The Norwegian company Omya Hustadmarmor supplies calcium carbonate slurry to European paper manufacturers from a single processing plant, using chemical tank ships of various sizes to transport its products. Transportation costs are lower for large ships than for small ships, but their use increases planning complexity and creates problems in production. In 2001, the company faced overwhelming operational challenges and sought operations-research-based planning support. The CEO, Sturla Steinsvik, contacted Møre Research Molde, which conducted a project that led to the development of a decision-support system (DSS) for maritime inventory routing. The core of the DSS is an optimization model that is solved through a metaheuristic-based algorithm. The system helps planners to make stronger, faster decisions and has increased predictability and flexibility throughout the supply chain. It has saved production and transportation costs close to US$7 million a year. We project additional direct savings of nearly US$4 million a year as the company adds even larger ships to the fleet as a result of the project. In addition, the company has avoided investments of US$35 million by increasing capacity utilization. Finally, the project has had a positive environmental effect by reducing overall oil consumption by more than 10 percent.

Key words: transportation: freight, materials handling; decision analysis: multiple criteria.
The Omya Group is the major shareholder of Omya Hustadmarmor, a production company located close to the town of Molde on the west coast of Norway. Omya Hustadmarmor produces calcium carbonate slurry that the European papermaking industry uses as a filler and a coating pigment. In fact, high-quality paper may contain more than 50 percent calcium carbonate, which explains why the periodical *National Geographic*, for example, is quite heavy.

Omya Hustadmarmor is the largest production unit within the Omya Group, with yearly production of more than three million metric tons. The main input in the slurry production is marble stone, which comes from a quarry in northern Norway and from some local quarries. Omya Hustadmarmor transforms the marble stone into slurry in a wet grinding process, adding various chemicals and water. It then ships 15 or 16 slurry variants from the plant to the paper mills, storing them on route in 10 first-tier tank farms, located in Germany, the Netherlands, the United Kingdom, Sweden, and Finland (Figure 1). It supplies customers from the first-tier tank farms but also maintains a few second-tier tank farms located near some major customers. Omya Hustadmarmor expects to start supplying the North American market soon.

The company uses chemical tank vessels, currently ranging from 2,400 to 16,000 metric tons, to transport slurry from the plant to the first-tier tank farms and smaller barges, rail, or truck to transport it from the tank farms to the paper mills. Transportation times from the plant to the first-tier tank farms run between two to five days in summer and six days in winter. The company also uses barges to transport slurry between first-tier and second-tier tank farms, up the Rhine and Maas rivers. It generally uses direct (single-destination) shipping in the transportation from the plant to the first-tier tank farms. Gallego and Simchi-Levi (1990) analyzed the benefits of using a direct shipping strategy.
Since the early 1980s, Omya Hustadmarmor has grown from a yearly production volume of less than 200,000 metric tons to over three million (Figure 2), investing frequently in production, storage, and vessel capacity.

The Omya Group is a majority owner of many of the vessels in the tank-vessel fleet. Anders Utkilens Rederi (AUR), a shipping company based in Bergen, Norway, is the other shareholder. AUR, which also takes care of the spot market trading, ship management, and crewing, has been transporting slurry for Omya Hustadmarmor since 1984.

When vessels are not transporting slurry from Omya Hustadmarmor, they are used in the spot market. Hence, use of the vessels carries a high opportunity cost. Their most important spot-market activity is transporting methanol from Russia to Western Europe. After vessels deliver slurry to the tank farms in Sweden and Finland, they often pick up methanol in Russia before heading west out of the Baltic Sea.

The company can take advantage of economies of scale in transporting slurry from the plant to the tank farms, with large vessels costing much less per ton than small vessels. However, planning for large vessels is challenging because they require more storage space at the plant and at the tank farm.

The vessel transportation costs constitute a major part of the total product costs. Hence, for the slurry business to be profitable, Omya Hustadmarmor must use large vessels as much as possible and load them fully on trips from the plant to the tank farms.

**Operational Challenges**

To plan trips from the plant to the tank farms, the company takes two steps. Planners (1) decide which vessel should depart on which day for which tank farm, and (2) decide what mix of products each vessel should carry. To fully utilize the capacity of each vessel, it must always ship multiple slurries. Planners must coordinate the replenishment of different slurries.

The planners must ensure that the tank farm inventories do not reach uncomfortably low levels before a vessel arrives to replenish them. If they did not receive raw materials in time, the papermills would have to stop production. Because the investment cost for one paper machine can be in the magnitude of one billion US dollars, it is crucial that Omya Hustadmarmor delivers slurry on time. Historically, it has never had a stockout situation. To maintain this record, the company keeps very high safety stocks at the tank farms. The cost of capital tied up in the safety stocks is low compared to its other costs, such as production and transportation costs. However, the high safety stocks consume storage space in the tank farms, limiting the space left for replenishment stocks and limiting the use of large vessels. Planners must consider the available storage capacities and the safety stocks for the various slurries at each destination tank farm in using large vessels. It can be difficult to find a plan that will fill a large vessel from inventory at the plant and discharge its contents into the available storage capacity at the destination tank farm.

The planning is further complicated by constraints on minimum transportation quantities. Because the slurries are quite dense (between one and a half and two metric tons per cubic meter), vessels reach their weight capacities (metric tons) before they reach their volume capacities (cubic meters). Hence, a full vessel will normally have some empty tanks or some partially filled tanks. However, any partially filled vessel tank must be at least 60 percent full by volume to prevent dangerous slurry movements (sloshing) in stormy weather, which could at worst crush the tank.

Planners must take into consideration several interdependencies, or domino effects. For example, the choice of product mix for one vessel will restrict the possible product mix for the next vessel leaving the plant. If the plant ships too much of a given slurry on the first vessel, it may have too little of this slurry available for the next. The shortage could prohibit using the full capacity of the second vessel or failing to supply tank farms on time.

Because its production and storage capacities are limited, the plant must closely coordinate production planning and distribution planning. The production process is a multistage divergent process, in which the last stage consists of approximately 30 parallel lines. Each line can produce multiple, but not all, slurry variants. To change production from one slurry variant to another, the workers must fine-tune the process to reach the right quality slurry. This changeover
time consumes production capacity. Hence, production efficiency depends on the plant’s producing large production lots with few changeovers between slurries.

The plant stores finished, as well as intermediate, products in huge storage tanks. The finished product storage capacity at the plant covers two or three weeks of production at an aggregate level, while the largest vessels can carry about two days’ production volume. At the individual slurry level, the plant’s storage capacity may cover a considerably shorter time period, and one shipment normally requires several days of production volume.

One reason for a changeover could be that the plant must stop production of a slurry because its storage tank at the plant is full. From the production planner’s point of view, an ideal distribution plan will call for shipping out a slurry before its storage tank is full, so that the plant does not have to stop production of this slurry.

Distribution planners must also take into account the limited loading capacity at Omya Hustadmarmor’s quay. Because it has only one quay, the company can load only one vessel at a time. Loading a vessel can take between five and 15 hours, depending on the size of the vessel. The planners therefore try to avoid more than two vessels arriving on a single day.

Because of uncertainty, on both the demand side and the supply side, planners must often revise their plans. For some products and some customers, demand varies considerably. A paper manufacturers’ use of a certain slurry variant depends on its production volume and on its product mix. A paper mill’s total production volume is usually rather stable, but the mix of paper products it produces may vary. Because the various paper qualities require different slurry variants, a mill’s consumption may suddenly change between slurries.

On the supply side, vessels may arrive late at the plant or at tank farms because of bad weather. Vessels may also become temporarily unavailable because they take on transportation work for external customers on the spot market. When they get requests for such spot market activities, the shipping company AUR asks the distribution planners whether it can change its schedule.

Omya Hustadmarmor’s operations have grown in complexity as its products, customers, and vessels have increased over the years. When we started our research collaboration in 2001, the company scheduled shipments from the plant to the tank farms manually through an informal process that involved the Omya sales office in Germany, the local tank farm managers, the spot market trader at AUR, and the logistics department at Omya Hustadmarmor.

Somewhat simplified, the planning process was as follows. Whenever the inventory for one of the products (the triggering slurry) at a tank farm reached a fairly low level, the Omya sales office ordered a vessel of the appropriate size. The shipping company AUR then had to provide a suitable vessel on short notice. Because slurry transportation from Omya Hustadmarmor is the backbone of AUR’s business, it had to keep a number of vessels within a short distance from the plant in case it needed a vessel to transport slurry. This need for slack transportation capacity limited AUR’s revenue from the spot market.

Manual planning worked quite well for years. For a long period, Omya coped with the growing complexity by steadily investing in new production, storage, and transportation capacity. It maintained operational flexibility by using mainly small vessels. However, the continuous investments and the use of small vessels created a financial burden for the company. Furthermore, the company’s profitability was threatened by increasing costs for electricity, fuel, raw materials, and other inputs.

Around 2000, the company decided to limit further investments in capacity and use large vessels much more extensively. As could be expected, it encountered problems caused by the reduced flexibility. A changed departure date, destination, or product mix for a large vessel of 16,000 metric tons creates more severe domino effects than it would for a relatively small vessel of 6,000 metric tons. In slurry production, such effects include extra changeovers on the production lines to accommodate a product mix different from that originally planned. The increases in changeovers, in total sales volume, and in product variants combined to reduce the utilization of production capacity. The frequent changes in transportation and production plans often delayed
planned preventive maintenance, which led to frequent machine breakdowns in the production facility. In some instances, maintenance specialists from Germany returned home without performing planned maintenance because a sudden change in the production plan meant the plant had to use the machine scheduled for work to produce a specific slurry for an arriving vessel.

The lack of predictability also created quality problems. Frequently the plant had to reprocess some of the slurry produced because it was not within the limits defined by the product specifications.

When we started the project in 2001, the main actors in the supply network communicated often, but they spent most of their time trying to reach an agreement on how to handle sudden changes caused by delayed vessels, production problems, or changed customer orders (Figure 3).

In response to difficult situations, the supply planners commonly changed the distribution plan in such a way that the production planner was forced to change the production plan, which led to increased setups and to quality problems. The company sometimes solved quality problems by reprocessing the slurries using a screening process when they arrived at the tank farms. The production planner had little influence over the distribution plan, and the planning horizon was seven to 10 days.

All in all, the stress at different levels and within different functions of the organization had become unbearable, and the company sought improved operational planning tools. The top managers at Omya Hustadmarmor contacted the nearby institute Møre Research Molde, which is the contractual research unit at Molde University College. After some initial meetings, the company and the researchers drew up formal contracts. We conducted a preliminary study financed by Omya Hustadmarmor.

Our main focus in the preliminary study was to analyze customer demand and to identify the key performance drivers in Omya Hustadmarmor’s supply chain. The demand analysis showed that for most customers and slurries, the demand uncertainty was less severe than commonly perceived. However, a few very demanding customers created disturbances. As a first step, we recommended that the company increase the safety stocks of the slurries bought by these customers at the nearby tank farms and reduce the safety stocks for some other slurries.

Further analysis showed that vessel transportation was the key performance driver in the supply chain, partly because of its great cost and the freight structure’s economies of scale, and partly because the lack of proper planning tools led to unpredictability and low responsiveness. We concluded that developing a planning tool for vessel transportation would be the key to stabilizing the company’s whole supply chain. Planning would need to include routing vessels and replenishing inventories at the tank farms. Hence, the problem was an inventory-routing problem. We started a development project, cofinanced by Omya Hustadmarmor and the Norwegian Research Council.

Like most industrial operations research projects, this project started with initial discussions and company visits. The company and the researchers maintained close contact in an effort to capture the relevant aspects of the operational-planning situation.

Modeling and Solving the Inventory-Routing-Optimization Problem

We needed to understand and model all the constraints of the distribution-optimization problem. We realized after some preliminary analysis that it was a complex inventory-routing problem because we had to determine both the shipment quantities and the schedules of the vessels and thus the constrained
inventory levels at the tank farms. We first modeled the optimization problem as a mixed-integer linear program (appendix) and solved it using a standard solver. Only small instances were solved optimally, and we could not find a feasible solution after a few hours for larger instances. Five main characteristics make this inventory-routing problem difficult to solve. On the other hand, one characteristic facilitates its solution: vessels almost never deliver products at two different destinations on the same trip. We did not have to explicitly consider the few cases that they do in the optimization. Users can manually impose multidelivery trips with the decision-support system.

Discrete and Continuous Variables
The first well-known difficulty encountered when solving most inventory-routing problems is the combination of large continuous variables (shipment quantities and inventory levels) and discrete variables (choice of routes and vehicles). A consequence is that one obtains poor bounds with linear relaxation of the integer-linear-programming model. Moreover, the general cutting planes in standard solvers (such as Gomory cuts, knapsack covers, and lifter cover inequalities) are not effective for these types of problems.

Multiple Products
We need to explicitly manage multiple products. Inventory-routing researchers usually consider single products or single families of products. With multiple products, it is impossible to easily disconnect the optimization of the shipment quantities and of the vessel schedules.

Time-Varying Demands
Because product demands are dynamic, shipment quantities of the various products naturally may vary from one shipment to another.

A Heterogeneous Fleet of Vehicles
The heterogeneous fleet of vehicles has several impacts, and it is not often considered. Inventory-routing researchers usually consider only vehicles of the same size. With a heterogeneous fleet of vehicles, we cannot disconnect the optimization of shipment quantities and vessel schedules. Moreover, because shipping on large vessels is less expensive per metric ton than shipping on small vessels, the bounds obtained by linear relaxation of the integer-linear-programming model become very poor. Only the binary variables associated with large vessels become positive in the linear relaxation, which means that the branch-and-cut algorithms used in standard solvers are not guided towards feasible (not to mention good...) solutions.

Nonlinear Objective Function
Our first integer-programming models had a linear objective function minimizing the sum of transportation and inventory costs during the planning horizon. However, after some experimental testing, we realized that using a linear transportation cost function on a finite time horizon may actually lead to nonoptimal solutions from Omya Hustadmarmor’s point of view. The model might suggest sending a small vessel to a tank farm during the planning horizon even if the company could use only large vessels. We decided to use a more appropriate objective function, namely, the sum of the (nonlinear) transportation costs per ton multiplied by the demands on the horizon plus the (linear) inventory costs (appendix).

To obtain realistic solutions, we had to consider additional constraints, such as storage capacities at the tank farms, minimum quantities of products to be loaded on vessels, vessel availability during the planning horizon, and daily loading capacity at the plant quay.

During the project (2002 to 2003), we could find no published research concerning problems with all the main characteristics of our problem, and this still seems to be the case. For instance, Kleywegt et al. (2004) and Gaur and Fisher (2004) considered a single homogeneous product. Moreover, Christiansen et al. (2004, p. 8) noted, “Inventory routing has rarely been discussed in a marine context.” Ronen (2002) explicitly considered multiple products but separated planning shipments from scheduling vessels and proposed methods only for planning shipments. To obtain realistic solutions to Omya Hustadmarmor’s problem, we focused on integrated approaches.

In the first mixed-integer linear-programming model we formulated (appendix), the linear objective function could produce suboptimal solutions for the actual
nonlinear objective function. In several other models, we tried to reduce the number of integer variables, for instance, by imposing additional conditions on the distribution plan. We tried various cuts that were efficient for hypothetical instances we generated but not for real-life instances. We tried a column-generation approach in which the columns represented the possible routes of the vessels. Again, mainly because the fleet consists of heterogeneous vessels, the linear relaxation of the resulting model was too weak to solve large instances. Finally, we performed all our experiments on the linear-integer-programming models on a 28-day horizon. In some cases, the distribution plans we obtained were wrong because of errors known as end effects, that is, “what is optimal over the short horizon may be suboptimal over the long run” (Fisher et al. 2001, p. 679). Hence, in the solution procedure that we implemented in our DSS, we based the optimization on a horizon of 84 days, even though the user is working with a planning horizon of 28 days.

We based the optimization in the DSS on a metaheuristic, a memetic algorithm (also called a genetic local search or hybrid genetic algorithm), a population-based approach that combines local search heuristics with crossover operators. The first key component of the metaheuristic is a greedy heuristic that determines, for a given fixed order of the tank farms, the transportation plan for each tank farm. We then use a local search algorithm that swaps tank farms in the fixed order to strictly improve the solution. On top of this approach, we use a genetic algorithm, where a chromosome is a tank farm order, to better explore the solution space. The idea is to visit very different portions of the solution space. We used crossover and mutation operators that are close to those Sevaux and Dauzère-Pérès (2003) used for a one-machine scheduling problem. We developed several versions of the metaheuristic in which we improved the performance (speed and quality) of the greedy heuristic and the local search algorithm. In particular, we redesigned the code to improve the implementation of the algorithms, which proved to be very effective. We obtained very good solutions in about an hour with the first version of our approach and in few minutes with the last version. We compared these solutions when possible and for small instances to the ones obtained with a standard solver and found that they were often optimal. For large instances, we verified the quality of the solutions by comparing them with a straightforward lower bound that consists of sending only the most profitable vessels to each tank farm. Our approach proved to be sound from a practical point of view in all the practical instances we tested; no simple change in the proposed solution could improve it.

The Decision-Support System (DSS)
We developed the optimizer engine in C++ and made the user interfaces of Excel sheets with numerous VBA macros that, among other things, automatically formatted and updated the sheets. Using a menu, users can move between sheets, start the optimization, load inventory levels and demands, forecast future demands, and so forth. The DSS allows users to enter various input data, in particular, inventory data (current and maximum levels, safety stocks), demands (per product, destination, and day of the 84 days), transportations costs (per vessel and tank farm), travel times (for each vessel, the number of days to go to and come back from each tank farm), loading capacities at the factory quay (per day), and vessel data (for each vessel: capacity, minimum quantity to load, number of tanks, loading time, and unavailability periods). Moreover, users can load current inventory levels and demands on a user-specified horizon from the Omya Group’s Web-based information system.

Planners can incorporate their practical insight in replanning by manually changing and freezing some shipments before optimization takes place. This ability is particularly useful in coping with such random events as vessel delays or in discussing schedules with the shipping company or the production department.

The system produces different forms of output, which are useful in interacting with the various actors in the supply chain. The company provides the shipping company with the planned routes of the vessels. It provides tank-farm managers with the planned future inventory for each product at each tank farm (Figure 4). The planner can visualize, for each product in the tank farm, whether the planned inventory lies above the safety stock level and below the maximum
inventory level given the storage capacity at the tank farm. The DSS can simultaneously show the inventory levels for all products at a given tank farm. Planners use this view, with the list of vessels arriving at the tank farm during the planning horizon and their contents, in discussions with the tank-farm managers. The system will also list the product quantities to be loaded at the factory for each day of the planning horizon, output important to the production manager.

**Implementation and Use of the DSS**

The DSS supports decisions at the operational and tactical level and at the long-term strategic level. For the distribution planner to use the DSS as an operational and tactical tool, we needed daily demand and inventory data for the various slurries at the tank farms. When we began the DSS development project, the Omya Group had just invested in a basic information system that could supply these data. It uses radar-based equipment to measure the daily inventory level of each storage tank at the tank farms. The tank-farm managers enter these data into the information system, together with planned customer orders. The optimization-based DSS we developed reads the data from the information system so that the distribution planner can base decisions on updated information.

Planners use the DSS as an operational tool more or less every day to ensure that changes in input data, such as increases in demand and changes in vessel availability, do not create problems. The distribution planner uses a planning horizon of 28 days, trying to use as many large vessels as possible while satisfying capacity and safety-stock constraints. When necessary to cope with changed parameters, the distribution planner uses the DSS to reoptimize the distribution plan. Such replanning normally takes place once or twice a week. The planner also uses the DSS to evaluate the costs of changes in the distribution plan when, for instance, the shipping company wants to change the planned departure date of a vessel to take advantage of a profit opportunity in the spot market. After evaluating the feasibility of the change and the resulting increase in costs, the planner can accept the change if it is feasible and if the shipping company will cover the increase in cost.

Frequent communication among different actors is essential in operational and tactical planning. The distribution planner at Omya Hustadmarmor must interact closely with the production planner, the shipping company, and the sales office in Germany (Figure 5).

With the DSS, decision power has been centralized with the distribution planner, who plans for a horizon of 28 days instead of seven to 10 days, and the production planner is a discussion partner in planning distribution. The distribution planner and the production planner sit together and, using the DSS, try to find a distribution plan that is close to optimal with regards to production costs and transportation costs. To some extent, they include the person
responsible for detailed inventory planning, that is, allocating products to storage tanks. Even though the plant does not use an optimization tool to plan production or inventory, it spends much less time on short-term firefighting than it did simply because there is more predictability for all parties and fewer problems. Moreover, planners can do any replanning much faster than in the past with fewer negative effects.

We developed a special version of the DSS for use as a simulation tool to analyze different scenarios and study the long-term effects of various decisions. It differs from the operational and tactical version of the DSS in having a longer time horizon. The company has used it to analyze market extensions, fleet investments, and changes in tank-farm storage capacities or safety stocks. The company relied on the tool in making its decisions to acquire new, larger vessels and to enter new markets.

The simulation studies showed that the company’s ability to use large vessels depends on balancing (1) the tank farm’s storage capacity for different products and (2) the tank farm’s safety-stock levels. We conducted follow-up projects to optimize the allocation of storage capacity and to analyze safety stocks at the tank farms.

By adopting the DSS for planning daily distribution, the organization centralized planning. The user of the tool naturally gained decision power. Company managers considered it crucial to coordinate distribution planning and production planning closely. Hence, they decided that the distribution planners at the plant should be the users of the system and should be located near the production planners.

To realize the DSS’s potential for improved coordination, its user needed a mandate to make the final decisions regarding vessels’ departure dates, destinations, and product mixes. As could be expected, other parties in the system were sceptical about changing the decision point and resisted it.

Several key persons in the Omya Group supported the final successful implementation of the DSS. We relied on the advice and insight of the distribution planners at the plant to formulate an optimization model that was sufficiently realistic to provide the final DSS with the necessary credibility. We also relied on other project champions in the Omya Group and at the Hustadmarmor plant. Without their support and faith in the DSS, we would have had great difficulty in gaining acceptance for the new way of working. A balanced scorecard project that the Omya Group initiated has been instrumental in quantifying the impact of the DSS. Finally, top management’s awareness of the benefits of operations research and support of the project has been essential.

Quantifiable Benefits
Because of the project, Omya achieved considerable savings, largely because of the increased predictability throughout the entire supply chain. The production department has taken advantage of the reliable shipping plans and four-week planning horizons the DSS provides. The savings in production costs from reduced waste, raw materials, and energy consumption result from the more reliable distribution plan, which stabilizes production and reduces changeovers (Figure 6). By increasing its use of production capacity by four percent, Omya Hustadmarmor has also avoided large investments in production capacity of nearly US$13 million. This is important because this type of production is very capital intensive.

Product-quality problems that require reprocessing have almost disappeared since we implemented the DSS because the number of changeovers has dropped by 40 percent and because workers can perform preventive maintenance, quality testing, and fine-tuning of the production processes as planned. With the improved reliability of the distribution plan came improved stability of the production plan, which has facilitated maintenance of the production facility.

Since Omya Hustadmarmor’s need for transportation capacity has become more predictable, the risk connected to selling vessel capacity to external customers on the spot market has been reduced. The vessel owners have obtained more business on the spot market, increasing their yearly spot market revenues by over US$600,000. The Omya Group benefits from this increase because it is a partial owner of the fleet.

The inventory-routing DSS has helped distribution planners to take advantage of economies of scale in transportation. The volume shipped in large vessels has increased from 39 percent to 65 percent, sharply reducing annual transportation costs by over US$1.8 million, and manpower costs for loading and discharging vessels at tank farms by US$30,000.
Moreover, total oil consumption has dropped by 10 to 12 percent because large vessels consume approximately 40 percent less oil per ton transported than small vessels.

In the near future, AUR expects to acquire new vessels with a capacity of up to 22,000 metric tons, which should further reduce transportation costs. Only with the support of the DSS would Omya Hustadmarmor consider it possible to operate vessels of this size. By using the DSS for inventory routing, optimizing storage-capacity assignment, and analyzing safety stock, Omya has improved its utilization of existing storage capacity at the tank farms. Without this improvement, Omya estimates that it would have had to invest in 14,000 cubic meters of new storage tanks.

Unquantifiable Benefits

The DSS has also improved supply chain reactivity and control. The company can now replan quickly to cope with vessel delays, machine breakdowns, and other sudden interruptions.

Three simultaneous incidents demonstrated the DSS’s capabilities in helping Omya to recover from operational accidents and to maintain customer goodwill. In October 2004, near Scotland, the vessel Kilstraum collided with a submarine that suddenly surfaced in the middle of the night. Fortunately, no one was injured, and the vessel was able to continue to its destination, but it had to be taken out of service for repairs. At the same time, another vessel developed engine problems and was taken out of service. To make matters worse, a machine broke down at the plant. The simultaneous occurrence of three such incidents is extremely rare, but thanks to the DSS, the planner could immediately see the impact on the distribution system and replan to minimize their negative effects and deliver the slurries on time. Before we implemented the DSS, such an extreme situation would have delayed deliveries and could have damaged customer relationships.

The DSS has improved transparency throughout the supply chain; people now understand the consequences of decisions in one part of the supply chain on other parts.

Because of the DSS and the improved planning processes, Omya Hustadmarmor can increase production volumes without making large investments to expand
Table 1: Total yearly savings are US$14 million, with a total present value of over US$152 million, based on a five percent real interest rate and 15 years.

<table>
<thead>
<tr>
<th>Production</th>
<th>Transportation</th>
<th>Storage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Yearly savings</td>
<td>Present value</td>
</tr>
<tr>
<td>Direct, realized savings</td>
<td>Production cost savings</td>
<td>4,310</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avoided capacity investments</td>
<td>Production</td>
<td>1,190</td>
</tr>
<tr>
<td>Projected future savings</td>
<td>A second quay at the plant</td>
<td>920</td>
</tr>
<tr>
<td></td>
<td>Fleet optimization with three larger vessels</td>
<td>3,950</td>
</tr>
</tbody>
</table>

The project and the resulting DSS led to yearly savings of about US$14 million (Table 1), about five percent of the company’s total costs. The company needed savings to maintain its profitability as it faced increased costs of electricity, raw materials, and other inputs. The DSS has also improved Omya Hustadmarmor’s control of its supply chain. Our analysis and the principles behind the system we developed for Omya Hustadmarmor can be used in other industrial settings that require consistency between shipment-planning and vessel-scheduling decisions (for example, the situation Ronen (2002) described).

We conducted several follow-up projects after we completed the DSS for distribution optimization. First, we performed many strategic analyses concerning such questions as the right size of the vessel fleet, the profitability of acquiring new larger vessels, and the impact of increased demands. After finding that the company’s ability to use large vessels to deliver to a tank farm depended on its allocating storage capacity correctly among the different products and on its safety-stock levels, we designed and implemented a DSS for allocating tanks to products optimally. The objective of this system is to maximize the average vessel size that can be sent to a tank farm. In another project, we determined the correct sizes of safety stocks, taking into account uncertainties in supply to tank farms, and in demand. We found that the company’s safety stocks were too low for some products and too high for others.

Our project has demonstrated the possibilities for improving efficiency within the entire Omya Group by introducing an operations-research based DSS in one part of the group, Omya Hustadmarmor. Even though Omya Hustadmarmor is the largest production unit within the group, it should be able to achieve additional savings through optimization over larger parts of the value chain. For example, it could optimize coordination among several production units and optimize distribution planning from tank farms to paper mills to integrate large parts of the supply system. It could also consider supply chain problems from the shipping company’s point of view to increase efficiency and work on optimizing fleet usage for both the supplier and the buyer of transportation services. Furthermore, the methodology we developed should interest other industries with substantial transportation costs and demand (the oil and gas industry, for example). As globalization and competition increase, the demand for synchronizing transportation also increases.
Finally, Omya Hustadmarmor may want to further improve its control of its complete supply chain in the future. First, it might take into account additional constraints, such as production and storage capacity constraints at the plant, when optimizing shipments and vessel routes, although these constraints are currently not critical. An interesting and seemingly very profitable project would be to design a DSS for optimizing production planning and scheduling, which the company now does manually. Omya Hustadmarmor could further increase its production capacity by reducing the number of changeovers while satisfying storage capacity constraints for finished products.

Appendix

The Mathematical Model

The factory produces \( P \) (about 16) different product types that it ships to \( K \) (about 10) different tank farms in Europe using a fleet of \( J \) (about 17) vessels of different sizes. It stores the products in tanks (often using several tanks for one product) in the tank farms. Renting a vessel to carry products from the factory to a tank farm has a given fixed cost, which depends on the size of the vessel and the distance to the tank farm. The goal is to determine an optimal distribution plan, that is, departure dates, tank farms, and shipments (quantities of various product types) for each vessel in the planning horizon such that the overall distribution cost is minimized and the constraints are satisfied. Planners must ensure 100 percent customer service, that is, that product inventory levels never fall below given safety stock levels.

The parameters of the model follow:

\( P \): number of products.
\( J \): number of vessels.
\( K \): number of tank farms.
\( T \): number of days in the horizon.
\( c_{jk} \): total cost for sending vessel \( j \) to tank farm \( k \).
\( h_{pk} \): inventory cost for product \( p \) at tank farm \( k \) per product unit and per day.
\( d_{pkt} \): total demand for product \( p \) at tank farm \( k \) in day \( t \).
\( a_{jk} \): number of days for vessel \( j \) to go to tank farm \( k \).
\( b_{jk} \): number of days for vessel \( j \) to go to and come back from tank farm \( k \) (\( b_{jk} > a_{jk} \)).
\( Z_j^{\text{max}} \): capacity of vessel \( j \).
\( Z_j^{\text{min}} \): minimum quantity of product \( p \) that must be in vessel \( j \) if \( p \) is included in a shipment (tank filling).
\( I_{pk}^{\text{init}} \): initial inventory of product \( p \) at tank farm \( k \).
\( I_{pk}^{\text{max}} \): storage capacity for product \( p \) at tank farm \( k \).
\( I_{pk}^{\text{min}} \): minimum inventory (safety stock) for product \( p \) at tank farm \( k \).
\( lh_j \): number of hours necessary to load vessel \( j \) at the plant.
\( NH_t \): number of hours during which vessels can be loaded at the plant in day \( t \).

The variables follow:

\( Y_{jkt} \): \([0, 1]\) variable that indicates whether vessel \( j \) leaves from the factory for tank farm \( k \) in day \( t \) \((t \leq T - a_{jk})\).
\( Z_{pkjt} \): quantity of product \( p \) shipped with vessel \( j \) arriving in day \( t \) at tank farm \( k \) \(( t \geq a_{jk} + 1)\).
\( W_{pkjt} \): \([0, 1]\) variable that indicates whether product \( p \) is shipped with vessel \( j \) arriving in day \( t \) at tank farm \( k \) \(( t \geq a_{jk} + 1)\).
\( I_{pkt} \): inventory level of product \( p \) at tank farm \( k \) at the end of day \( t \).

Minimize

\[
\sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} c_{jk} Y_{jkt} + \sum_{p=1}^{P} \sum_{k=1}^{K} \sum_{t=1}^{T} h_{pk} I_{pkt}
\]

subject to

\[
\sum_{j=1}^{J} Z_{pkjt} - I_{pk0} + I_{pk,t-1} = d_{pkt} \quad \forall p, k, t, \quad (2)
\]

\[
I_{pk0} = I_{pk}^{\text{init}} \quad \forall p, k,
\]

\[
I_{pk} \leq I_{pk}^{\text{max}} \quad \forall p, k, t,
\]

\[
I_{pk} \geq I_{pk}^{\text{min}} \quad \forall p, k, t,
\]

\[
\sum_{p=1}^{P} Z_{pkjt} \leq Z_j^{\text{max}} Y_{jkt-a_{jk}} \quad \forall j, k, t \text{ s.t. } t - a_{jk} \geq 1, \quad (6)
\]

\[
Z_{pkjt} \geq Z_j^{\text{min}} W_{pkjt} \quad \forall p, j, k, t,
\]

\[
Z_{pkjt} \leq Z_j^{\text{max}} W_{pkjt} \quad \forall p, j, k, t,
\]

\[
\sum_{k=1}^{K} \sum_{t=1}^{T} Y_{jkt} \leq 1 \quad \forall j, t,
\]

\[
\sum_{j=1}^{J} \sum_{k=1}^{K} lh_j Y_{jkt} \leq NH_t \quad \forall t,
\]

\[
Y_{jkt-a_{jk}} \geq W_{pkjt} \quad \forall p, j, k, t \text{ s.t. } t - a_{jk} \geq 1,
\]

\[
Y_{jkt-a_{jk}} \leq W_{pkjt} \quad \forall p, j, k, t \text{ s.t. } t - a_{jk} \leq 1,
\]

\[
Y_{jkt-a_{jk}} \leq W_{pkjt} \quad \forall p, j, k, t \text{ s.t. } t - a_{jk} \leq 1,
\]

\[
Y_{jkt-a_{jk}} \leq W_{pkjt} \quad \forall p, j, k, t \text{ s.t. } t - a_{jk} \leq 1,
\]
The objective function (1) minimizes the sum of the transportation costs and inventory costs at the tank farms. The inventory costs are very small compared to the transportation costs and may be omitted. Constraints (2) correspond to the inventory balance equations. Constraints (3) initialize the inventories at the beginning of the planning horizon. Constraints (4) specify that the inventories for a given product at a given tank farm cannot be higher than the corresponding storage capacity in each day. Constraints (5) ensure that the inventories for a given product at a given tank farm cannot be smaller than the safety stock in each day. Constraints (6) ensure that the total quantity transported by a vessel is not higher than the capacity of the vessel. Constraints (7) guarantee that, if a product is loaded into a vessel, a minimum quantity is loaded. Constraints (8) are used to force variable $Z_{pjkrt}$ to be equal to zero if variable $W_{pjkrt}$ is equal to zero. Constraints (9) ensure that a vessel cannot be sent to more than one tank farm at one time (scheduling constraints). Constraints (10) specify that there is a maximum number of hours that can be spent to load vessels at the factory in each day. Constraints (11) link variables $Y_{jkt}$ and $W_{pjkrt}$, that is, a product can be shipped on vessel $j$ arriving on day $t$ at tank farm $k$ only if vessel $j$ actually leaves from the factory for tank farm $k$ on day $t - a_{jk}$.

The nonlinear objective function used in the meta-heuristic can be written as follows:

$$K \sum_{k=1}^{K} \left[ \sum_{j=1}^{J} \sum_{t=1}^{T} c_{jkt} Y_{jkt} \right] + \sum_{p=1}^{P} \sum_{k=1}^{K} \sum_{t=1}^{T} d_{pkt} I_{pkt}$$

The goal is to minimize the sum for all tank farms of the transportation costs per ton times the demands on the horizon (which can be viewed as weights for all the tank farms) plus the inventory costs (which are the same as those in the linear objective function).

Acknowledgments
The project activities were partly organized within More Research Molde, the contractual research organization at Molde University College. We gratefully acknowledge the financial support from the Norwegian Research Council (NFR).

References