AI and Simulation-Based Techniques for the Assessment of Supply Chain Logistic Performance

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Abstract

The effectiveness of logistic network design and management for complex and geographically distributed production systems can be measured in terms of direct logistic costs and in terms of supply chain production performance. The management of transportation logistics, for instance, involves difficult trade-offs among capacity utilization, transportation costs, and production variability often leading to the identification of multiple logistic solutions. This paper defines and compares three different modeling approaches to systematically assess each identified logistic alternative in terms of actual transportation costs and expected production losses. The first modeling approach examined in the paper is a mathematical model which provides the statistical basis for estimating costs and risks of production losses in simple application cases. The second model is a stochastic, discrete event simulation model of bulk maritime transportation specifically designed to capture the dynamic interactions between the logistic network and the production facilities. The third one is an AI-based model implemented as a modular architecture of Artificial Neural Networks (ANNs). In such an architecture each network establishes a correlation between the logistic variables relevant to a specific sub-problem and the corresponding supply chain costs. Preliminary testing of the three models shows the relative effectiveness and flexibility of the ANN-based model; it also shows that good approximation levels may be attained when either the mathematical model or the simulation model are used to generate accurate ANN training data sets for each transportation/production sub-problem.

1. Introduction

A key objective of supply chain management is to ensure smooth and efficient operations at the production side of the chain. As the complexity of the production processes increases, involving for instance multiple products and distributed production sites, the design and the management of the logistic infrastructure become increasingly critical to the performance of the supply chain as a whole. Decision-makers need to assess and compare alternative logistic solutions accounting not just for their direct costs and benefits but, most importantly, for their impact on production performance. For instance, the main purpose of transportation logistics is to ensure that raw materials and intermediate products are timely delivered to the production sites, thus minimizing the production losses associated to stock-out/over-stock events at the different facilities.

When planning and scheduling transportation resources in terms of resource number, required capacity and routes, the direct costs of transportation are quite simple to estimate in terms of hourly/daily costs of resources and actual transportation times. However, much more significant from the perspective of the supply chain as a whole, is the estimate of the potential production losses determined by the stochastic variability of the plants production rates and of the arrival times of each resource at the designated production sites, in relation to the storage capacity available at each facility. In several instances the costs of such production losses may well exceed the direct costs of transportation.

The objective of the work described in this paper is to capture the interdependencies between the nature of the logistic solution and the corresponding production performance of the supply chain. In particular, the paper identifies suitable performance measures and proposes quantitative means to estimate their value for specified industrial contexts. Performance measures include the expected costs and risks (i.e. probability of occurrence) of production losses and of loading/unloading delays causing transportation resources to be idle.

2. Application context

The paper examines the problem of establishing quantitative means for estimating supply chain logistic

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performance in the context of multi-product and multi-site chemical processing. Specifically, the paper addresses the impact of transportation logistics on production performance, focusing on the expected production losses, for a large company running multiple operations across geographically distributed production sites. Given the significant product volumes involved, transportation occurs mainly by sea: an entire fleet of vessels needs to be managed defining the number of ships, their individual capacities, their routes, and scheduling their trips according to product quantities and transportation requirements (compatibility etc.). In this context, a first objective of transportation logistics is that of maximizing ship capacity utilization by defining ship missions that involve the simultaneous transportation of multiple products and a sequence of multiple ports where both loading and unloading operations may take place.

A second objective is that of minimizing the variability of delivery/pick up times while keeping transportation costs within a specified budget. Ideally, as the number of ships employed on a given route increases, holding total capacity constant, the impact of time delays for one particular ship become less and less significant from the perspective of the performance of the whole production system. However, the corresponding transportation costs rise significantly as economies of scale are being traded for less variability in the delivery/pick up process: it is necessary to keep in mind that the cost of ship hire as well as fuel costs do not vary linearly with ship capacity. The complexity of the trade-off among capacity utilization, transportation costs, and process variability leads to the identification of multiple logistic solutions, which can be assessed in terms of overall costs, including both actual logistic costs and expected production losses. In the following three distinct approaches for the assessment of these overall costs are presented: a mathematical model, a stochastic, discrete event simulation model, and an AI-based model implemented using artificial neural networks.

3. Supply chain logistic performance

With reference to the application context described in the previous section, a tactical mission is defined as a transportation route consisting of a defined sequence of ports and specified groupings of compatible product quantities to be loaded and unloaded in each port of the sequence. The logistic performance of each tactical mission can be evaluated as the combined performance of each individual ship mission for all the ships allocated to that route. The actual cost of each ship mission is driven by ship capacity, navigation times, port wait and operations times.

Another relevant measure of performance is actual capacity utilization, which can be expressed in the form of a cost as cost of non-utilized capacity. As the final objective of transportation logistics is that of feeding a multiplicity of production processes geographically distributed across multiple production sites with specified quantities of raw materials and intermediate products, a third measure of performance can be built based on the so called mission risk, intended as the cumulative probability that the defined mission will cause the occurrence of stock-out and over-stock situations at any of the storage facilities involved, with corresponding production losses and/or additional ship costs due to unaccounted for delays and port wait times.

3.1. Actual mission cost

The cost of each mission can be calculated as indicated in equation 1

$$\text{Mission\_Cost} = \text{Cost\_Coeff} \cdot Q_{max} \cdot \text{Cycle\_Time} \qquad (1)$$

In the equation, Cost_Coeff measures the cost of ship hire per unit capacity and per unit time. Such a cost depends upon the type of products to be transported (influencing the type of ship required), the type of contract, and the class of size of the ship (defined in terms of capacity ranges).

Q_{max} is the capacity committed or, in other words, the minimum ship capacity capable of meeting the transportation requirements for the whole mission. Assuming that the mission consists of “s” legs, each leg being the sailing distance between two subsequent ports reached by the ship.

$$Q_{max} = \text{Max}(Q_{leg\text{-}j}) \text{ with } 1 \le j \le s \qquad (2)$$

In equation 2, $Q_{leg\text{-}j}$ is the sum of the product quantities to be transported between the two ports defining leg j. The equation simply calculates Q_{max} as the largest among the capacities required on each leg. The actual Q_{max} will be the commercial ship capacity closest to the calculated value.

Mission Cycle_Time (equation 1) can be expressed as the sum of several stochastic components. Referring to a single mission leg between port A and port B these components are:

- time_to_enter_port_A = f(t_{enterA}, Port_A_factor)
- port_A_wait_time = f(t_{waitA}, Port_A_factor)
- port_A_docking_time = f(t_{dockA}, Terminal_A_factor)
- terminal_A_set-up_time = f($t_{set\text{-}upA}$, Terminal_A_factor)
- port_A_unloading_time =

= (quantity_to_unload_in_A)/(unloading_rate_in_A)

- port_A_loading_time =

  = (quantity_to_load_in_A)/(loading_rate_in_A)
- port_A_undocking_time =

  = f($t_{undockA}$, Terminal_A_factor)
- navigation_time = [distance / (ship's average speed)] (1+ meteo_factor)
- time_to_enter_port_B = f(t_{enterB}, Port_B_factor)
- port_B_wait_time = f(t_{waitB}, Port_B_factor)
- port_B_docking_time = f(t_{dockB}, Terminal_B_factor)
- terminal_B_set-up_time =

  = f($t_{set-upB}$, Terminal_B_factor)
- port_B_unloading_time =

  = (quantity_to_unload_in_B)/(unloading_rate_in_B)
- port_B_loading_time =

  = (quantity_to_load_in_B)/(loading_rate_in_B)
- port_B_undocking_time =

  = f($t_{undockB}$, Terminal_B_factor)

In the expressions above,

$$f\,(t_X, \text{Port/Terminal\_X\_factor}) = t_{avgX} \cdot (1 + \text{Port/Terminal\_X\_factor}) \qquad (3)$$

where Port/Terminal_X_factor is an index of port/terminal traffic and resources utilization level for port/terminal X. Such an index is expressed in a scale ranging from zero to one (one indicating the highest traffic/resource utilization level), and t_{avgX} is the average time required to complete the specified operation in port/terminal X. Whenever large enough sets of historical data are available, it is also possible to write the same expression as

$$f\,(t_X, \text{Port/Terminal\_X\_factor}) = t_{avgX} + \lambda_X \cdot \sigma_X \qquad (4)$$

where σ_X is the measured standard deviation and λ_X is a user-specified safety coefficient.

Finally, in the expression for navigation_time, the meteo_factor is an index, again in a scale from zero to one, which accounts for the meteorological conditions in the geographic area of interest.

If more then one ship is allocated to a given tactical mission, the same procedure can be followed to calculate the total cost of each ship mission, while the cost of the tactical mission as a whole is calculated as the sum of the costs for all of its constitutive ship missions.

3.2. Cost of unused capacity

The additional cost incurred for non-utilized capacity, is calculated as a measure of performance to penalize the logistic solutions that do not make the best use of committed ship capacity. Such cost is calculated for all the mission's legs such that Qleg-j < Qmax. With reference to the same variables defined to calculate the actual mission cost, this additional cost of unused capacity can be expressed as

$$\text{Addit\_Cost} = \Sigma_j[\text{Cost\_coeff} \cdot (\text{Qmax} - \text{Qleg-j}) \cdot \text{Cycle\_time\_leg\_j}] \text{ with } 1 \le j \le s \qquad (5)$$

where Cycle_time_leg_j, is cycle time calculated for leg j only.

4. Costs and risks of production losses

This section provides the statistical basis for estimating costs and risks of production losses. The methodology first implemented into a mathematical model is illustrated with respect to a simple case: the transportation of a single product quantity between two production sites, identified as A and B, respectively.

It is assumed that the probability distributions for the production and consumption rates (of the specified product) at the two facilities are known. Whenever the distributions are not actually known it is possible to define either a triangular or a beta distribution fitting a set of three known values, these are: the most frequent/likely, the minimum, and the maximum value of the stochastic variable examined.

The same is assumed for the probability distribution associated to the ship's arrival time. The ship, of known capacity, is assumed to depart from port A at time zero and its time of arrival at port B is distributed according to a known probability function. The storage capacity available at each facility's site is also known in terms of maximum capacity and current level. Given this information, the mathematical model enables to calculate both the risk and the expected cost of production losses caused by the occurrence of over-stock and stock-out events at either production site.

The logistic network for bulk maritime transportation of chemical products shows high levels of stochastic variability. An a priori estimate of the costs and risks associated to each transportation plan may be obtained using a mathematical model to statistically determine the impact of

- Ship early/late arrival at designated ports

- Plant production/consumption variability
- Unexpected changes in available storage capacity/inventory levels

Such phenomena generate risks of stock-out and over-stock events, which can be quantified in terms of expected costs and corresponding probability of occurrence.

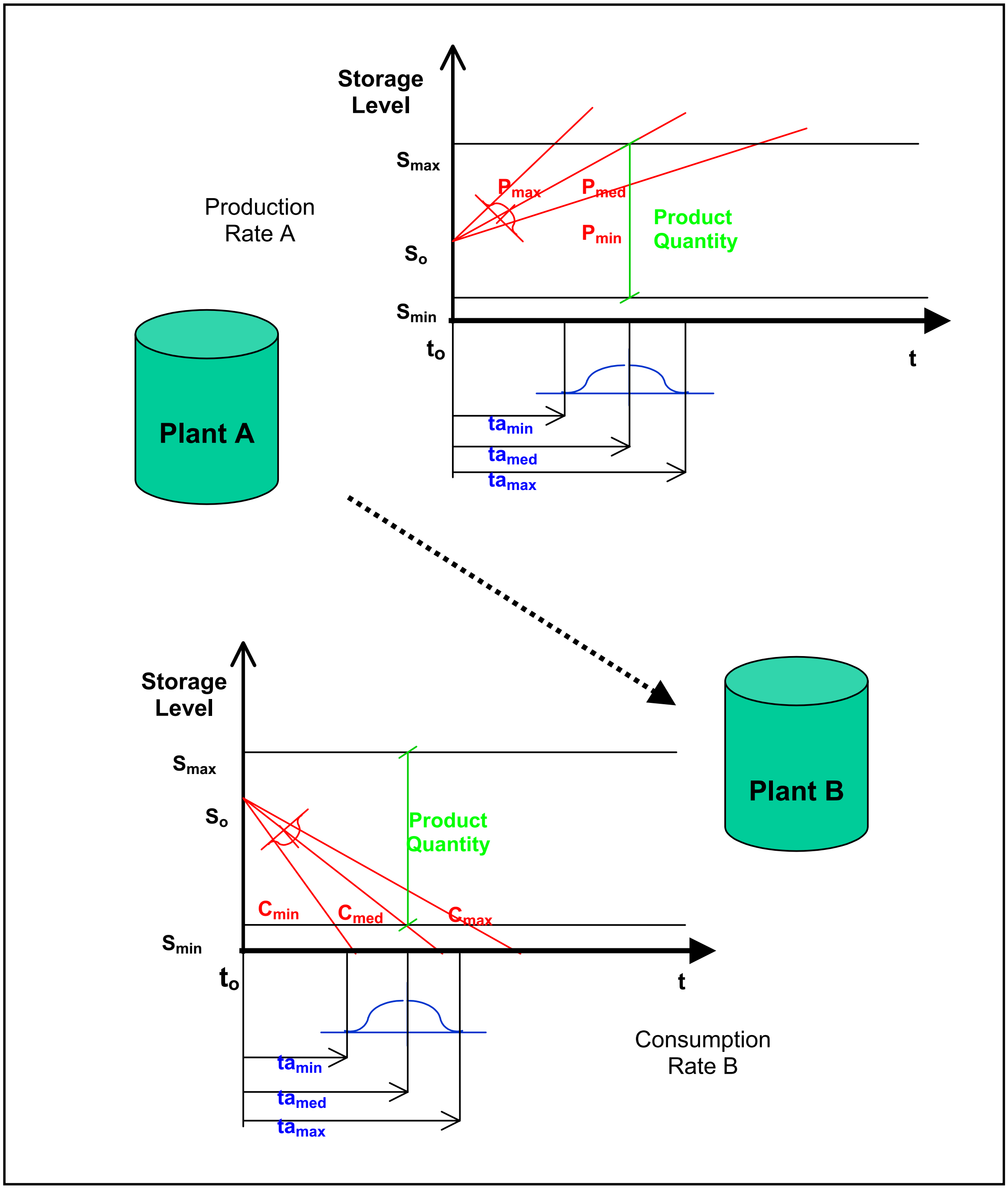

Figure 1. Example application case for cost and risk estimating

A stock-out event occurs whenever inventory levels are not sufficient to cover plant production or product delivery requirements. An over-stock event occurs whenever there is an excess of product to be allocated (plant production or ship delivery) respect to the storage capacity currently available. The mathematical model implemented for a priori risk assessment is described with respect to the two-port, single-product example illustrated in figure 1.

For the purposes of cost and risk estimating, the probability distributions for ship arrival time and plant production/consumption rate are discretized as shown in figure 2. With reference to figure 1 the variables to be considered include:

- maximum storage capacity S_{max} at Plant A and B
- minimum storage level S_{min} (for product extraction) at Plant A and B

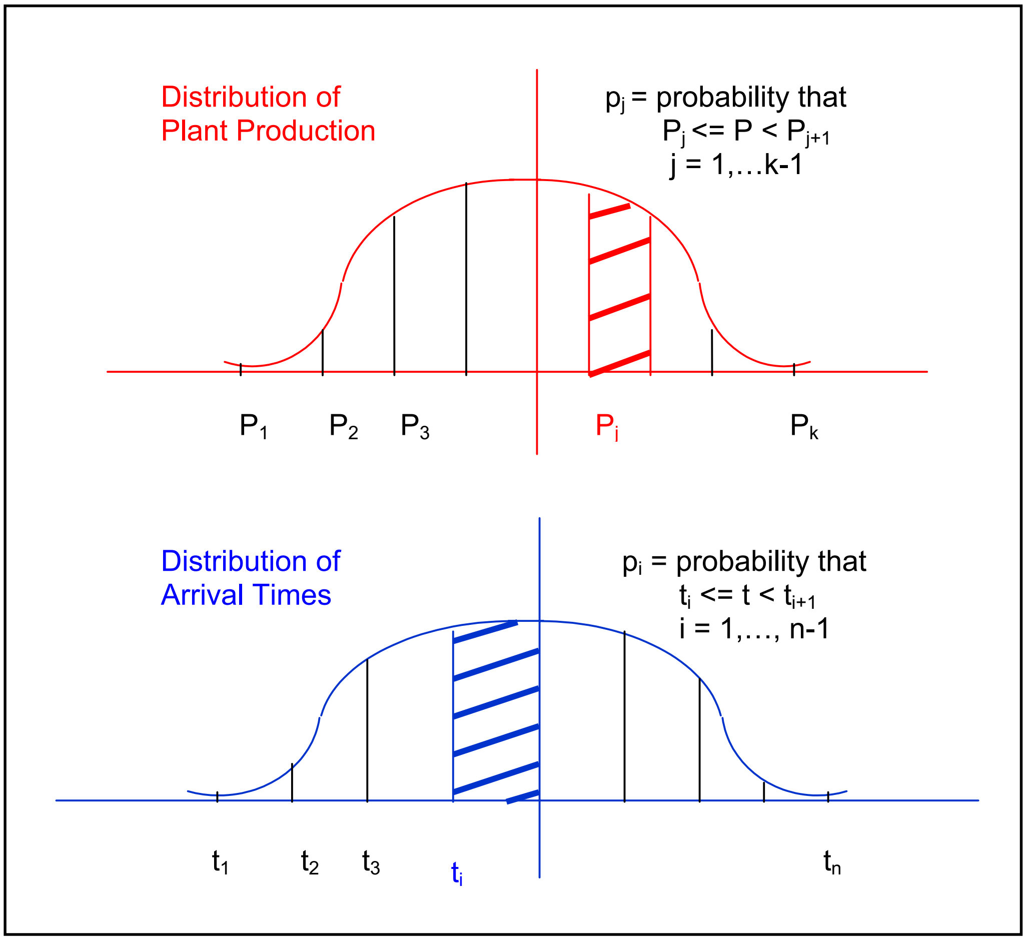

Figure 2: Probability distributions for plant production and ship's arrival time

Figure 1 shows plants A and B producing and consuming, respectively, a given chemical.

For each plant the probability distribution of ship arrival times and the probability distribution of production/consumption rates are supposed known as they can typically be built based on historical data.

- initial inventory level S_0 at Plant A(B)
- cost of ship's wait per unit time C^{SW} due to loading/unloading delays in A and B
- cost of production losses per unit time C^{PL} for Plant A and B

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4.1 Estimating costs and risks for plant A

Observing the discretization of the probability distributions shown in figure 2, the probability of occurrence of over-stock events at plant A can be calculated according to equation 6.

$$P_A^{OS} = \sum_j^{k-1} \sum_i^{n-1} p_j \cdot p_i \qquad (6)$$

where:

$p_j \cdot p_i = p_j \cdot p_i$ if $S_0 + P_j \cdot t_i - S_{max} > 0$ (over-stock condition)

$p_j \cdot p_i = 0$ if $S_0 + P_j \cdot t_i - S_{max} \leq 0$

Similarly, the probability of occurrence of stock-out events at plant A can be calculated according to equation 7.

$$P_A^{SO} = \sum_j^{k-1} \sum_i^{n-1} p_j \cdot p_i \qquad (7)$$

where:

$p_j \cdot p_i = p_j \cdot p_i$ if $S_0 + P_j \cdot t_i - L - S_{min} < 0$ (stock-out condition)

$p_j \cdot p_i = 0$ if $S_0 + P_j \cdot t_i - L - S_{min} \geq 0$

Correspondingly, the expected cost of over-stock can be calculated once the shortest ship's arrival time t(j), capable of causing over-stock at the current production rate P_j has been determined. As shown in the following, the difference between each possible arrival time t_i and t(j) will establish whether an over-stock event occurs, its probability of occurrence, and its possible duration. Once this set of information is known for each combination (i,j) of ship's arrival time and production rate, the expected cost can be estimated (equation 9). The time t(j) can be calculated solving $S_0 + P_j \cdot t(j) - S_{max} = 0$ for t(j)

$$t(j) = \frac{S_{max} - S_o}{P_j} \qquad (8)$$

If $S_0 + P_j \cdot t_i - S_{max} > 0$, or equivalently, if $t_i - t(j) > 0$ the combination (t_i , P_j) will determine an over-stock situation, and the corresponding duration will be given by $\Delta t_{ij} = [t_i - t(j)]$. The expected cost of over-stock for the combination (t_i , P_j) can be expressed as indicated in equations 9 and 10.

If $t_i - t(j) > 0$

$$C_{ij_A}^{OS} = C_A^{PL} \cdot [t_i - t(j)] \cdot p_i \cdot p_j$$

If $t_i - t(j) \leq 0$ (9)

$$C_{ij_A}^{OS} = 0$$

The overall cost of over-stock for plant A will then be calculated as

$$C_A^{OS} = \sum_j^{k-1} \sum_i^{n-1} C_{ij_A}^{OS} \qquad (10)$$

Following exactly the same procedure it will be possible to calculate the overall cost of stock-out at plant A. For each value of P_j it is possible to calculate the time t(j) which first causes a stock-out occurrence and the corresponding duration. Setting $S_0 + P_j \cdot t(j) - L - S_{min} = 0$ and solving for t(j)

$$t(j) = \frac{S_{min} + L - S_o}{P_j} \qquad (11)$$

If $S_0 + P_j \cdot t_i - L - S_{min} < 0$, or equivalently, if $t_i - t(j) < 0$ the combination (t_i , P_j) will determine a stock-out situation, and the corresponding duration will be $\Delta t_{ij} = [t(j) - t_i]$. The expected cost of stock-out for the combination (t_i, P_j) can be expressed as indicated in equation 12.

If $t_i - t(j) < 0$

$$C_{ij_A}^{SO} = C_A^{SW} \cdot [t(j) - t_i] \cdot p_i \cdot p_j$$

If $t_i - t(j) \geq 0$ (12)

$$C_{ij_A}^{SO} = 0$$

The overall cost of stock-out for plant A will then be calculated as shown in equation 13.

$$C_A^{SO} = \sum_j^{k-1} \sum_i^{n-1} C_{ij_A}^{SO} \qquad (13)$$

4.1 Estimating costs and risks for plant B

With reference to the discretization of the probability distributions shown in figure 2, the probability of occurrence of over-stock events at plant B can be calculated according to equation 14.

$$P_B^{OS} = \sum_j^{k-1} \sum_i^{n-1} p_j \cdot p_i \qquad (14)$$

where:

$p_j \cdot p_i = p_j \cdot p_i$ if $S_0 - C_j \cdot t_i + L - S_{max} > 0$ (over-stock condition)

$p_j \cdot p_i = 0$ if $S_0 - C_j \cdot t_i + L - S_{max} \leq 0$

The probability of occurrence of stock-out events at plant B can be calculated according to equation 15.

$$P_B^{SO} = \sum_j^{k-1} \sum_i^{n-1} p_j \cdot p_i \qquad (15)$$

where:

$p_j \cdot p_i = p_j \cdot p_i$ if $S_0 - C_j \cdot t_i\ (-S_{min}) < 0$ (stock-out condition)

$p_j \cdot p_i = 0$ if $S_0 - C_j \cdot t_i\ (-S_{min}) \geq 0$

Correspondingly, the expected cost of over-stock can be calculated once the largest ship's arrival time t(j), capable of causing over-stock at the current consumption rate C_j has been determined.

As shown in the following, the difference between t(j) and each possible arrival time t_i will establish whether an over-stock event occurs, its probability and its possible duration. Once this set of information is known for each combination (i,j) of ship arrival time and plant consumption rate, the expected cost can be estimated (equations 17 and 18). The time t(j) can be calculated imposing $S_0 - C_j \cdot t(j) + L - S_{max} = 0$ and solving for t(j)

$$t(j) = \frac{S_o + L - S_{max}}{C_j} \qquad (16)$$

If $S_0 - C_j \cdot t(j) + L - S_{max} > 0$, or equivalently, if $t_i - t(j) < 0$ the combination (t_i, C_j) will determine an over-stock situation, and the corresponding duration will be $\Delta t_{ij} = [t(j) - t_i]$. The expected cost of over-stock for the combination (t_i, C_j) can be expressed as indicated in equation 17.

If $t_i - t(j) < 0$

$$C_{ij_B}^{OS} = C_B^{SW} \cdot \left[t(j) - t_i\right] \cdot p_i \cdot p_j$$

(17)

If $t_i - t(j) \geq 0$

$$C_{ij_B}^{OS} = 0$$

$$C_B^{OS} = \sum_j^{k-1} \sum_i^{n-1} C_{ij_B}^{OS} \qquad (18)$$

Following exactly the same procedure it is possible to calculate the overall cost of stock-out at plant B.

For each value of C_j it is possible to calculate the time t(j) which first causes a stock-out occurrence and the corresponding duration. Setting $S_0 - C_j \cdot t(j) - S_{min} = 0$ and solving for t(j)

$$t(j) = \frac{S_o - S_{min}}{C_j} \qquad (19)$$

If $S_0 - C_j \cdot t_i - S_{min} > 0$, or equivalently, if $t_i - t(j) > 0$ the combination (t_i, C_j) will determine a stock-out situation, and the corresponding duration will be $\Delta t_{ij} = [t_i - t(j)]$. The expected cost of stock-out for the combination (t_i, C_j) can be expressed as indicated in equation 20.

If $t_i - t(j) > 0$

$$C_{ij_B}^{SO} = C_B^{PL} \cdot \left[t_i - t(j)\right] \cdot p_i \cdot p_j$$

(20)

If $t_i - t(j) \leq 0$

$$C_{ij_B}^{SO} = 0$$

The overall cost of stock-out for plant B will then be calculated as

$$C_B^{SO} = \sum_j^{k-1} \sum_i^{n-1} C_{ij_B}^{SO} \qquad (21)$$

The overall costs of supply chain logistic inefficiencies can be quantified as the sum of the expected stock-out and over-stock costs for both plant A and plant B (equation 22).

$$C_{tot}^{AB} = C_A^{OS} + C_A^{SO} + C_B^{OS} + C_B^{SO} \qquad (22)$$

5. Simulation modelling of supply chain logistics

The mathematical model presented in the previous section shows how complex the calculation of the relevant performance measures may be even in the very simple case of single product transportation between two designated ports [1]. As the complexity of the tactical mission to be modeled is increased, for instance a cyclical mission reaching several ports with multiple products to be loaded and unloaded at each production facility, the mathematical model is no longer capable of efficiently handling the exact calculations of the identified measures of supply chain logistic performance. The calculation of the overall costs of logistic inefficiencies becomes especially critical as the procedure indicated in section 4 needs to be iterated for each product, for each mission's leg, and for each ship allocated to the tactical mission. In response to these difficulties a stochastic discrete-event simulation model was developed for logistic scenario testing [2,3]. The model, developed in C++, provides the context for effective analysis of maritime logistic plans by representing the entire set of processes involved in the tactical mission employing a user-specified number of ships (n). In particular the model may be run in a stochastic operation mode, enabling it to represent the natural randomness of the logistic network's operations [4,5]. The model accounts for the stochastic variability of ship's navigation time, of loading/unloading delays (due to both port/terminal traffic and current inventory levels), and of plant production/consumption of each given product. During each simulation run, the Monte Carlo technique [6,7] is employed to extract punctual values of each stochastic variable out of the corresponding probability distribution [8,9]. The model manages storage inventory levels and records stock-out and over-stock events to compute actual production losses and additional ship and port-related costs caused by delays. The minimum length of the simulation run was estimated observing the evolution of the Mean Square Pure Error (MSPE) as a function of simulated time [3,5]. The MSPE measures the experimental error determined by the random extraction of punctual data out of the probability distributions of the stochastic process variables: for short simulated times the MSPE assumes high values since relatively few values are extracted for each stochastic variable, making the simulated process not entirely representative of the stochastic behavior of the actual system [2,4]. It is only after a long enough simulated run that the number of values extracted out of each distribution is large enough to be representative of the actual variability of each stochastic parameter. For this particular application it was observed that the value of the MSPE tends to settle in the vicinity of 6000 days of simulated time, therefore 6000 days was assumed as the required length for each simulation run. The simulation model was verified and validated using reference data produced by the mathematical model on a set of scenarios based on actual data provided by the chemical company. In particular, the ranges of input parameters referred to in the scenarios involve:

- Ship navigation time: average = 6-12 days, standard deviation = 2-5 days
- Ship capacities = 3000-12000 tons (allocated to multiple products)
- Plant production/consumption rates: average = 50-100 tons/day, standard deviation = 10-40 tons/day
- Plant storage capacities = 2000-4000 tons (per product)

A set of 20 scenarios obtained combining high, low, and intermediate levels of each variable input parameter was tested through simulation and the corresponding estimates of production losses were compared to the ones actually calculated using the mathematical model. The comparison showed a good match between the results produced by the simulator and by the mathematical model: the maximum difference observed across the 20 scenarios was less than 9% with an average of approximately 5%.

6. ANN-based metamodelling for efficient performance estimating

The strength of ANNs as metamodeling systems lies in their ability to establish sensible experiential correlations among the set of variables that describe a given phenomenon or process [10,11]. This ability makes ANNs especially effective when the complexity of the application excludes the possibility of developing suitable mathematical models [12,13]. An ANN modular structure was chosen in order to break the problem of modeling the behavior of an entire tactical mission into sub-problems more easily and accurately handled by individual ANNs. In such a structure each ANN is a separate module, designated to the estimate of either the costs of production losses or the costs of ship loading/unloading delays for one or more ports/production facilities. This way each problem is addressed by two sets of one or more ANNs each, thus minimizing the number of variables (input parameters) involved in each individual ANN's modeling task [13]. In particular the set of relevant input parameters common to the two sets of ANNs are:

- t_{avg} and σ_t = ship's average arrival time and standard deviation measured in hours

- P_{avg} and σ_P = plant average production rate and corresponding standard deviation (with the convention that negative production rates are actually consumption rates) measured in tons/hour
- L = product quantity to be loaded/unloaded at the plant facility measured in tons
- $\Delta S = S_{max} - S_0$ = storage capacity currently available measured in tons
- C^{PL} or C^{SW} = costs incurred per unit time for production losses and ship's wait in port, respectively.

The only difference between the two sets of ANNs at the input level are the costs incurred per unit time: C^{PL} for the estimate of production losses and C^{SW} for the estimate of ship delays. Multiple ANNs per set may need to be built and separately trained if the variability ranges of the input parameters are significantly different for each of the ports/plants involved in the tactical mission. However, the basic ANN architecture remains unchanged across these different ANNs, effectively it remains unchanged even across the two sets, since both the categories of input/output parameters and the type of correlation to be established between them are the same in nature. For the purposes of this study, only two ANN modules were developed, one for each identified set; each one of them was trained on relatively wide ranges of input values reflecting the typical industry levels (same ranges as indicated in section 5) [13,14]. In particular each network was trained on both positive and negative ranges of plant production rates, and thus required to learn two distinct correlations to account for both ship loading/plant production and ship unloading/plant consumption situations at the same production site [15,16]. The corresponding ANN's output variables are, respectively, the expected costs of production losses and the expected costs of ship loading/unloading delays for one particular port/production facility. For missions involving multiple ports and product transportation requirements, it is sufficient to provide as many input sets as the number of ports and the number of different products to instantly obtain the corresponding estimated costs for each port and product. With reference to routes involving sequences of more than two ports, it is necessary to adjust the probability distribution of the ship's arrival time at one port to account for possible delays or early arrivals determined by the corresponding probability distribution describing the arrival time at the immediately preceding port in the sequence. For instance, when dealing with standard distributions, the actual time distribution for ship arrival at port j+1 will be obtained based on the corresponding distribution for ship arrival at port j, by adding the respective average values ($t_j + t_{j+1}$) and the respective standard deviations ($\sigma_j + \sigma_{j+1}$), as stated by the central limit law.

6.1. ANN modules design: architecture and learning algorithm

Systematic testing was conducted on multiple ANN designs to identify successful design criteria for the specific metamodeling requirements[13,14]. The performance measures chosen for the assessment of the different ANNs and for the optimization of their architecture include precision, learning time, and generalization ability [13,17,18]. For the purposes of this study, precision is measured by the RMS (normalized Root Mean Square) of the error with respect to the real system. The learning time is measured by the number of learning iterations (over a set of training data) to convergence. The generalization ability is a measure of the ability to reproduce the response of the real system for a combination of input data not previously included in the learning set. This ability is quantified by the difference in output precision measured on the learning set and on the testing data set, respectively. While no established rules exist to select the optimal network design for a given application, prior experimental work led to the identification of general design criteria that apply to specific classes and types of problems. In particular, both the literature [11,12,18] and the Authors' experience [13,15,16,19] supported the choice of feed-forward, fully-connected networks with two hidden layers of neurons (i.e. intermediate layers of neurons placed between the input layer and the output layer), which ensure high generalization ability [14,16,19]. Other performance considerations narrowed the choice among possible learning algorithms to either Back Propagation [13,17,20,21] or Direct Random Search (DRS) [13,14,19]. The two algorithms sit on opposite sides of the performance spectrum, but strong arguments can be made in favor of either one. The former is simpler in nature, widely used, quickly trained and easily applied to real life problems because of its relatively short learning times [13,14,18,19]. The latter, although much more elaborate in nature and computationally intensive, shows higher precision and excellent generalization ability [16,17,18]. Three major factors drive the architecture of the hidden layers. Specifically, the number of neurons required on the hidden layers is a function of the total number of data available, of the theoretical complexity of the problem, and of the range of analysis (as defined by the data ranges) [13,19,21]. The results from an extensive experimental study conducted by the authors on a large number of network architectures, specifically developed for a variety of industrial applications, provided effective guidelines for the specification of the hidden layers.

These include 9 neurons in the first hidden layer and 7 neurons in the second one.

The design of the neural model for these purposes is based upon simple feed-forward fully-connected neural networks with a double hidden layer of neurons [12,16]. This type of structure is known to provide a good level of approximation on a single and complex unknown function. Given the highly stochastic nature of several influencing variables, easy and fast network training were the main objectives driving the choice of the learning algorithm. The choice of back propagation as learning algorithm entirely reflects this objective [20].

6.2. ANNs training and testing

ANNs output accuracy and generalization ability strongly depend on training data sets and time. The data required for network training was obtained running the simulation model on specific sub-problems involving individual product transportation requirements between two ports. Alternatively the mathematical model could be directly employed, but given the high number of data points required to train the network, it was chosen to accept an average 5% error in the learning data sets, which falls well within the natural randomness of the process. As a matter of fact the simulation model requires only a few seconds of run time to provide cost estimates on small sub-problems, thus making it very efficient in generating network learning data. In order to minimize the number of simulation runs, while ensuring to properly cover the entire ranges of variability of the input parameters, Design of Experiments (DoE) techniques were employed to choose the initial set of combinations of high, medium and low value levels for each input parameter. In particular the so called "k-factorial project" was adopted to generate a first set of $2^k + k$ sets of input parameters and corresponding simulation output. For the problem examined the number of input parameters is 7, thus leading to a set of $2^7 + 7$ simulation experiments, leading to a total of 128 + 7 data points. Of these, the additional k = 7 points were replications of the same simulation experiment, obtained keeping the input parameters fixed at their central value, thus providing all together a measure of the natural randomness of the process. Another 128 data points were included in the training set to provide the networks with a set of intermediate reference values, leading to a total of 263 data points. An identically structured set of 263 data points was then included to allow for learning of correlations involving negative ranges of plant production, thus representing situations of plant product consumption. These two sets of 263 data points were fed to the networks as training data. After 500 learning iterations on the given data sets, the networks were able to reproduce the output corresponding to the training input data with an error always smaller than 7%, averaging 4.3% on the entire training set. In order to test the network generalization ability another 128 data points, different from the ones used during training, were generated through simulation, and testing of the networks was conducted on these new data points. Testing of the networks' generalization ability showed an error always smaller than 11%, averaging 6.5% on the entire set of new data points. The results of this preliminary testing demonstrate the ability of the networks to establish effective correlations between the designated sets of input parameters and the chosen output variables, even with limited sets of training data points as compared to the complexity of the problem. Important benefits can be accrued from the application of neural networks in this context because of their ability to be re-trained on additional sets data points to extend their ranges of operation (as ANNs do not extrapolate output effectively) and to be virtually be re-built by training on completely different ranges of data. Thus their flexibility of operation and accuracy of response, makes them ideal for modeling dynamic situations such as the one described in this example application.

3. Conclusion

The work described in this paper addresses the logistic performance of the supply chain in the specific context of maritime logistics for the chemical industry. In particular, the paper identifies a set of performance measures to quantitatively assess and compare alternative logistic management solutions. These measures include the actual logistic cost, the cost of un-used resources (i.e. ships capacity) and the expected costs of production losses. The paper stresses the importance of estimating the costs of production losses, as a measure of how different logistic solutions may impact production, considering that the ultimate objective of logistic management is to ensure smooth and efficient production operations across the entire logistic network. Most importantly the costs of production losses often exceed the actual logistic costs incurred, hence the significance of providing accurate estimates when designing the logistic network, planning and scheduling resources. The paper first illustrates the statistical basis for calculating the expected costs and risks of production losses. The application of this mathematical approach even to the simplest case of single product transportation between two ports is quite complicated and definitely not suited for quick cost estimates in more complex cases involving multiple products and multiple ports. The paper describes two alternative methodologies, one based on simulation and the other based on modular structures of artificial neural networks. Testing of both models reveals that the ANN-based approach, thanks to the chosen modular structure, effectively addresses cost estimating in complex logistic situations building from elementary single plant-single ship blocks. Individual networks of identical structure can be built and trained to model logistic sub-problems at this simple level, while providing all together cost estimates for complex logistic networks in times of the order of a few seconds. Often, if the variability of the plants structural and functional characteristics is limited across the same logistic network, the same data sets may be used to train the entire group of ANN modules for the whole logistic network, and ideally the same network module could be built, trained and copied, or directly used, for multiple estimates, thus accruing significant benefits in terms of data collection and training time.

10. References

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