, designed to cut fuel consumption, correlates AIS data with live weather feeds to calculate the vessel's speed over the ground (SOG) and uses a variety of [machine learning techniques](#), including gradient boosting regressors (GBRs), linear regression (LR), polynomial regression, extra trees regressors (ETRs), and random forest regressors (RFRs).

Machine learning can help with the unloading and deployment of a vessel by improving scheduling, internal routing, and general readiness for the port's particular technical environment:

- Research funded by the Ministry of Science in Korea²⁰ proposes a novel system to speed Interterminal Truck Routing (ITT) optimization with the use of deep reinforcement learning via a Deep Q Network. The research analyzed 576,000 combinations of states and actions in order to develop an AI-driven model of the Busan New Port terminal in South Korea.
- The Port Of Montreal has adopted machine learning to optimize freight planning by comparing the ways that a number of loose variables (such as storage capacity, staff availability, vessel arrival times and rail deliveries) impact the fluidity of port activities²¹.
- German port operator Hamburger Hafen und Logistik (HHLA) uses machine learning to improve container location selection and stack location, to reduce 'dwell time' for unloading vessels at a major port²². The initial database model was generated from historic data from container handling operations and is now constantly updated. The developers foresee a long-term improvement in prediction accuracy of 33% for outgoing traffic and 26% for predictions of dwell time²³.

AI is already used to create optimal delivery routes, and here's how.

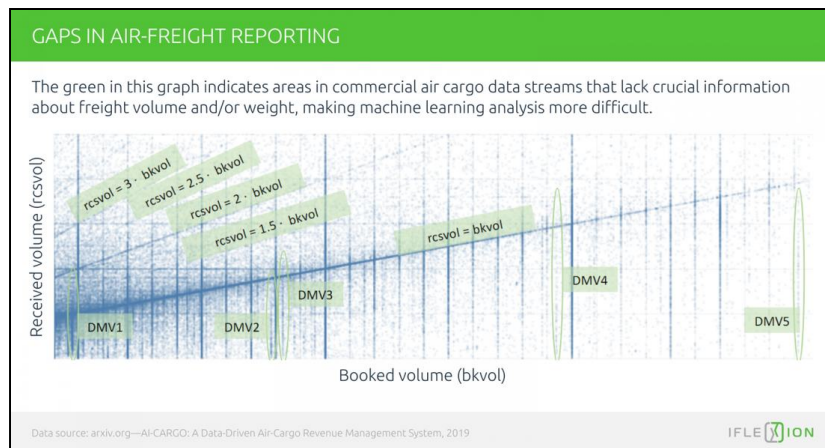
AI in Freight Aviation

The need for human oversight rises rapidly for commercial aviation routes, and here the private sector has less leverage against state governance and international regulation than with land-based and maritime delivery.

The commercial air-freight industry is recognized to be hindered by legacy data technologies and non-digitized workflows²⁴. It is also bound by a compelling commitment to security and a NASA-style skepticism regarding the latest technological trends²⁵.

Nonetheless, the challenges of the COVID-19 pandemic have accelerated the lagging digitization of the industry²⁶, just as new initiatives emerge to improve logistical operations through machine learning.

- Research from the Qatar Computing Research Institute²⁷ proposes an AI-based revenue management system designed to predict the received weights and received volume of air freight. The study consequently identified 'prolific' systemic gaps in the reporting systems in the air-freight industry (see image below) — a practical problem that may require [AIoT solutions](#) on the front line in order to generate better data for machine analysis.
- Under financial pressure from 'no-show' cargo consignments, American Airlines built a GPU-accelerated machine learning model that analyzed half a million air cargo records over 12 months to help predict which consignments were most likely not to arrive as scheduled²⁸.
- Lufthansa Cargo launched a project for AI to replace manual pricing estimates, with instant quotes driving customer attention and retention²⁹.



Warehouse Automation through AI

While a recent industry report estimates that only 12% of logistics businesses have currently adopted AI technologies³⁰, the global market of [warehouse robotics](#) is forecast to grow at a CAGR of 27% from US\$ 6.12 billion in 2019 to US\$25.8 billion by 2025³¹.

A key area for AI in warehouse automation is Automated Storage and Retrieval Systems (ASRS), wherein machines deposit and retrieve items from inventory.

Emerging machine learning approaches are leveraging cutting-edge sensor technologies including [computer vision](#), haptic feedback, 3D vision, 'Light coding' with lasers, and laser triangulation. Additionally, ASRS is perceived as beneficial to wider fields of machine learning and to the development of AI benchmarking standards³².

After nearly a decade of research into warehouse logistics, Amazon is now deploying increasing levels of AI, including the automatic tracking and scanning of items³³, into its fulfilment centers. Though the company has stated that fully automated warehouses are a decade away³⁴, it has made waves with the introduction of the Italian-made Carton 1000 automated packing system at a number of locations³⁵ and has a long-term commitment to increasing AI-based deployment logistics automation solutions³⁶.

Pallet detection and tracking is another popular area of research in this sector. With over five billion wooden pallets in circulation in the EU and US combined³⁷, computer vision is able to identify individual pallets from surface wear and wood grain and even to assess when they have reached end-of-life³⁸.

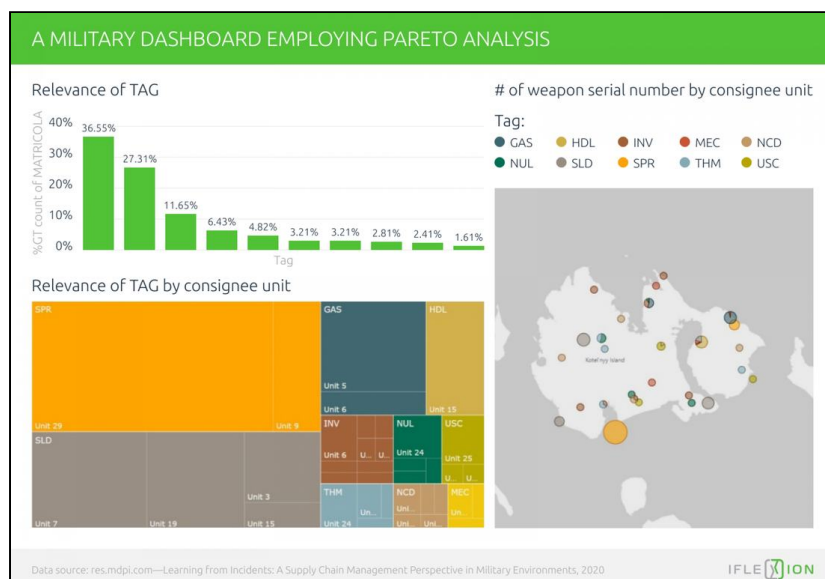
Optimizing the Supply Chain with AI-Enabled Pareto Analysis

It's easy (and expensive) to over-engineer AI-based solutions, and it can be difficult to understand which parts of a physical process or state will benefit most from automation.

One method for deconstructing a supply chain process is Pareto analysis, which, applied to SCM, presumes that an 80/20 imbalance is likely to exist somewhere in any organically-developed production process. The 80/20 principle is broadly representative — it's enough to locate and address any significant imbalances that Pareto analysis might reveal.

Machine learning can also help in the application of Pareto analysis to existing supply chain models. For instance, Supply Chain Risk Management (SCRM) is an active area in AI research, with Pareto optimization widely used to identify potential bottlenecks or areas of inefficiency³⁹.

The military logistics sector also has a deep interest⁴⁰ in Pareto analysis. A recent study⁴¹ into supply chain management in military environments was able to identify that three particular types of damage were apparently causing 75% of weapons failure issues in a deployment zone.

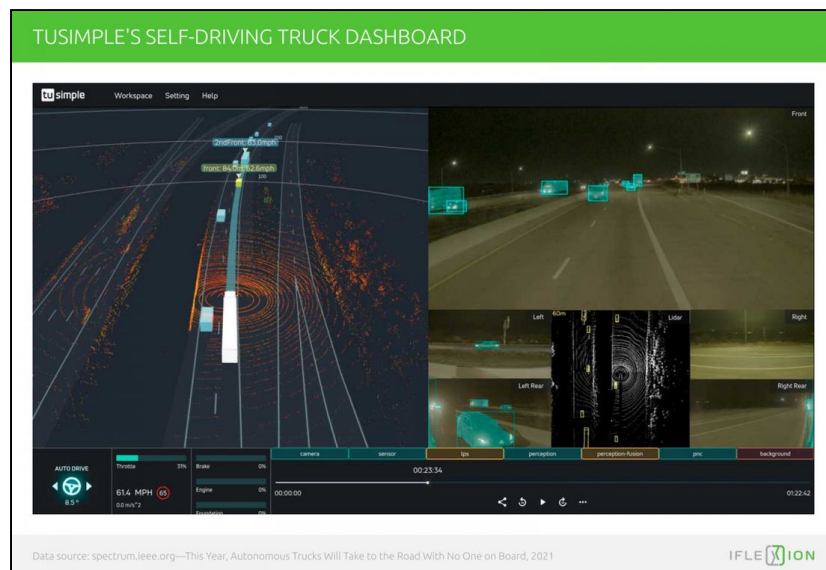


AI-driven Pareto analysis can also help to develop a purchasing strategy, and to identify 'core suppliers' in a crowded market. In one case, a Korean automobile component manufacturer used a Random Forest approach to analyze five years of e-invoice data covering 125 suppliers⁴². As a result, it was possible to identify 36 core suppliers on whom the company had perhaps become over-dependent, and to subsequently spread the general risk of procurement across a wider base of suppliers.

Unmanned SDVs in the Supply Chain

While representing a fair bit less than 20% of actual deployed and functional AI-based SCM technologies, self-driving/piloting vehicles arguably occupy more than 80% of popular headlines around AI in the supply chain. For example:

- In 2016 industry participants in the European Truck Platooning Challenge completed a cross-continental journey with a convoy of robotic trucks shepherded by a human driver in the lead⁴³.
- One US self-driving truck startup has just launched a 4D Lidar system on its fleet of self-driving trucks (all of which must have a human operator) after a \$350 million funding round in 2020 (see image below)⁴⁴. Level 4 (driver-free) autonomy is anticipated in the near future in restricted environments and weather conditions.
- Rolls Royce's autonomous shipping program⁴⁵ is the current emblem of a growing market⁴⁶, with its autonomous marine systems subsequently absorbed into Kongsberg Gruppen's ambitious plans for unmanned short-range cargo vessels⁴⁷.
- IBM's 'AI captain' took control of a crewless research vessel off the coast of the UK in 2020⁴⁸.
- Airbus reports the successful development of unmanned aviation, though customer confidence in a pilot-free airplane is currently lacking⁴⁹, while legal oversight and insurance costs are further obstacles⁵⁰.



If we don't dwell on the topic here, it's because the pace of development in this sector is far, *far* ahead of [the AI regulation environment](#) and the revised definitions of 'liability' necessary for unsupervised, long-distance SDVs to embed deeply into the supply chain; and because the necessary future developments around this sector are at least as sociological and political as they are technological.

The necessary future developments around self-driving vehicles in supply chain are as sociological and political as they are technological.