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Production and Distribution Planning in Danone Waters China Division

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Abstract. For a logistics manager, the problem of making decisions on production and distribution planning is important but difficult to solve, especially when these decisions involve many products and complicated constraints. This work addresses the development of a decision support system (DSS) and its mathematical model to solve such problems at Danone Waters China Division, one of the China's largest producers and wholesalers of water and beverages. The DSS is a multistage integration project designed with the objective of integrating operations research tools and techniques into the production and distribution planning process. We first formulate this problem as a mixed-integer program, which involves the production, transportation, and storage costs and the constraint conditions. We then provide customizable options to the Danone Waters managers through simple graphical interfaces. We next develop a method of data collection and preprocessing and solve the model using optimization algorithms. The results show that this approach significantly increases efficiency and reduces total cost. In this paper, we also identify an approach for integrating operations research tools and techniques into the planning process.

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Keywords: production and distribution planning • mixed-integer programming • integrated OR models • decision support systems • DSS graphical interface • networks

Danone, which was established in 1966 and operates in 120 countries, is a global producer and distributor of foods and beverages. The company has extended its suite of major products to include infant nutrition and bottled water brands, such as Nutricia, Nutrilon, Cow & Gate, and Evian. Danone entered the Chinese market in 2008 to develop its water brands, including Mizone (MZ), HB, and Robust (RBW). Danone Waters China Division (Danone Waters) in Guangzhou is responsible for the production and distribution of these three brands. Since 2008, the sales scope in China has expanded, and the scale of business has grown considerably. In 2015, Danone Waters produced and distributed 500 million cases, representing 45% of Danone China's total income. As sales have increased, the production plans for factories (including outsourcing) and the distribution plans between plants and cities have become increasingly complex.

Compared with the rapid growth of sales, the development of scientific management processes in Danone Waters has been extremely slow. Prior to the commencement of this project, the company's production and distribution plans were determined by planners based on their hunches and guesswork. The decisions were often made sequentially with little thought given to their impact on other products, and the products were assigned to sales areas based on proximity rather than optimization.

To cope with its increased growth and maintain operational efficiency, the company proactively partnered with our academic team to develop a decision support system (DSS) to address this issue. The DSS was a multistage integration project designed with the objective of integrating operations research (OR) tools and techniques into the production and distribution planning process. First, the project team developed algorithms and integrated them with a mixed-integer programming framework. The objective was to find a joint cyclic production and delivery schedule so that the total cost per unit time was minimized over a planning horizon; this needed to include production costs, inventory costs in company-owned (in-warehouses) and third-party (out-warehouses) warehouses, and transportation costs. It was a global optimization problem because of the interdependencies between production and distribution operations and the trade-offs between the costs associated with them. We formulated this problem using linear programming (LP) and integer linear programming. We also provided Danone China's managers with customizable options through simple graphical interfaces, which shielded them from unnecessary complexity. In this project, we successfully simplified the decision-making process, developed data models, and automated the manual planning tasks using optimization algorithms.

The main contribution of this paper is the identification of a process to integrate OR tools and techniques into the planning process. It also describes an optimization approach to address the production and distribution planning problem. The model balances the interdependencies between production and distribution operations and the trade-offs between their associated costs. The algorithm incorporates data that are applicable to all of the company's products (e.g., distribution center [DC] number, plant capacity), data using different metrics (e.g., transportation price, forecast demand), and data that change over time and situation (e.g., transportation cost, production cost, inventory). We illustrate the framework and logic flow of the proposed DSS using figures to ensure that the reader can easily understand the flow.

We organized this paper as follows. It begins with the *problem definition and challenges* section in which we present the problems that Danone Waters faces in production and distribution planning. Next, the *production and distribution problems* section reviews the previous methods used to address these problems. In *Danone Waters' production and distribution system*, we describe Danone's production and distribution system and the logical flow of our planning. The *data collection and processing* and *optimization process* sections detail the optimization process. The results in the *implementation and results* section show that our production and distribution planning method is effective. Finally, the *impact value and future research* section offers concluding remarks and discusses future research. For completeness, we provide the mathematical models for the production and distribution planning in the appendix. These models use linear and mixed-integer programs. This approach also provides a template of how OR practice can be applied to benefit other enterprises facing similar problems.

Problem Definition and Challenges

As a producer and distributor of water and drinks, Danone Waters faces three major challenges in ensuring compatibility between production and distribution because of the company's increasing size, big data processing, and nonstandard decision making.

First, the company has experienced significant growth in recent years. In 2012, Danone Waters sold approximately 450 million cases of its products; sales have since increased by approximately 5% annually. In response to the increasing demand, Danone has implemented a national distribution network from the factories to DCs and from DCs to local warehouses (LWs). In February 2012, the network covered approximately 1,200 counties; this number increased to more than 2,000 by early 2018. Danone Waters currently has 26 factories, 27 DCs, and more than 2,000 LWs (Figure 1). The company produces and delivers hundreds of thousands of products throughout the country and must, therefore, carefully plan its production and delivery processes to adapt them to market developments over time.

Second, optimized planning is challenging when large amounts of data are involved. Our planning encompasses three brands of products, and each brand has specific data; examples include historical sales, sales distribution, forecast demand, production cost, inventory, and output bounds. On a typical day, hundreds of thousands of products produced in Danone Waters' plants flow through its distribution network of thousands of nodes, generating millions of data points. This poses a significant challenge to the optimization model, which must then be able to process this large amount of data.

Third, there is no standard decision model. Prior to this project, the company's production and distribution planning was inefficient because it was based on the experience of individual planners with minimal ability for systematic thinking. The main issues can be summarized in three main points:

1. Production is allocated between factories and sales areas by experience based on proximity without any use of scientific evidence.

2. The company's production and distribution scheduling decisions are often made in a sequential manner with minimal thought given to their impact on other products. Clearly, such a sequential approach is suboptimal.

3. The company's processes could not be adapted to changes brought about by business growth and demand fluctuation.

To cope with these three issues, the project team built a DSS that focuses on innovation, service, and operational efficiency. Through this process, the production and distribution systems were optimized throughout the entire company.

Production and Distribution Problems

In Danone's processes, which involve made-to-order and time-sensitive (the product shelf life is three months) products, finished orders are delivered immediately after being produced. Consequently, the production and outbound distribution are linked closely and must be scheduled jointly to achieve on-time delivery performance at minimum total cost. Pundoor and Chen (2009) showed that there is a significant benefit gained from using the optimal integrated production–distribution schedule.

Chen (2010) captures this type of problem as an integrated production and outbound distribution scheduling (IPODS) problem and divides it into two levels: the strategic and tactical planning level and the detailed scheduling level. The former level jointly schedules production and delivery at the aggregate planning level. The latter level attempts to optimize detailed order-by-order production and delivery scheduling at the individual order level. In our situation, the allocation of capacity to products in a given planning horizon and delivery schedules over shorter periods of time are often used as inputs to generate detailed order-by-order processing. As such, our study concerns the tactical planning level.

In the past two decades, a tremendous amount of research has been done on various integrated production–distribution models at the strategic and tactical planning levels. Many survey articles on such models are in the literature; examples include Goetschalckx et al. (2002), Bilgen and Ozkarahan (2004), Chen and Pundoor (2006), and Viergutz and Knust (2014).

A typical production–distribution problem includes plants and customers. Each plant has a capacity limit with a concave function as the production costs and linear distribution costs. A solution to the problem seeks a production and distribution plan that minimizes the total production and distribution costs. In this paper, various IPODS problems in the literature are classified based on three dimensions—the decision level, the integration structure, and the problem parameters—and are summarized in four types.

The first type has a single plant and a single demand. Lee and Chen (2001) take two types of transportation situations into consideration: transporting a semifinished job from one machine to another and delivering a finished job to the customer or warehouse. Li and Ou (2005) consider the issues of receiving and delivering at the same time. Viergutz and Knust (2014) extend the problem for a product with a short life span and a predefined customer sequence using time windows and made-to-order production.

In the second type, multiple production plants and multiple customers are considered with only a single product involved. Problems of this type generally involve only a single period. Kuno and Utsunomiya (2000) study a problem with a more general structure in which there are multiple warehouses in addition to two production plants that can supply the customers. Jiang et al. (2016) take information sharing into account by evaluating a situation in which the manufacturer possesses better demand-forecast information than the downstream retailer.

In problems of the third type, the objective is to find a joint cyclic production and delivery schedule so the total cost per unit time is minimized over an infinite horizon. Goyal and Nebebe (2000) show that, under a given set of policies, there is an integer number of delivery cycles with nonidentical delivery quantities. Bilgen and Çelebi (2013) address the problem in dairy plants with production lines of multiple products, key features that typically arise in the dairy industry. Chang et al. (2014) consider an integrated problem in which jobs are first processed by one of the unrelated parallel machines and then distributed to corresponding customers.

Unlike the second type, which involves only a single product and a single period, and the third type, which seeks optimal solutions among a given set of policies assuming an infinite planning horizon with a constant demand, the fourth type of problem involves multiple products and (or) multiple periods with a finite horizon and dynamic demand over time and seeks optimal solutions among all feasible solutions. Furthermore, although the previous problems address only two stages (manufacturer and customers or suppliers and manufacturer), problems of this type involve three or more stages (e.g., suppliers, manufacturers, warehouses, and customers). Sabri and Beamon (2000) consider a four-stage problem with both strategic and tactical decisions. Dhaenens-Flipo and Finke (2001) study a three-stage, multiple-product problem involving multiple plants, warehouses, and customers. Bilgen (2010) address the production and distribution planning problem in a supply chain system that involves the allocation of production volumes and the delivery of products.

The problem Danone Waters faced has characteristics from each of the problem types summarized and, thus, cannot be grouped indiscriminately with them. Its problem involves multiple plants, multiple DCs, and multiple local demands similar to the second type, which is a three-stage problem similar to the fourth type. Three products are produced at the plants and shipped from the plants to the DCs and from the DCs to the LWs. Each plant has a capacity limit, and the production costs are linear for the RBW and HB brands or all-unit discount for the MZ brand. At the DC, there is a linear inventory holding cost. The distribution costs are linear. The demand is deterministic. The problem is to find a joint cyclic production and delivery schedule such that the total cost per unit time is minimized over an infinite planning horizon, again similar to the third type (Table 1). As such, in the next section, we describe how we built a schedule based on the existing optimization method.

Danone Waters' Production and Distribution System

Danone Waters' logistics network comprises three types of nodes: plants, DCs, and LWs. A plant is the location at which products are produced. After production, products are transported to and stored in DCs, which consist of in-warehouses and out-warehouses. The use of out-warehouses is required because the in-warehouse capacity is limited. Each DC then distributes the products to the LWs in all its sales-coverage regions. Customer demands are satisfied by the nearest LW. In this project, we had to optimize only the production and distribution;

therefore, we treated all the demands of a city as a demand point. The production- and delivery-cycle length are one month each. In our initial conceptualization of this project, our objective was to find a joint cyclic production and delivery schedule such that the total cost per unit time, including production costs, inventory costs at both the in- and out-warehouses, and transportation costs, were minimized over an infinite planning horizon. We illustrate the interdependencies between production and distribution operations and the trade-offs between their associated costs.

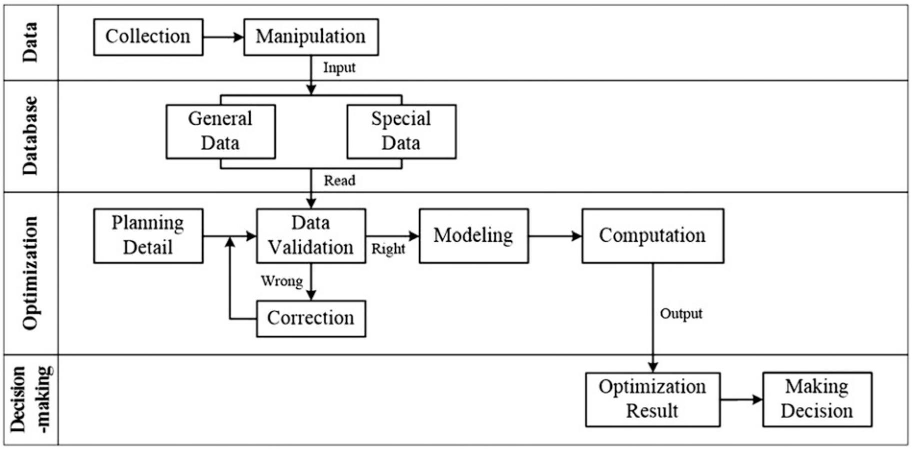
From a production perspective, production can meet the demand within its sales coverage region and can also satisfy the cross-regional demand. Therefore, the production plan must solve two problems: the number of products to be produced and where they should be allocated to meet the demand. The number of products is determined by the production cost and future demand and constrained by the production capacity. The allocation of the products is determined by the transportation cost and the total future demand.

From a distribution perspective, once the products have been produced, they are distributed from the plant to the DCs and from the DCs to the LWs. The final retail outlets are supplied through LWs. The plant can choose to store its products in either a nearby or a distant DC. If the nearest DC is chosen, the initial distance is shorter, but the total cost of transportation may be higher. If a distant DC is chosen, the total transportation cost may be lower, but the transportation time may be higher.

As a result, the solution should encompass global optimization and minimize the total cost under constraints. Figure 2 shows the framework and logic flow of the proposed DSS. First, the decision-related data are collected, preprocessed, and stored in a database. Next, the optimization model is constructed and solved. In this second step, we choose the planning detail, validate data, build the model, and do the calculation. Finally,

Figure 1. (Color online) Danone Waters' National Distribution Network in China

Figure 2. The Framework of Our Proposed DSS



the optimization result is generated as output and given to managers to provide them with decision support.

Data Collection and Processing

Two types of data were needed in the DSS (Figure 3). The first is general data, which are the same for all product categories (e.g., the distribution cost from plants to DCs and from DCs to LWs). The second is specific data, which vary among product categories (e.g., historical sales, demand forecasts, unit production costs, inventory, plant capacity). We collected these data from the production, transportation, and finance departments and from third-party suppliers. Some of the data, such as the DC number and plant capacity, could be stored in the database without preprocessing because they could be applied directly to the model; others require preprocessing. The first type of data that had to be preprocessed includes data recorded using different metrics. Another type varies over time and situation. In the *reconciliation of data units* and *data processing* subsections, we describe the processing steps we followed.

Reconciliation of Data Units

Some data are not described in terms of a single valuation measure. For example, transportation prices were aggregated by counties; however, the forecast demands were aggregated by the provinces. Both data sets are not aggregated for the same resolution of administrative division. However, a uniform metric was required for the planning process. Next, the appropriate data precision and accuracy had to be set. Higher data precision means higher planning precision but at the expense of more computing time. In contrast, lower data precision means lower planning precision but with less computing time required. The terms of this trade-off depend on management preference. Considering the balance between processing time and precision, Danone Waters decided that the data should be standardized in the resolution of a city. We illustrated this standardization using the transportation costs and the forecast demand as examples. Note that the city used here and in the rest of this paper was defined as a city of a prefectural level and, thus, ranked higher than a county.

The transportation price was provided by the third-party logistic suppliers and was aggregated by county, which was too precise for the model. Thus, we had to convert the data to the city level based on the sales ratio. First, we listed the county price and the corresponding sales ratio. We then calculated the weighted average of the county price to determine the city price. In Figure 4, we use the route from the city of Kun Ming to the city of Lin Cang as an example. Lin Cang has two counties: Lin Xiang and Yun Xian. We calculated the transportation price from the city of Kun Ming to the counties of Lin Xiang and Yun Xian, respectively; however, we instead required the route data from the cities of Kun Ming to Lin Cang. According to the historical sales data, 45% of the sales from Lin Cang were from Ling Xiang and 55%

Figure 3. (Color online) The Basic Data Management Module in the Proposed DSS

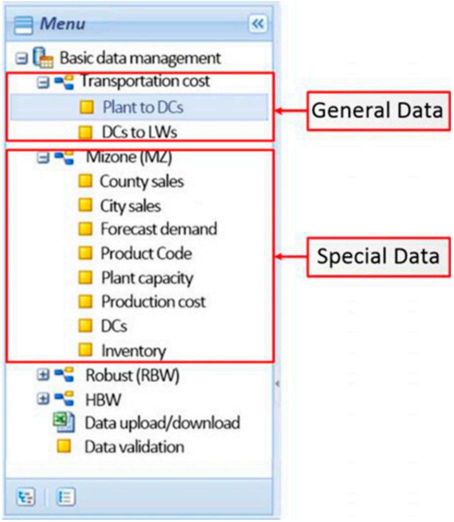
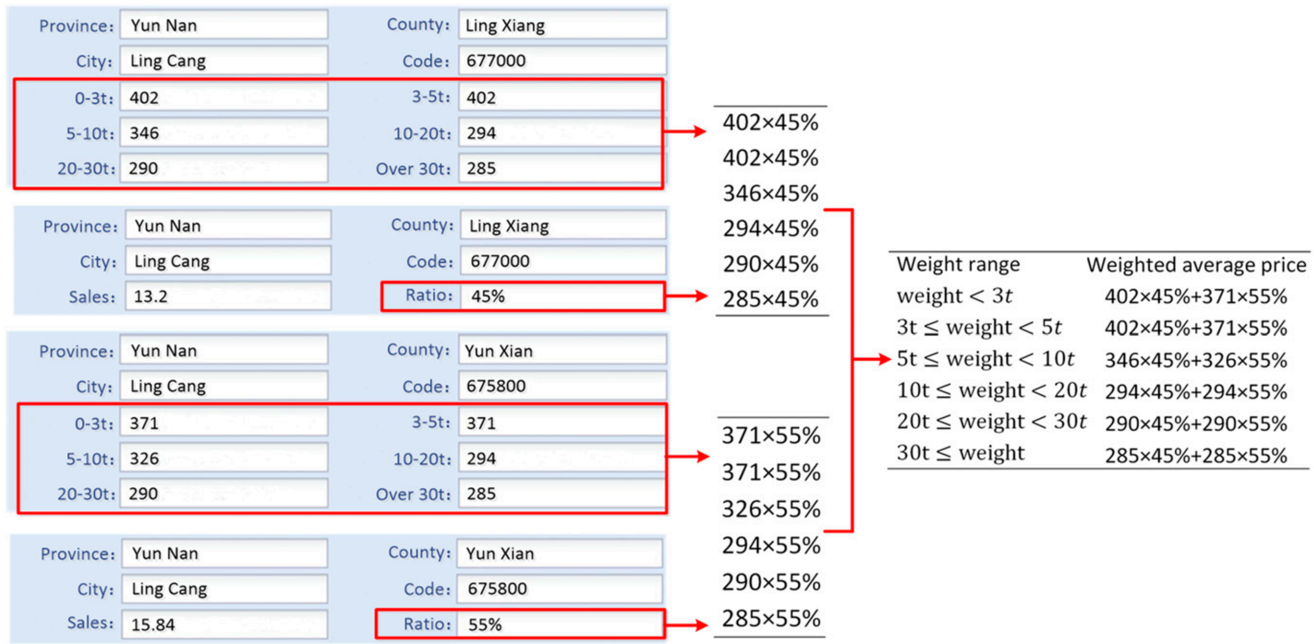


Figure 4. (Color online) The Transportation Cost Reconciliation Process



of the sales were from Yun Xiang. Thus, from the historical transportation cost of the two counties and the sales ratios, we used the weighted average to calculate the transportation cost from Kun Ming to Lin Cang.

The forecast demand data were aggregated by province; however, the results were insufficiently precise for the model. Therefore, we had to convert these data to the city level based on the sales ratio. In Figure 5, we use the forecast demand for the city of Zheng Zhou in Hen Nan Province as an example. First, note that the historical sales of Zheng Zhou accounted for 55% of total sales in Hen Nan Province. We multiply the total forecast demand of Hen Nan Province by 55% to obtain the forecast demand for Zheng Zhou.

Data Processing

Some data vary over time and situation, adding complexity to the optimization process. This project included three kinds of data: transportation costs, production costs, and inventory. Each type had to be preprocessed differently.

The transportation costs changed constantly. Real-time updates required an excessive amount of computational time and resources; however, if the update

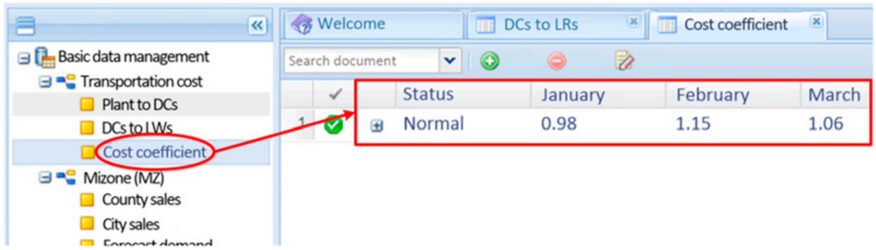
Figure 5. (Color online) The Demand Data Reconciliation Process

interval was long, planning was inaccurate. After analyzing Danone Waters' historical transportation costs, we defined the transportation costs as a percentage change from the previous period. Thus, the transportation costs were modeled as a base cost multiplied by a cost coefficient (Figure 6). To ensure that the problem size remained manageable, we updated the base cost annually and the cost coefficient monthly.

The production costs changed significantly depending on the product categories, the corresponding plants, and the production output. Hence, we created a production cost table to record the cost of each product category. Products can be produced in two types of plants: company-owned plants and outsourced plants. Company-owned plants permit lower production costs but have limited production output. Thus, if extra demand arises, some production must be handled in outsourced plants. The production costs in company-owned plants are standardized and do not need additional processing, and the production costs in outsourced plants have an all-unit discount structure. In the all-unit discount cost structure, the production costs decrease as the production output increases. For example, in the KunSan-ZF plant, the production cost is ¥641.7 when the production output is below 4,800 tons; however, the cost would drop to ¥577.6 if the production output increased to more than 6,000 tons (Figure 7). The striping data were used to record the all-unit discount cost and the corresponding model was the step function.

The inventory changes because the products expire. The product shelf life is three months, and Danone Waters destroys expired products by burning them. The model would become more complicated if these

Figure 6. (Color online) The Adjustment of Transportation Cost via Time



expired products were included in the inventory data (i.e., not burned). To provide an optimal solution within a reasonable time limit, we processed these data before entering them into the model as the storage value. The production date and the shelf life are recorded in the inventory database. This record is automatically deleted when the corresponding product has expired. This approach ensures that the inventory data are valid, thus making the production and distribution planning feasible.

Optimization Process

We proposed an optimization-based, data-driven approach to allow Danone Waters to optimize its logistics system and built a platform to ensure ease of use. The optimization process included planning detail selection, data validation, model building, and calculations.

Planning Details

Prior to implementing our planning process, it was necessary to ensure that the desired optimization details were selected, including which product category to optimize, the time span of the optimization model, the upper-bound limit on the optimization time, whether the all-unit discount cost existed, and the optimization objectives (Figure 8).

In Figure 8, longest time refers to the upper-bound limit on the optimization computational time, not including the time required to validate the data and build the parameters. Normally, the optimal solution can be obtained within 10 minutes, depending on the server's performance. The "all-unit discount cost" means that the production cost decreases as the production output increases. If the user selects "all-unit discount cost," the software builds the integer linear programming model; otherwise, it builds the linear programming model by default. The user can select from several optimization objectives, such as storage planning, capacity planning, distribution planning, in-warehouse planning, and out-warehouse planning. One important factor to note is that as more objectives are selected, more computing time is needed.

Data Validation

After selecting the optimization details, it was necessary to validate the integrity of the input data. We used two types of data validation. The first was a completeness check, including a primary key check, a correlation check, and a nonnull check, which ensured that the model was solvable. The second was another constraints check, including a path check and a range check, which ensured the solution was feasible. Only when all the validation steps were complete could the planning continue. If any data errors occurred, the reason was displayed for the user to address before continuing the planning process (Figure 9).

Figure 7. (Color online) The All-unit Discount Structure of the Production Cost at an Outsourced Plant

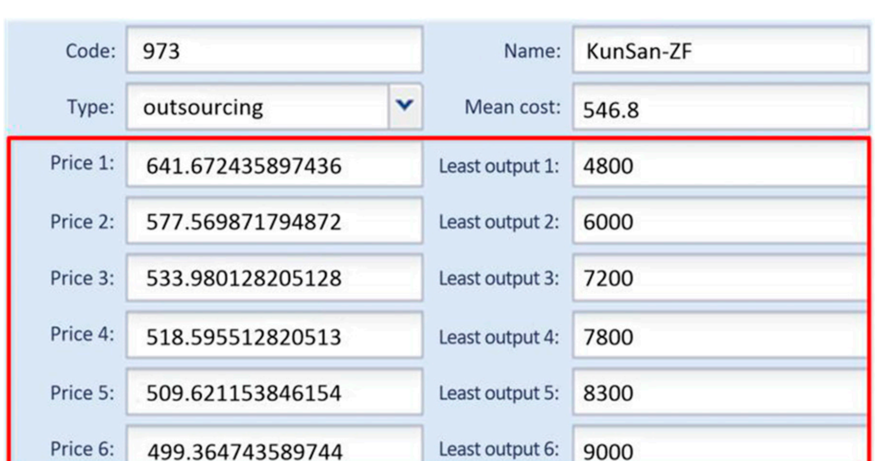
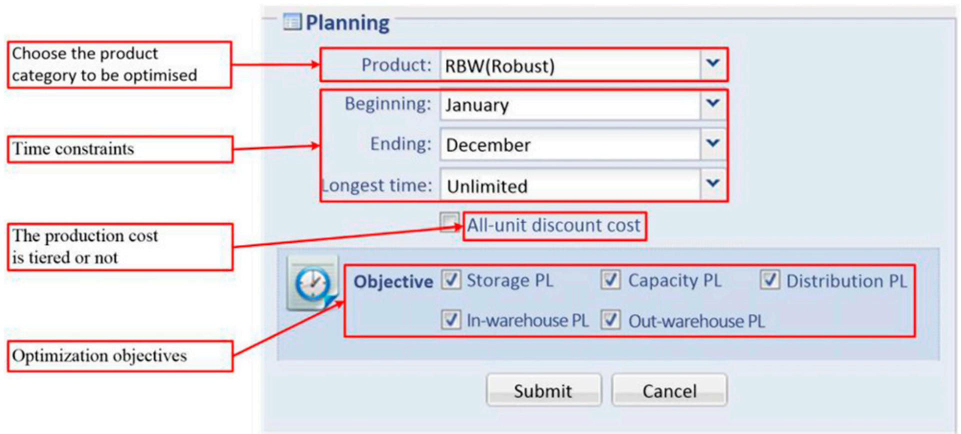


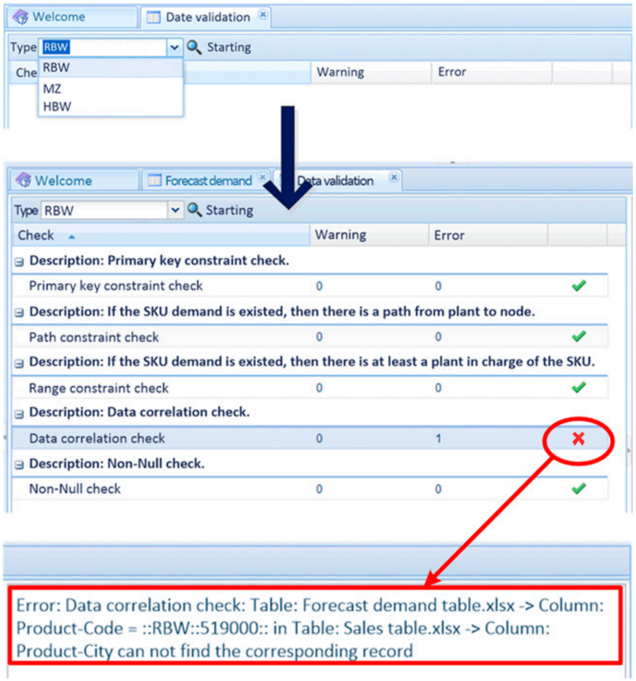
Figure 8. (Color online) Options of the Desired Planning in the Proposed DSS



Modeling

Our study included multiple production plants, DCs, and LWs. Three products were produced at the plants and shipped from the plants to the DCs, then from the DCs to the LWs. Each plant had a capacity limit. The production costs were linear (RBW and HB) and all-unit discounts (MZ). At the DC, there was a linear inventory holding cost. The transportation costs were linear. The demand was deterministic. The problem was to find a joint cyclic production and delivery schedule so that the total cost per unit time (one month) was minimized; this included production costs, inventory costs at both the in-warehouse and out-warehouse, and transportation costs.

Figure 9. (Color online) An Example of Output from the Data Validation Process in the Proposed DSS



This problem contained a large amount of data, and most models could not be solved in polynomial time, corroborating the findings of other researchers (e.g., Hochbaum and Hong 1996). It is important to avoid making too many simplifying assumptions. On the whole, the linear programming model best met this study's requirements and is suitable for practical application. The RBW and HB products incur linear production costs and, thus, are suitable for the linear programming model. MZ incurs all-unit discount production costs and, thus, is suitable for the integer linear programming model. The linear and integer programming models are similar; however, the integer model is a step function because of the all-unit discount costs. The details are provided in the appendix.

Next, the data are combined subject to two types of constraints. The first are general constraints for this model, including balance and nonnegative constraints. A balance constraint means that the product inflow equals the product outflow for all nodes. A nonnegative constraint means the values for production, transportation, and stock are always nonnegative. The second type are other constraints, which differ depending on the situation. Such constraints ensure that the solution is feasible. The three main types of other constraints are listed here.

- Ending-stock constraint in each period: The ending stock must be greater than or equal to the safety stock. Danone Waters' safety stock equals the ending-stock coefficient times the distribution value from the DC to the LW. The ending-stock coefficient is calculated based on (s, S) policies (Iglehart 1963).
- The decision to use out-warehouses: When Danone Waters' in-warehouses cannot meet demand, the products are stored in out-warehouses. If out-warehouses are used, their capacity must be greater than or equal to the ending stock minus the capacity of the in-warehouses.
- Production capacity of the plants: Each plant can produce only the specific products it has on the production line and cannot exceed its capacity.

Computation

Because of the large size of the LP models, we used the optimization engine with a large-scale LP solver (GLPK Simplex Optimizer, v4.47) to solve this LP. The engine can be used to find LP and mixed-integer programming solutions with no limit on the scale.

The solution time on a 900 MHz Pentium 3 PC was approximately 10 minutes. The solution time changed little when we reoptimized a model to include several changes because most of the run time was spent in the setup process.

Implementation and Results

To ensure that the model optimization was robust and to estimate the savings achieved using this approach, we compared the performance of the optimized strategy that the approach recommended with the performance of the historical strategy. For the statistical estimation procedure, we used historical data on production and transportation availability over a period spanning three years of operations (2010–2012). We applied the DSS to this data set to determine the production and transportation costs using the optimized strategies. Compared with the historical values, our planning method showed a cost reduction of between 4% and 7% (Figures 10 and 11); this reduction is more significant in the peak sales season. These tests proved that the solutions were robust and that the optimization algorithm consistently converged to the true optimal solution.

Encouraged by the results and recognizing the potential for cost reduction, Danone Waters management began to use this model-based approach to guide its production and transportation decisions in 2013. The implementation and rollout of the DSS at Danone Waters began in the production and logistics planning departments in Guangzhou. Because the project was initiated in the corporate headquarters in Guangzhou, the project team decided to test the ideas in South China before expanding the scope of the implementation. The product managers and transport managers in Guangzhou were technology savvy and eager to implement the tool, making them ideal candidates. The team believed that this method would be less of a top-down approach and would result in less resistance when it expanded the scope.

Figure 10. A Comparison of the Production Costs After Optimization with Costs Provided in Historical Data (i.e., Real Data)

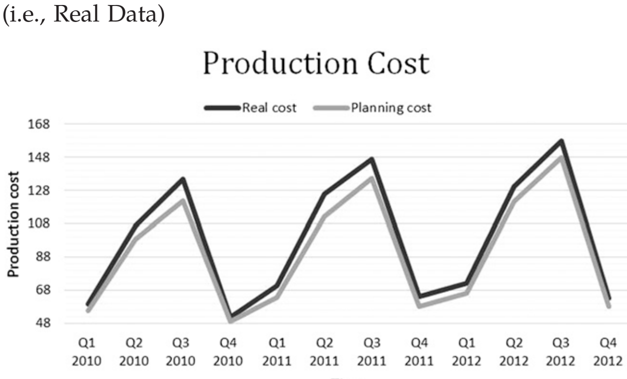
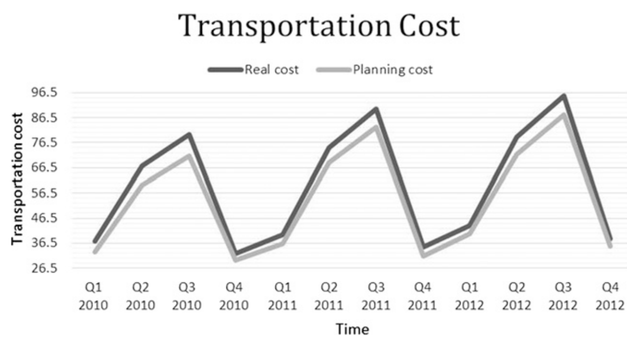


Figure 11. A Comparison of the Transportation Costs After Optimization with Costs Provided in Historical Data (i.e., Real Data)



According to the finance department's assessment, the total cost incurred in 2013 was ¥665.626 million, a decrease of 4.6% from its estimated budget of ¥698.305 million, including production costs of ¥414.878 million, a decrease of 3.8% from ¥431.018 million, and transportation costs of ¥250.748 million, a decrease of 6.2% from ¥267.286 million. An additional benefit to managers was that the DSS reduced their decision time and improved their working efficiency.

After successfully applying the DSS in South China, Danone Waters began a nationwide implementation. To facilitate this process, the project team developed a comprehensive user manual. The finance department's calculations show that the cost savings rate remained above 3.5% in subsequent years.

This project has dramatically changed Danone Waters' decision-making approach and accuracy. The approach achieved compelling results with the following strategies.

(1) Global optimization. The object is to find a joint cyclic production and delivery schedule such that the total cost per unit time is minimized over an infinite planning horizon. Because of the interdependencies between production and distribution operations and the trade-offs between their associated costs, the solution, which minimizes the total cost, including production costs, inventory costs, and transportation costs, can be implemented globally (i.e., across all products).

(2) Data preprocessing. The original data were not standardized and, therefore, could not be applied directly to the model. This issue is commonly encountered in practice. The preprocessing step helps to ensure that the problem size remains manageable in size and provides an optimal solution within a reasonable time limit.

(3) Hiding complexity from the user and allowing user customization. Few users are trained in operations

Table 1. The Models in the Existing Literature that Address the Production–Distribution Problem and How They Contrast with Our Model

Authors and year	Integration structure	Planning horizon	Number of nodes	Number of products	Nature of demand	Production cost function
Lee and Chen (2001)	Inbound and outbound transportation	Two periods	Single plant, single demand	Single product	Deterministic	Time costs
Li and Ou (2005)	Inbound and outbound transportation	Two periods	Single plant, single demand	Single product	Deterministic	Time costs
Viergutz and Knust (2014)	Production and outbound transportation	One period	Single plant, single demand	Single product	Deterministic	Time costs
Kuno and Utsunomiya (2000)	Production and outbound transportation	One period	Multiple plants, multiple demands	Single product	Deterministic, must be satisfied	Concave, separable
Jiang et al. (2016)	Production and outbound transportation	One period	One plant, one demand	Single product	Deterministic	Constant
Goyal and Nebebe (2000)	Production and outbound transportation	Infinite horizon	Multiple plants, multiple demands	Multiple products	Constant demand	Concave
Bilgen and Çelebi (2013)	Production and outbound transportation	Infinite horizon	Multiple plants, multiple demands	Multiple products	Deterministic	Concave
Chang et al. (2014)	Production and outbound transportation	Infinite horizon	Multiple plants, multiple demands	Multiple products	Deterministic	Heterogeneous
Sabri and Beamon (2000)	Three or more stages: inbound transportation, production, and outbound transportation	One period	Multiple suppliers, plants, DCs, customers	Multiple products	Deterministic, must be satisfied without backlog	Linear
Dhaenens-Flipo and Finke (2001)	Three or more stages: inbound transportation, production, and outbound transportation	Multiple periods	Multiple plants, warehouses, customers	Multiple products	Deterministic, must be satisfied without backlog	Linear
Bilgen (2010)	Production and outbound transportation	Finite horizon	Multiple plants, multiple demand	Multiple products	Dynamic	Concave, separable
The Danone Waters problem	Production and outbound transportation	Infinite horizon	Multiple plants, DCs, LWs	Multiple products	Deterministic, no penalty cost	All-unit discount

research; therefore, the DSS provides managers with customizable options through simple graphical interfaces in a format that is familiar to them.

(4) Field support. A field support team is available to assist users. For example, a user might want to understand the reasons underlying a particular occurrence or request assistance in creating a route to meet specific local conditions. The user can send all relevant information to the team, including questions and (or) concerns. The team will analyze the solution and provide feedback to the user. A user manual is also available. In this manual, the framework and logic flow of the proposed DSS are illustrated using figures (e.g., Figure 2) to help the users understand the process and the DSS.

(5) Project organization and team structure. The insights of Danone Waters' management helped establish accurate project boundaries and enabled the researchers to engage these managers at the beginning of the project. This proved to be critical in developing practical solutions.

The managers' eagerness to implement the system was also crucial to making this implementation successful.

Impact Value and Future Research

The project's impact may be broadly categorized in three ways, which we describe here:

(1) Direct financial impact to Danone Waters: According to Danone Waters' tests, this new DSS has significantly reduced its annual production and transportation costs. The estimated total cost savings in 2013 was 4.6%, including production cost savings of 3.8% and transportation cost savings of 6.2%. The savings rate remained above 3.5% in subsequent years.

(2) Nonfinancial and indirect benefits to Danone Waters: First, the DSS has made managers' jobs easier. Previously, although managers realized the trade-offs between the production and transportation costs, they did not have the appropriate tools and methodology to accurately calculate them; thus, they often had to act on hunches and guesswork. By providing easy-to-use graphical interfaces and allowing customized planning based on product-specific data, the DSS enables managers to quantify the impact of trade-offs; thus, they are empowered to make data-driven decisions, rather than resorting to guesswork. With the implementation of the system, the managers are relieved of most decision-making complexities.

Second, the DSS has caused managers to think in new ways. They have started making local adjustments to the logistics system based on the results they have seen. It is apparent that the real value of modeling is not only in the specific numerical solution; the insights that the solution provides are also useful. At any time in the future, managers can adjust the models as customers demand changes. This use of optimization modeling has been the catalyst for Danone Waters managers to adopt a new way of thinking.

(3) Impact on other organizations: Intense competition in today's global market and heightened expectations of customers have forced companies to invest aggressively to reduce their costs by reducing inventory levels across the supply chain and simultaneously being more responsive to customers. This inventory reduction has resulted in closer linkages between the production and distribution functions. Detailed scheduling-level integration of production and distribution operations is not only possible but also necessary in increasingly more competitive situations. Joint scheduling enables firms to optimize the trade-offs between various costs, total revenue, and delivery timeliness. Many firms in China are likely to face difficulty when doing joint scheduling; some lack the will to begin because of reluctance to change, and others do not know how to start. This work provides a reference for both types of firms.

The model still has several limitations. The main one is the simplification of inventory to control the calculation time. It considers only the shelf life of the inventory; in reality, the ordering of the queue (e.g., first in, last out) should also be a consideration. In future research, we will consider inventory optimization by including a penalty value for the inventory time. The longer a product is stored, the greater the penalty value should be. This will ensure that the products are distributed as soon as possible. The difficulty lies in determining this penalty value. Making such a determination will require that we perform many experiments using different sets of initial values.

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Appendix

In this appendix, we provide the equations used for the optimization. Our study included I production plants, J DCs, and K LWs. Three products were produced at the plants and shipped from the plants to the DCs, then from the DCs to the LWs. Each plant i had a capacity limit (Ca). The production costs (pc) were linear (RBW and HB) and all-unit discounts (MZ). At the DC, there was a linear inventory holding cost (hc). The transportation costs ($transC$) were linear. The demand D was deterministic. The problem was to find a joint cyclic production and delivery schedule so that the total cost per unit time (one month) was minimized; this included production costs, inventory costs at both the in-warehouses and out-warehouses, and transportation costs.

Linear Programming Model

The linear programming model is suitable for the RBW and HB products, which have a linear, not an all-unit discount, production cost. When the product is MZ and the user does not choose the all-unit discount cost, the system will automatically create a linear programming model. The notation is as follows.

Parameters

I = number of plants (including OEM)
J = total number of DCs including in-warehouses and out-warehouses (warehouses in the same city count as one)
K = number of local warehouses
S = number of SKUs of the products
$\mathbb{S}_i$ = type of SKUs that plant i can produce
T = number of planning periods (monthly)
i = subscript of plants
j = subscript of DCs
k = subscript of local warehouses (demand point)
s = subscript of SKUs
t = superscript of periods
D^t_{ks} = demand for the sth SKU in period t for k
$transC_{ij}$ = unit transportation cost from plant i to DC j
$disC_{jk}$ = weight average transportation cost from DC j to local warehouse k, including the handling cost of DC j
$inhc_j$ = unit storage cost of in-warehouse (one kind of DC)
$exhc_j$ = unit storage cost of out-warehouse (another kind of DC), including rent, drayage, handling cost
pc_{is} = unit production cost of the sth SKU of plant i
$inCa_j$ = capacity of the in-warehouse
PCa^t_i = maximum capacity of plant i in period t
SaS^t_{js} = safety factor of the sth SKU of the DC j in the period t
$Canproduct_{is}$ = whether plant i has the capacity to produce the sth SKU
$inits_{js}$ = initial inventory of the sth SKU of DC j

Decision Variables

x^t_{ijs} = freight volume from plant i to DC j
y^t_{jks} = distribution (delivery) quantity from DC j to local warehouse k
z^t_{is} = output of the sth SKU of plant i in period t
w^t_{js} = final inventory of DC j (in and out) in period t
ew^t_{js} = final stock of the out-warehouse j in period t

Linear Programming Model

$$\begin{aligned}\text{Min } &\sum_{t=1}^{T}[\sum_{i}^{I}\sum_{j=1}^{J}(transC_{ij}\cdot\sum_{s=1}^{S}x^t_{ijs})+\sum_{j=1}^{J}\sum_{k=1}^{K}(disC_{jk}\cdot\sum_{s=1}^{S}y^t_{jks})\\ &+\sum_{i=1}^{I}\sum_{s=1}^{S}pc_i\cdot z^t_{is}+\sum_{i=L+1}^{I}\sum_{m=1}^{M}Opc^m_i\cdot oz^{m,t}_i+\sum_{j=1}^{J=1}(hc_j\cdot\sum_{s=1}^{S}w^t_{js}\\ &+(ehc_j-hc_j)\cdot ew^t_j)]\end{aligned} \tag{A.1}$$

General Constraints

Production balance constraint:

$$z^t_{is}=\sum_{j=1}^{J}x^t_{ijs},\ t=1,\ldots T;\ i=1,\ldots I;\ s\in\mathbb{S}_i \tag{A.2}$$

Demand balance constraint:

$$D^t_{ks}=\sum_{j=1}^{J}y^t_{jks},\ t=1,\ldots T;\ k=1,\ldots K;\ s=1,\ldots S \tag{A.3}$$

Warehouse stock balance constraint:

$$w^t_{js}=w^{t-1}_{js}+\sum_{i=1}^{I}x^t_{ijs}-\sum_{k=1}^{K}y^t_{jks},\ t=1,\ldots T;\ s=1,\ldots S \tag{A.4}$$

Nonnegative constraint:

$$x^t_{ijs},y^t_{jks},w^t_{js},ew^t_j,z^t_{is}\ge 0,\ t=1,\ldots T;\ i=1,\ldots I;\ j=1,\ldots J;\ k=1,\ldots K;\ s=1,\ldots S \tag{A.5}$$

Other Constraints

SKU capacity constraint:

$$\sum_{s\in\mathbb{S}_i}z^t_{is}\le PCa^t_i,\ t=1,\ldots,T;\ i=1,\ldots,I \tag{A.6}$$

External warehouse constraint:

$$ew^t_j\ge\sum_{s=1}^{S}w^t_{js}-Ca^t_j,\ t=1,\ldots T;\ j=1,\ldots J \tag{A.7}$$

Final stock constraint (except the final period):

$$w^t_{js}\ge SaS^t_{js}\cdot\sum_{k=1}^{K}y^{t+1}_{jks},\ t=1,\ldots T-1;\ j=1,\ldots J;\ s=1,\ldots S \tag{A.8}$$

Final stock constraint of the final period:

$$w^T_{js}\ge SaS^T_{js}\cdot\sum_{k=1}^{K}y^T_{jks},\ j=1,\ldots J \tag{A.9}$$

Mixed-Integer Linear Programming Model

The mixed-integer programming model is suitable for MZ when the all-unit discount price is selected. The integer programming and linear programming models are very similar. The difference is that the integer programming model has one additional constraint to determine where the all-unit discount cost falls. The notation is as follows. The same notation applies to the LP model; thus, we do not repeat it.

Parameters

qc_{in} = unit production cost of the nth fragment of plant i
QCa_{in} = the minimum production of plant i in the nth period
PQ_i = the capacity that has been used by plant i

Decision Variables

Z_{in} = the production of plant i in the nth period
δ_{in} = 1 means that the planned production of plant i falls in the nth period

Integer Linear Programming Model

The integer linear programming model is the same as the linear programming model above (A.1).

Constraints

(A.2)–(A.9) and (A.10):

$$\sum_{n=1}^{N} Z_{in} - \sum_{t=1}^{T}\sum_{s\in\mathbb{S}_i} z_{is}^{t} \geq 0, i = 1, \ldots, I$$
$$QC_{i,n} \cdot \delta_{in} \leq Z_{in} \leq QC_{i,n+1} \cdot \delta_{in} \qquad \text{(A.10)}$$
$$\sum_{n=1}^{N} \delta_{in} \leq 1, i = 1, \ldots, I$$

References

Bilgen B (2010) Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem. *Expert Systems Appl*. 37(6):4488–4495.

Bilgen B, Çelebi Y (2013) Integrated production scheduling and distribution planning in dairy supply chain by hybrid modelling. *Ann. Oper. Res*. 211(1):55–82.

Bilgen B, Ozkarahan I (2004) Distribution planning problem: A survey. Ahr D, Fahrion R, Oswald M, Reinelt G, eds. *Proc. Internat. Conf. Oper. Res.* (Springer, Berlin), 39–46.

Chang YC, Li VC, Chiang CJ (2014) An ant colony optimization heuristic for an integrated production and distribution scheduling problem. *Engrg. Optim*. 46(4):503–520.

Chen Z (2010) Integrated production and outbound distribution scheduling: Review and extensions. *Oper. Res*. 58(1):130–148.

Chen Z, Pundoor G (2006) Order assignment and scheduling in a supply chain. *Oper. Res*. 54(3):555–572.

Dhaenens-Flipo C, Finke G (2001) An integrated model for an industrial production distribution problem. *IIE Trans*. 33(9):705–715.

Goetschalckx M, Vidal CJ, Dogan K (2002) Modeling and design of global logistics systems: A review of integrated strategic and tactical models and design algorithms. *Eur. J. Oper. Res*. 143(1): 1–18.

Goyal SK, Nebebe F (2000) Determination of economic production-shipment policy for a single-vendor-single-buyer system. *Eur. J. Oper. Res*. 121(1):175–178.

Hochbaum DS, Hong SP (1996) On the complexity of the production-transportation problem. *SIAM J. Optim*. 6(1):250–264.

Iglehart DL (1963) Optimality of (s, S) policies in the infinite horizon dynamic inventory problem. *Management Sci*. 9(2):259–267.

Jiang BJ, Tian L, Xu YF, Zhang FQ (2016) To share or not to share: Demand forecast sharing in a distribution channel. *Marketing Sci*. 35(5):800–809.

Kuno T, Utsunomiya T (2000) A Lagrangian based branch-and-bound algorithm for production-transportation problems. *J. Global Optim*. 18(1):59–73.

Lee CY, Chen ZL (2001) Machine scheduling with transportation considerations. *J. Scheduling* 4(1):3–24.

Li CL, Ou J (2005) Machine scheduling with pickup and delivery. *Naval Res. Logist*. 52(7):617–630.

Pundoor G, Chen ZL (2009) Joint cyclic production and delivery scheduling in a two-stage supply chain. *Internat. J. Production Econom*. 119(1):55–74.

Sabri E, Beamon BM (2000) A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega* 28(5):581–598.

Viergutz C, Knust S (2014) Integrated production and distribution scheduling with lifespan constraints. *Ann. Oper. Res*. 213(1): 293–318.

Verification Letter

Jane Wu, Logistics Analysis Manager, Supply Chain Department, Danone (China) Food & Beverage Co., Limited, 24/F Onelink Center, No. 230 Tianhe Road Tianhe District, Guangzhou, Guzngdong, China, writes:

"Danone is one of the world's most successful health food marketers, producers, and distributors. Since Danone Waters started the water business in November 2008, it has expanded its scale to 18 factories, 41 offices, more than 6,000 employees, and nearly 2,000 sales regions. With the rapid development of business, scientific management is becoming more and more challenging.

"From July 2012, our company has cooperated with the authors and their team. They developed a production and transportation scheduling system. The system has proven effective, and is still in use today.

"By testing, this new system will significantly reduce annual production and transportation costs. We take MIZONE 2013 as an example because of the new data involving trade secrets. According to the original plan, the budget for the company's logistics cost is 698.305 million yuan, which includes a production cost of 431.018 million yuan and a transportation cost of 267.286 million yuan. After optimization, the total cost decreased by 4.7% to 665.626 million yuan. The production cost is 414.878 million yuan. The logistics cost is 250.748 million yuan."

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