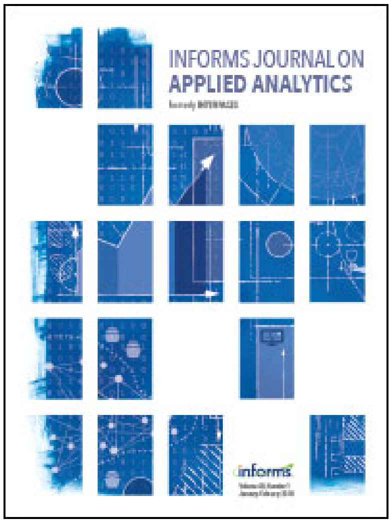

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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

McDonald's China Adopts Operations Research for Network Design

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Abstract. The supply chain network design (SCND) problem is a typical optimization problem that determines the structure of a supply chain and affects its costs and operational performance. SCND deals with various decisions, such as determining the number, size, and location of facilities and the optimal material and product flows of the entire supply chain network. Therefore, SCND is one of the most crucial planning problems in supply chain management. In this paper, we present a practical approach in which we adopt a mixed-integer programming (MIP) mathematical model to solve a real industry SCND problem for McDonald's China. As a result of this project, McDonald's China has saved millions of dollars in logistics costs and reduced CO_2 emissions by more than 10%. In our approach, size-reduction techniques were successfully applied to deal with a large-scale model, making it possible to analyze hundreds of scenarios before coming to a consensus.

Keywords: network design • supply chain optimization • large-scale MILP model • mathematical modeling • Edelman award

Introduction

McDonald's is a world-leading food service brand with over 40,000 restaurants across the globe, serving more than 68 million people each day. McDonald's mission is to make feel-good moments easy for everyone. Across the business, McDonald's strives to live up to its purpose, to feed and foster communities. The first McDonald's restaurant in the Chinese mainland opened in 1990. Today, China is the second-largest and fastest-growing McDonald's market. McDonald's China is committed to providing great taste and value anytime and anywhere. With multiple business platforms, including restaurants, McDelivery, McCafé, Dessert Kiosk, and Drive-Thru, McDonald's China proudly serves a menu with global classics and local favorites, such as Big Mac, French Fries, Spicy Chicken Filet Burger, and McCrispy Chicken.

As a globally recognized food service brand, McDonald's diverse menu extends far beyond its iconic hamburgers and fries. With an objective of fostering communities, McDonald's has woven itself into the fabric of Chinese urban life since its introduction in the early 1990s, boasting over 4,000 restaurants across the country by 2021. Looking ahead, McDonald's China aims to double its presence to 10,000 outlets by 2028, particularly targeting second- and third-tier cities to embrace new customers and opportunities. Figure 1 illustrates the geographic spread of McDonald's outlets in 2020, with the size of the circles representing the concentration of stores within each city; the figure demonstrates the presence of McDonald's outlets in many small cities in China.

This ambitious expansion, however, presents a unique set of challenges. The geographic diversity of these cities, while enriching, poses logistical hurdles for the McDonald's supply chain network. The task at hand is not merely about expanding store count but ensuring seamless product delivery to meet the varying needs of each location.

As McDonald's endeavors to heighten brand awareness in China, a critical aspect involves establishing a robust supply chain. Ensuring that thousands of products reach McDonald's restaurants daily in a timely, secure, and optimal condition is paramount. Recognizing the impact of a highly efficient network on operational effectiveness and reducing carbon emissions, McDonald's is committed to contributing to a greener planet.

Figure 1. (Color online) The Heatmap Illustrates the Distribution of McDonald's China Stores as of 2020

Notes. We used masked data to create this map. The size of the circles represents the concentration of stores within each city.

Xiahui Logistics, established through a joint venture in 2018 between SF Holding and HAVI, plays a pivotal role as a key logistics provider for McDonald's China, managing both inbound transportation from manufacturing plants to distribution centers (DCs) and outbound transportation from DCs to restaurants. With over 2,000 Xiahui trucks traversing the roads daily for McDonald's China, covering a yearly total mileage equivalent to nearly 2,000 trips around the globe, the scale of operations is immense. As McDonald's sets out to double its outlets by 2028, this expansion presents a significant business challenge for the Xiahui logistics team.

Recognizing the intricacies and challenges inherent in the supply chain network, McDonald's supply chain team and its logistics operation partner, Xiahui Logistics, have opted to leverage operations research technology. This strategic decision aims to formulate a comprehensive blueprint for the supply chain roadmap, guiding McDonald's operations in China through 2028.

It was necessary to establish a digital twin of the supply chain network to analyze the optimal configuration of the network roadmap, which we explain in the following sections.

1. Network structure: The model should simulate a three-layer network structure. It should replicate the flow of products from a factory to a DC and then from the DC to various demand points.

2. Cost:

2.1. The model should incorporate transportation costs. It must account for inbound transportation costs from the factory to the DC and outbound transportation costs from the DC to the demand points. The network's structure should impact the total transportation cost, and the optimization model should identify the optimal locations for the DCs, with the objective of minimizing total cost.

2.2. The model should account for storage costs, which are influenced by the overall stock levels. The total stock encompasses both cycle stock and safety stock. The quantity of cycle stock is a user input expressed in terms of days of inventory for each stockkeeping unit (SKU). Safety stock, on the other hand, is computed using the square root law, where the total inventory is proportional to the square root of the number of locations at which a product is stocked (Maister 1976).

2.3. The model should consider handling cost; the locations of DCs influence handling cost because labor cost could be higher in developed cities in the country.

3. Business constraints:

3.1. The model should ensure compliance with factory production capacity constraints.

3.2. In each McDonald's China DC, three distinct storage areas exist: frozen, chilled, and dry. The model is required to enforce capacity constraints for each of these storage areas within each DC.

3.3. The model should enforce the total capacity constraint of each DC.

3.4. If an existing DC should be retained, it cannot be closed and reopened.

3.5. Users can control which year an existing DC should be closed.

3.6. Users can control the opening year and closing year of a new DC.

3.7. If a DC is opened and later closed, it cannot be reopened.

The digital twin must demonstrate the ability to effectively simulate all specified requirements and produce a high-quality solution, utilizing optimization technology to address the following questions:

1. Until year 2028, with the imperative of satisfying all demand while minimizing logistics costs, what constitutes the optimal DC roadmap for McDonald's China?

2. What is the optimal configuration for the coverage setup plan (the optimal flow quantity from the plant to the DC, and from the DC to the restaurants for each SKU each year) to ensure efficient and effective operations?

Various approaches can be employed to tackle the network design problem we outline above. The next section, titled Introduction to Supply Chain Network Design, serves as an introduction to the approach and diverse methodologies we utilized in addressing this challenge.

Introduction to Supply Chain Network Design

Each supply chain has different levels of issues: (1) operational-level issues, such as daily transportation scheduling and stock replenishment plans; (2) tactical-level issues, which include decisions that are usually updated seasonally or annually, such as actual coverage of the network, SKU, and facility mapping; and (3) strategic-level issues, which deal with long-term decisions such as the number, location, size, and flow of the logistics network.

Supply chain network design (SCND) is a strategic-level optimization problem that creates a network of supply chain entities and includes a set of decisions about the location and role of supply chain entities, product allocations, capacity planning at the strategic level, and the establishment of transportation and informational links between these entities (Chandra and Grabis 2007). With some minor functional enhancements, such as fixing the number and location of the facilities, it can also address some tactical issues, like determining the optimal flow of the entire supply chain with a fixed set of locations.

Different approaches for SCND include mathematical programming, simulation, and multiple-criteria decision making. The use of mathematical programming models is a common approach for the SCND problem. The primary decision variables in SCND models related to facility location, sizing decisions, appropriate technology selection, and the selection of transportation modes between facilities are binary (Eskandarpour et al. 2015).

This project started during the pandemic, which exposed vulnerabilities in supply chains. We experienced unexpected closures of some food plants and disruptions in logistics routes. A resilient and sustainable supply chain enables McDonald's to respond swiftly and pivot to alternative suppliers and transportation routes when needed. This adaptability helps maintain a steady flow of food ingredients, ensuring restaurants remain stocked and operational. Therefore, the resiliency and sustainability of the supply chain garnered significant attention from the McDonald's management team. Supply chain resilience refers to the ability to recover from a disruption quickly and effectively (Behzadi et al. 2020, Ivanov 2021). In such turbulent times, the design of the supply chain is much more complex than before. There are certainly more "land mines" that supply chain executives need to be aware of, and thus, they must navigate their decision process accordingly (Cohen and Lee 2020). We first reviewed the research that had been conducted in the sustainable SCND domain.

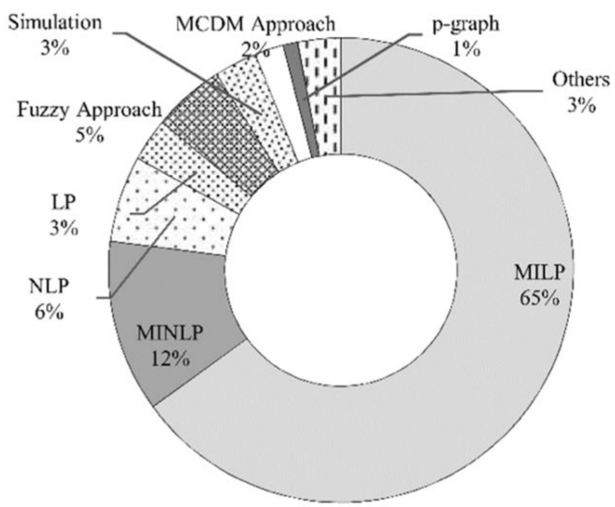
Asgharizadeh et al. (2019) offer a literature review on sustainable SCND, covering papers published from 1990 to 2016. In their review of 261 papers, the authors find that mixed-integer linear programming (MILP) is the most common approach among mathematical programming models, with 65% of the models utilizing it; see Figure 2.

Using mathematical programming models to address SCND problems offers several advantages. One significant advantage is the ability to obtain an exact optimal solution as a result of good modeling techniques and efficient mathematical solvers. This optimal solution ensures the efficiency of the entire supply chain network based on the specific setting and data provided. A second advantage is the interpretability of the model's results because it allows for a deeper understanding of the network design outcomes.

Furthermore, mathematical programming models are less sensitive to changes in data. Unlike heuristic- or simulation-based approaches where the quality of the solution can be sensitive to the change of data sets, a mathematically derived optimal solution maintains its quality even when the data change. This robustness is especially valuable for real-world industry applications, where reliable and consistent results are crucial.

However, using mathematical programming models for SCDN problems also has some disadvantages. First, the formulation becomes the MILP model because of

Figure 2. The Graphic Shows the Distribution of the Sustainable SCND Modeling Approaches Used in the Papers Reviewed by Asgharizadeh et al. (2019)



Note. MCDM Approach, multi-criteria decision making approach; LP, linear programming; NLP, non-linear programming; MINLP, mixed integer non-linear programming.

the need for binary variables. As the number of variables and constraints increases, solving the model becomes more challenging and may become intractable. Careful design and consideration are necessary to control the model's size and complexity, especially when dealing with large-scale industry problems.

Second, to solve MILP models efficiently, constraints and the objective function need to be linear. Although commercial solvers can handle some specific nonlinear problems such as quadratic programming (QP) or quadratically constrained programming (QCP) models, the solvability of these mathematical models is generally less efficient than linear programming models. Therefore, in practice, nonlinear requirements are often linearized whenever possible to ensure tractability and facilitate solution delivery.

In summary, mathematical programming models provide valuable benefits in addressing SCND problems such as generating optimal and interpretable solutions. However, careful consideration must be given to balancing optimality and solution speed and addressing the limitations of MILP models related to their size and linearity assumptions.

Technical Challenges

The challenges in the McDonald's supply chain businesses include, but are not limited to, the size of the network scope (e.g., 3,000 SKUs, 5,000 restaurants with a target of 10,000 by 2028, more than 100 factories for various products).

Transportation cost is a significant component, and its accuracy is crucial. It is directly proportional to the distance traveled and can be influenced by different factors, such as the service provider, region, product types (e.g., frozen, chilled, or dry; short or long shelf-life), and the economic scale of both the origin and destination cities.

The analysis for SCND is typically conducted based on average customer demand. In the context of fluctuating demand patterns, it becomes essential to allocate storage capacity strategically, reserving space for peak seasons. Determining the appropriate amount of storage capacity to reserve for peak seasons requires a meticulous analysis of historical data. Reserving too much capacity may result in resource wastage and low utilization rates, whereas too little reservation can lead to storage issues during peak seasons. Finding the right balance is crucial for optimal resource utilization and effective management of customer demands.

In addition, some unique requirements of the McDonald's China supply chain include the following:

1. Data availability and readiness: Because of the complexity of the McDonald's supply chain network, the project team, which included McDonald's supply chain users, Xiahui Logistics, and Optimization Analytics Technology, needed to collect vast amounts of data. However, many data silos were found with duplicate entries, outdated information, human mistakes, and even data stored only in file cabinets and human brains. Lack of data readiness was one of the most significant difficulties encountered. The project team received support from the McDonald's China management team to conduct over 40 interviews with different functional groups. The team collected, cross-checked, cleansed, and verified operational data to build a solid, structured data model for the system. This formed the foundation for ongoing analysis and potential advanced analytics projects in the future.

2. High model accuracy: The McDonald's China supply chain team set a high standard for accuracy in the model results. Specifically, the difference between the costs calculated by the model and the actual costs needed to be less than 1%. This required precise input data and a thorough model logic. Key input data included transportation costs for different segments, forecasted demand, and warehouse costs, all of which were crucial for the network planning application to yield meaningful results. Additionally, every detail of the business logic for the entire supply chain had to be incorporated into the model to achieve the 99% accuracy target.

3. Large-scale optimization model: McDonald's China needed to optimize its DC roadmap until 2028, considering potentially 10,000 stores, hundreds of DC locations, thousands of SKUs, and over 100 production sites. The decision needed to be made at the SKU level because it was related to the factory's supply capacity, and the

inbound transportation cost affected the number of locations for the DC. This meant that the size of the mathematical model could quickly increase beyond the capability of commercially available solvers.

4. Interpretable results: Although a mathematical model can generate optimal results, effectively presenting these results in a persuasive format to gain acceptance from all stakeholders is a different challenge. The project team members strived to achieve this, transforming their diligent efforts and convincing results into widespread acceptance among all stakeholders.

How We Approached the Challenges

Integrated Forecasting Models

Given China's vast size and economic development disparities, we employed a pattern recognition algorithm to analyze historical data encompassing various parameters such as demand and inbound/outbound transportation costs. As an illustration, transportation costs are typically expected to correlate with distance and volume. However, the actual cost function for transportation can vary significantly, especially in the western regions of China, where the road network is less developed than in the eastern regions. Additionally, finding return freight in these areas can pose challenges, influencing the overall transportation cost dynamics. This analysis led to the segmentation of data regions based on data types. To enhance accuracy, we conducted forecasting separately for each data region. The forecasting process integrates machine learning algorithms, regression technology, and user-friendly graphical user interfaces (GUIs). The GUIs facilitate advice and feedback collection from domain experts, ensuring a meticulous examination of each data set's characteristics and influencing factors.

Large-Scale Integer Programming Model and Model Decomposition Framework

The project's pivotal decisions revolve around the plant and DC roadmap until 2028, where uncertainty plays a significant role in shaping these decisions. Therefore, we employed a stochastic approach with recourse to enhanced decision making in the face of uncertainty. The application is crafted to facilitate easy reexamination and adjustment of decisions annually, taking into account the actual execution progress and related input data.

Although MILP models enable optimal solutions with explicability, challenges arise as solvability diminishes with an increase in model size. Consequently, we implemented various model size reduction techniques to address this challenge.

1. We opted for the following aggregations to reduce the model's size.

1.1. Demand aggregation: Rather than evaluating demand at the store level, which involves around 10,000 demand points, we considered demand at the city level, resulting in approximately 350 demand points.

1.2. SKU aggregation: Given the numerous distinct SKUs, many of which are interchangeable, we consolidated them into groups. For instance, we considered chili sauce from various suppliers, although they were treated as different SKUs in the data system, as the same item. In this way, we reduced the number of SKU groups from over 2,000 SKUs to around 150 SKU groups in the network design system.

2. Among all the decision variables, the outbound flow variable representing the quantity transported from each DC to each demand point of each SKU in each time period (i.e., $of_{i,d,s,t}$, as we discuss in the appendix) is the largest in size because it involves approximately 200 potential DC locations. Despite aggregating demand points to the city level, there are still around 350 cities and 150 SKU groups. Considering the model's five-year time horizon, the number of outbound flow variables totals 52.5 million. Despite being continuous variables, solving a model with such a vast number of variables would be time-consuming for any commercial solver; the original model took over 10 hours to solve but did not achieve an optimal solution. To address this issue, we implemented multiple techniques to reduce the number of variables.

2.1. Eliminating the SKU dimension from the outbound flow variable: After in-depth discussions, we observed that, in most cases, stores within each city were primarily served by a single DC for all SKUs. A different DC may become involved in supplying a city if and only if the assigned DC lacks stock, and there is urgent demand to be met—although such occurrences are exceedingly rare. Because of this pattern, we deemed it safe to eliminate the SKU dimension from the outbound flow variable. In this revised scenario, the outbound flow variable is represented as $of_{i,d,t}$. This modification led to a significant reduction in the number of variables. Consequently, in Constraint (A.5) in the appendix, the DC SKU flow balance constraint needed to be adjusted as follows:

$$\sum_f if_{f,i,s,t} = \sum_d of_{i,d,t} * \pi_{d,t,s} \quad \forall i, s, t$$

where $\pi_{d,t,s}$ is a parameter that represents the ratio between demand of SKU s and total demand (for demand point d in year t).

2.2. Eliminating unrealistic flows: Because of the expansive geography of China, as we show in Figure 3, it is challenging to envision stores in the far eastern section of the country being serviced by a DC in the far western section, and vice versa. Similar reasoning applies to the south and north regions.

Therefore, excluding potential flows between specific DC locations and stores within cities was prudent. We developed, tested, and implemented such meticulously crafted logic to eliminate about 60% of the variables.

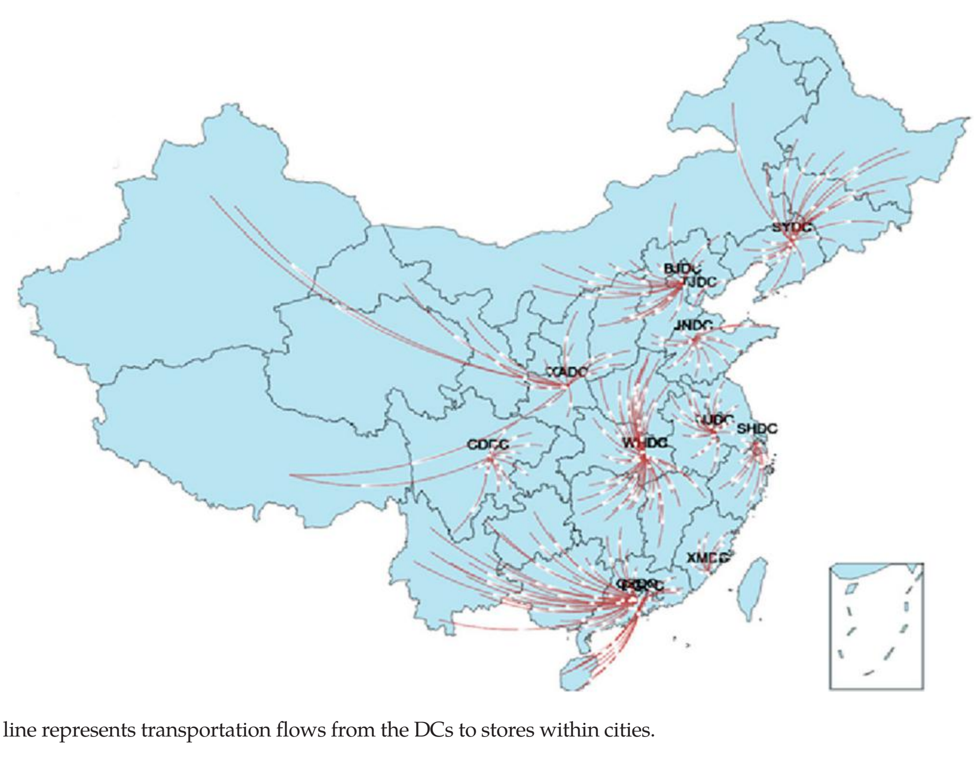
3. The number of potential DC locations significantly influences the model's size, impacting nearly all variables. We first ran a five-year model and then ran the model separately for each year; we then compared the DCs selected by the five-year model with the DCs selected by each single-year model. We observed that if any of the five single-year models did not choose a given DC, the five-year model would also not choose that DC. Employing this logic, the optimization process begins by running the five single-year models. Based on these results, specific DC locations are filtered out before executing the five-year optimization. Although it necessitates running a total of six models, the smaller size of each single-year model, when compared with the size of the entire five-year model, resulted in significantly reduced solving time.

By implementing the aforementioned model-reduction techniques, the total runtime was reduced from 20 hours to less than 10 minutes to reach optimality (with an optimality tolerance of 10^{-6}). This efficiency enabled the project team to analyze hundreds of scenarios before arriving at a conclusive decision. A supply chain network designed and planned for higher efficiency could unlock the greater potential of the optimization applications, whereas faster optimization applications can enable more simulation runs, which allow the evaluation of more scenarios, and thus improve the likelihood that executive decision makers will adopt the recommendations (Mehrotra et al. 2024)

Intuitive Graphical User Interface (GUI) for Visualization

To convey the value of operations research to business leaders, the GUI assumes a crucial role in showcasing the technology's efficiency and effectiveness. Through the GUI, the supply chain team can intuitively visualize the distribution of McDonald's outlets and the positioning of DCs. Key performance indicators (KPIs) include metrics such as the number of long-distance delivery stores, defined as those where the distance from the DC to the store exceeds 300 kilometers. Through parameter adjustments, selection of diverse KPIs, establishment of multiple control conditions, and modifications in input data, the GUI facilitates the creation and display of scenario comparisons side by side on the screen. Business insights are gleaned by conducting a comprehensive 360-degree sensitivity analysis for each scenario.

Figure 3. (Color online) The Map Illustrates Outbound Coverage from the DCs to Stores in China



Note. The dashed line represents transportation flows from the DCs to stores within cities.

The mathematical model incorporates structured requirements and KPIs. However, certain elements such as local government policy and local infrastructure standards cannot be incorporated into this model. To address these considerations, we developed a comprehensive and user-friendly GUI with the following functionalities:

First, the GUI enables users to quickly identify the drivers of optimization results; through the GUI, the system can present and analyze outcomes from various perspectives. It can also quickly respond to inquiries from various business stakeholders such as management, operations, data teams, and third-party logistics teams.

Second, the GUI incorporates user feedback and introduces controls to the optimization model for subsequent scenario runs; examples include adjustment of new restaurant opening plans and capacity of the DCs, thus ensuring the reflection of human input.

Third, the GUI swiftly assesses the monetary impact of human feedback controls. For example, the user can change the DC location to a neighboring city and analyze the cost implications of that change.

Some examples of GUI screens are as follows. As Figure 4 shows, users can display different segments of the overall coverage by adjusting control parameters, which include displaying only locations or flows (outbound, inbound, or both) or both by year, a DC or set of DCs, or an SKU or set of SKUs as a regular map or heatmap. Control parameters can be combined to exhibit partial results for in-depth analyses.

Figure 5 shows the cost analysis GUI screen, which comprises yearly component cost components as a table or pie chart and DC-related cost details.

Results Validation and Verification

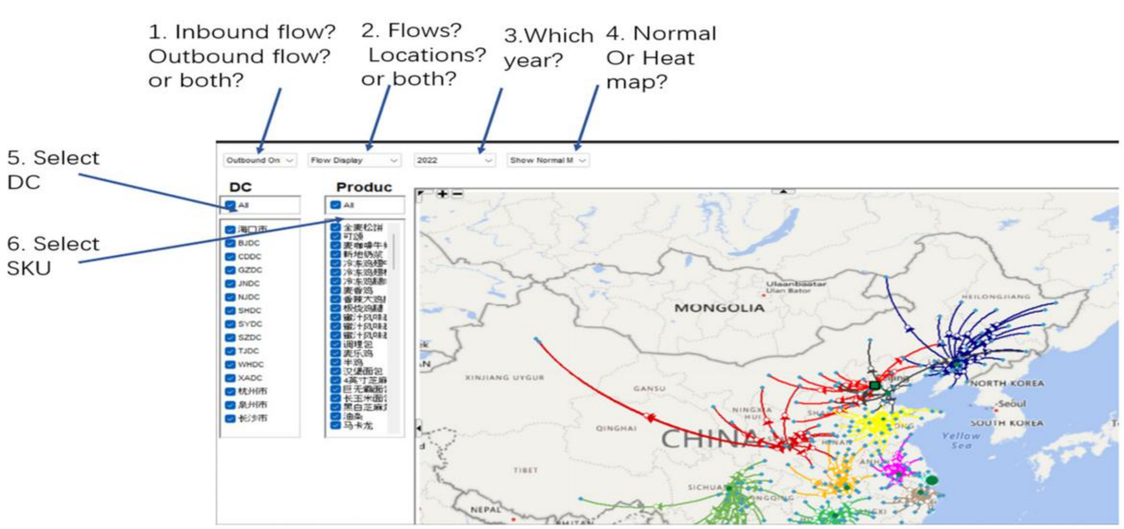
We used baseline data from the year 2020 to validate the project. We had an in-depth discussion about which year to choose as the baseline. We selected 2020 because it reflected the most recent fundamentals of the McDonald's China supply chain network. We recognized that 2020 was a unique year because of COVID-19. However, we concluded that the impact of COVID-19 on China in 2020 was temporary: the outbreak in Wuhan was quickly controlled and contained, affecting only a limited region (e.g., Wuhan city or Hubei province) for two months. Therefore, we chose 2020 as the baseline year.

We entered all relevant 2020 data, including demand, cost, and actual coverage data (both inbound and outbound), into the system. Subsequently, the system calculated detailed cost data for each component; examples include inbound transportation, outbound transportation, handling, and storage costs. The project team then compared each system-generated cost with the actual cost incurred and iteratively performed calibrations of parameters until the system-generated costs aligned with the predefined tolerance targets.

Impact

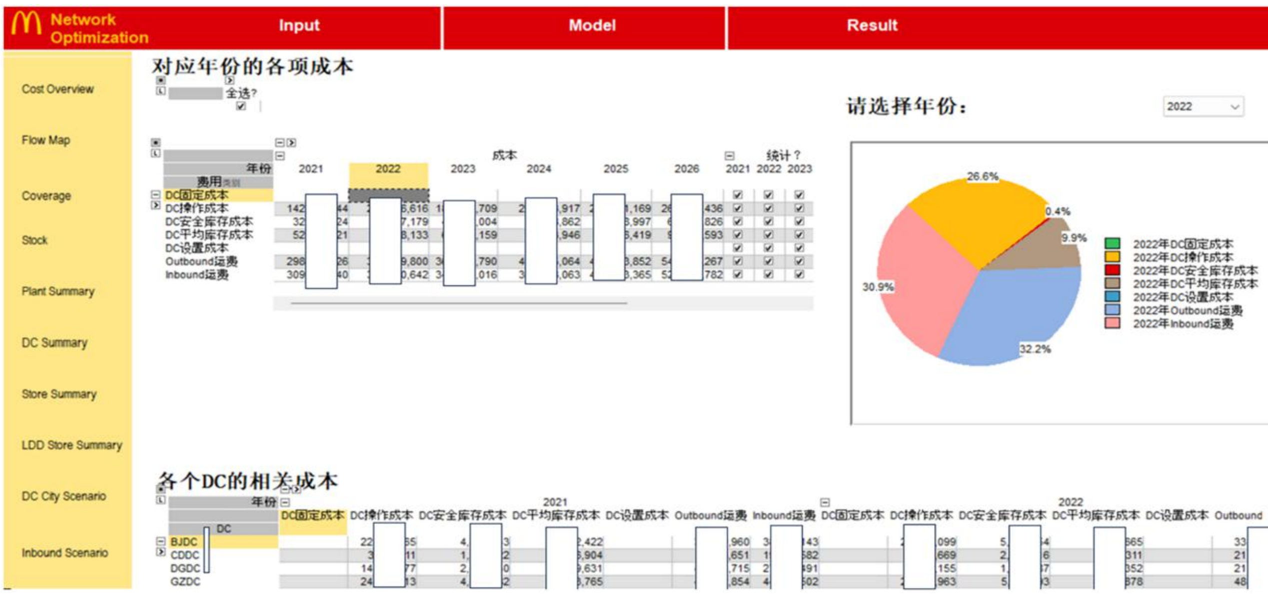
Starting on October 1, 2021, Optimization Analytics Technology, Xiahui Logistics, and the McDonald's China supply chain team collaborated for nine months to implement the SCND project. As shown in Figure 6, the project included five phases: business requirements analysis and design, data collection and cleansing and optimization model implementation, optimization model calibration, sce- nario analysis, and reporting of final results.

Figure 4. (Color online) The Graphic Shows the Graphical User Interface Displaying Outbound Flows for All DCs and All SKUs for a Year in a Normal Map



Note. Lines with arrows indicate the outbound flows from each DC to the demand points to which they provide transport.

Figure 5. (Color online) The Graphic Shows the System Graphical User Interface Displaying Cost Analyses



The SCND project, which was successfully implemented by June 30, 2022, has brought significant value to McDonald's business in China. The first example of a solution benefit is that the optimization model presented compelling digital evidence to management, strongly emphasizing that establishing a new bread factory in Tsingtao was not necessary for two reasons. First, the production capacity of existing bread factories was sufficient to meet the entire demand. Second, as Figure 7 shows, the location of Tsingtao was too close to the northeast border of China; in addition, a bread factory was already in an area to the north of China, closer to the DCs in northern China. Therefore, adding a new factory in Tsingtao would not result in any savings in logistics costs.

This information was readily apparent when visualized on the map and was corroborated by the calculated figures. However, using only Excel made it challenging to discern this information because Tsingtao was also a rapidly developing city with an increasing number of McDonald's outlets each year. Management followed SCND solution's recommendations and decided to cancel the construction of the Tsingtao bread factory, which avoided an investment cost of nearly USD 63.75 million.

As another example of a solution benefit, we presented strong evidence to senior management, substantiating the choice of the optimal location for a food town (i.e., a cluster of DCs and major supplying food plants, such as bread, beef, and chicken factories), because this location was almost at the center point of all DCs, as we display in Figure 8. This increased management's confidence in the optimal result from the model, especially because other scenarios demonstrated that no alternative choices were superior.

We also conducted a logistics cost savings analysis using baseline data from 2020. For a more representative measurement of accuracy, all inbound and outbound flows were fixed in the mathematical model according to actual supply quantities. The model was fine-tuned to ensure that all calculated costs had less than a 1% difference compared with the actual costs. After this fine-tuning, we relaxed the constraint of

Figure 6. (Color online) The Graphic Shows the Five Phases of the McDonald's China SCND Project

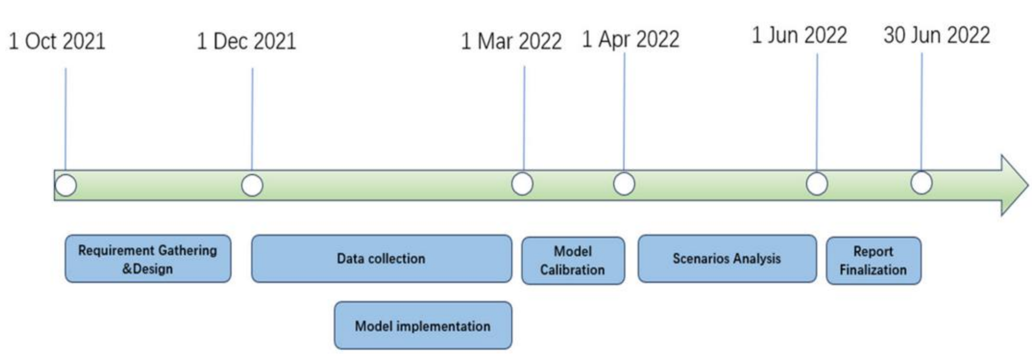
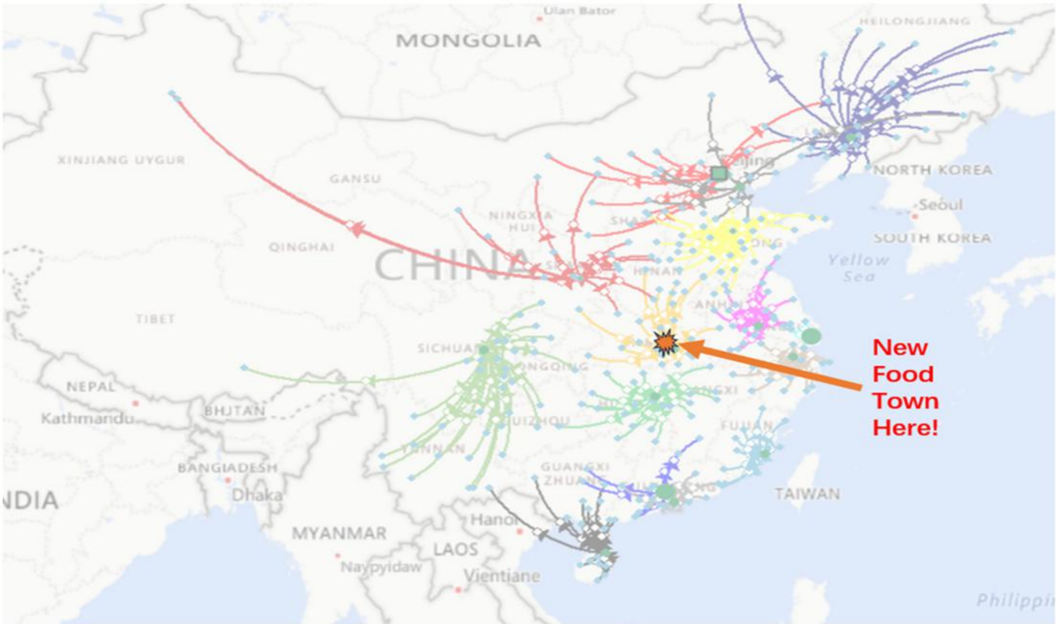


Figure 7. (Color online) The Map Illustrates Our Assessment of Placing a New Bread Factory in Tsingtao Through the SCND Model

fixed inbound and outbound flows in the model so that an optimized network design and its associated costs could be obtained using the baseline data. We could then easily calculate the savings in the logistics costs by subtracting the logistics cost of the optimal network from the actual baseline logistics cost. This cost savings, expressed as a percentage, could then be used to project future logistics cost savings. Applying this analysis, we found that by optimizing the location of potential food factories and DCs, the expected total average mileage reduction was about 28.5 million ton-kilometers each year, leading to a 10.6% CO_2 emission reduction and average annual savings of USD 8.9 million. Thus, this was an important project with significant potential impact, outlining the DC and plant setup roadmap for five years until 2028 to support the ambitious growth of McDonald's in China. We observe that the benefits could further increase as volume increases, particularly in a low-profit-margin industry like the fast food sector.

Figure 8. (Color online) The Map Shows the Optimal Location for a Food Town as Recommended by the SCND Model



Conclusion

An efficient and resilient supply chain network builds the foundation for business success. According to Andy Li, head of strategic procurement for McDonald's China supply chain, "There will be about 100 million cases moving on the supply chain network by 2026 … Success for the supply chain network planning roadmap relies heavily on advanced optimization and analytics methods."

The successful implementation of the SCND system and its compelling results instilled confidence in the McDonald's China management team, and support for optimization and data-driven decision support systems increased. Subsequently, the McDonald's China digital team proposed a series of subsequent actions:

- Integrating the SCND system into the McDonald's China supply chain digital platform.
- Improving the system to incorporate additional tactical functions, such as adjusting inbound and outbound coverage in the supply chain network with fixed DCs. This includes optimizing the supply side, managing how products are received from plants to DCs (inbound), as well as the demand side, coordinating how products are delivered from DCs to restaurants (outbound). This enhancement will allow McDonald's China to use the system for quarterly adjustments to DC coverage.
- Utilizing the integrated system to analyze the DC roadmap from 2024 to 2028 and aligning it with the new development plan.
- Delving into additional optimization opportunities within the organization.

In addition, using similar logic and techniques, supply chain network planning could be implemented in other industries, including pharmaceuticals, beverages, and oil and gas.

Appendix. Mathematical Model Used in This Study

	Description
Sets and indices	
I	Set of all potential sites and existing DC locations with index i
J	Set of all existing DCs with index j, a subset of I
F	Set of factories (suppliers) with index f
D	Set of demand points with index d
SKU	Set of SKU groups (aggregated SKUs) with index s
T	Set of time periods (years) with index t
P	Set of storage areas in a DC with index p
K	Set of integer numbers starting from one, with index k
Parameters[a]	
α_i	One-time building investment cost for DC i in RMB yuan
β_i	Fixed operational cost per time period for DC i in RMB yuan
$\gamma_{d,t,s}$	Demand of demand point d per time period t for SKU group s in cases
$\delta_{f,t,s}$	Supply capacity of factory f per time period t for each SKU group s in cases
ε_s	Storage area of SKU group s in cases
$\zeta_{i,t,p}$	DC volume capacity of storage area p in DC i per time period t in cases
η_p	Unit storage cost per day for storage area p in RMB yuan
$\theta_{i,s}$	Per-unit handling cost for SKU s in DC i in RMB yuan
ι_s	Current safety stock cost in number of days of demand for SKU s
κ_S	Current cycle stock level in number of days of demand for SKU s
$\lambda_{f,i,s}$	Unit inbound transportation cost from factory f to DC i for SKU s in RMB yuan
$\mu_{i,d,s}$	Unit outbound transportation cost from DC i to demand point d for SKU s in RMB yuan
v	Number of days in a time period.
ξ	Number of DCs in baseline setting (i.e., number of McDonald's China DCs in 2020)
$\pi_{d,t,s}$	The ratio (percentage) between SKU demand volume and total demand volume for each demand point d, time period t, and SKU s
Decision variables	
$x_{i,t}$	Binary variable, one if DC i will be opened at beginning of time period t, and zero otherwise
$y_{i,t}$	Binary variable, one if DC i will be closed at beginning of time period t, and zero otherwise
$z_{i,t}$	Binary variable, one if DC i exists during time period t, and zero otherwise
n_t	Integer variable, total number of DCs
$m_{k,t}$	Binary variable, one if the number of DCs in time period t is k
$if_{f,i,s,t}$	Nonnegative continuous variable, inbound flow volume from factory f to DC i of SKU s in year t
$of_{i,d,t}$	Nonnegative continuous variable, outbound flow volume from DC i to demand point d of SKU s in year t
$ss_{s,t}$	Nonnegative continuous variable, total safety stock volume for SKU s in year t
$cs_{s,t}$	Nonnegative continuous variable, total cycle stock volume for SKU s in year t

[a]The exchange rate from USD to RMB yuan is 1:7.12 as of this writing.

Constraints

$$\sum_{t} x_{i,t} \le 1 \quad \forall i \in I \tag{A.1}$$

$$z_{i,t} = \sum_{t1 \in T, t1 \le t} (x_{i,t1} - y_{i,t1}) \quad \forall i \in I, t \in T \tag{A.2}$$

$$\sum_{t \in Ti, t \ne 1} x_{j,t} = 0 \quad \forall j \in J \tag{A.3}$$

$$\sum_{f \in F, s \in SKU} if_{f,i,s,t} \le Big\_M * z_{i,t} \quad \forall i \in I, t \in T \tag{A.4}$$

$$\sum_{f} if_{f,i,s,t} = \sum_{d} of_{i,d,t} * \pi_{d,t,s} \quad \forall i,s,t,\ \forall i \in I, t \in T, s \in SKU \tag{A.5}$$

$$\sum_{i \in I} of_{i,d,t} = \Sigma_s \gamma_{d,t,s} \quad \forall d \in D, t \in T \tag{A.6}$$

$$\sum_{i \in I} if_{f,i,s,t} \le \delta_{f,t,s} \quad \forall f \in F, s \in SKU, t \in T \tag{A.7}$$

$$\sum_{s \in SKU | \varepsilon_s = p, f \in F} of_{f,i,s,t} \le \zeta_{i,p} \quad \forall i \in I, p \in P, t \in T \tag{A.8}$$

$$\sum_{i \in I} z_{i,t} = n_t \quad \forall t \in T \tag{A.9}$$

$$\sum_{k \in K} k * m_{k,t} = n_t \quad \forall t \in T \tag{A.10}$$

$$\sum_{k \in K} m_{k,t} = 1 \quad \forall t \in T \tag{A.11}$$

$$cs_{s,t} = \sum_{d \in D} \kappa_s * \gamma_{d,t,s} / v \quad \forall s \in SKU, t \in t \tag{A.12}$$

$$ss_{s,t} * sqrt(\xi) = \sum_{k \in K} sqrt(k) * m_{k,t} \sum_{d} l_s * \gamma_{d,t,s} / v \quad \forall s \in SKU, t \in T. \tag{A.13}$$

Constraint (A.1) ensures that any DC can open at most once; once a DC has been opened and subsequently closed, it cannot reopen. Constraint (A.2) establishes a link between the DC existence variable (variable z) and the DC open and closed variables (variables x and y, respectively). Constraint (A.3) is specific to existing DCs, stipulating that an existing DC can only be opened in the first year. Constraint (A.4) represents a Big_M constraint, signifying that if a DC does not exist during a particular year ($z_{i,t} = 0$), it cannot have any inbound flow volume. Consequently, because of Constraint (A.5), it will also not have any outbound flow volume. The value of Big_M should be carefully chosen, striking a balance between restricting DC capacity (if too small) and introducing scalability issues because of the size of the model (if too large); therefore, instead of using the same number for each DC, we analyzed the possible maximum coverage volume for each DC and used that number in the constraints. Constraint (A.5) enforces the flow balance, ensuring that during any time unit, for each SKU, the total amount flowing into a DC equals the total amount flowing out of that DC. Constraint (A.6) is the demand fulfillment constraint, ensuring that the total volume flowing into a demand point from DCs equals the demand. A slack variable can be introduced to this constraint to convert it from a hard constraint to a soft one, preventing infeasibility in the model. Constraint (A.7) represents the factory capacity constraint, ensuring that the total volume flowing from a factory does not exceed its capacity. Constraint (A.8) is the DC handling volume capacity for each storage area, specifying the total volume each DC can handle for each storage area during each time unit.

Constraints (A.9), (A.10), and (A.11) establish connections between variables related to the number of DCs in each time unit. These variables include the DC existence variable $z_{i,t}$, the total number of DCs variable n_t, and the binary variable representing the number of DCs, $m_{k,t}$. Constraint (A.12) calculates the cycle stock, and Constraint (A.13) computes the safety stock using the square root function, denoted as sqrt().

Objective Function

The mathematical model's objective function is to minimize the total cost, which comprises the following components:

$$z_1 = \sum_{f \in F, i \in I, s \in SKU, t \in T} if_{f,i,s,t} * \lambda_{f,i,s}$$

$$z_2 = \sum_{i \in I, d \in D, s \in SKU, t \in T} of_{i,d,t} * \mu_{i,d,s} * \pi_{d,t,s}$$

$$z_3 = \sum_{f \in F, i \in I, s \in SKU, t \in T} if_{f,i,s,t} * \theta_{i,s}$$

$$z_4 = \sum_{s \in SKU, t \in T} (ss_{s,t} + cs_{s,t}) * \eta_{\varepsilon_s} * v$$

$$z_5 = \sum_{i \in I, t \in T} \alpha_i * x_{i,t}$$

$$z_6 = \sum_{i \in I, t \in T} \beta_i * z_{i,t}.$$

The objective function is the amalgamation of the components above:

$$z = z_1 + z_2 + z_3 + z_4 + z_5 + z_6.$$

In the objective function, z_1 represents the total inbound transportation cost, z_2 denotes the total outbound transportation cost, z_3 denotes the total handling cost, z_4 represents the total storage cost, z_5 corresponds to the total new DC construction cost, and z_5 reflects the total annual fixed cost of all DCs.

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