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Simulation of Maritime Transport and Distribution by Sea-Going Barges: An Application of Multiple Regression Analysis and Factor Screening

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Summary

The authors present an application of multiple regression analysis and factor screening to the study of transport by pusher barges compared to sea-going ships. A simulation model is described and mathematical techniques are used to simplify the parameters involved to such a level that the model can be investigated with a minimum of simulation runs.

1. Introduction

In the near future the use of coal for energy purposes, and therefore the maritime transport of coal, will increase. A review of maritime coal imports in North-West-Europe is shown in Table 1. Coal imports from distant production areas: Australia and South-Africa will exceed 30%. For the transport of coal from these parts of the world to Europe large bulk carriers (VLBCs, Very Large Bulk Carriers) will be used, in oder to keep freight rates low (Table 2). The deadweight capacity of a VLBC exceeds 250,000 DWT and it's draught 20 m. Australian and South-African ports will be enlarged to enable ships of the size of 250,000 DWT to sail in. Unfortunately, only a few European ports will be approachable to VLBCs, according to recent studies on port development (Table 3). There are two possibilities to overcome this difficulty:

a) The use of smaller ships that can be accomodated by European ports.
b) The use of VLBCs for the transport of coal to a central port in North West Europe, where they are (partially)

Table 1: Main European imports of energy coal in the year 2000 (10^6 ton/year, Wilson [7])

	EXPORT						
IMPORT	Australia	USA	South Africa	Poland	Canada	Others	Total
West Germany	6	5	3	2	1	3	20
UK/Ireland	1					1	2
Netherlands/Belgium	6	2	6	6	1	2	23
France	7	4	8	5	3	11	38
Norway/Sweden	4	2		4	3	4	17
Denmark	1		2	3	1	2	9
Finland		1		5	1	2	9
Others	18	14	13	16	3	12	76
Total	43	28	32	41	13	37	194

Table 2: Average size of the ships used for transport of coal to North West Europe in the year 2000 in 10^3 Dead Weight Tons (DWT), (Nedlloyd [8])

EXPORT COUNTRY	AVERAGE SHIPSIZE
Australia	250
USA	100
Poland	60
Canada	60
South Afrika	250
Others	60

Table 3: European import/export-terminals and the maximal shipsize allowed in 10^3 DWT (Cargo Systems [9])

IMPORT/EXPORT-TERMINALS	MAXIMUM SHIP SIZE
Belgium	
1 Zeebrugge	125
Denmark	
2 Asnaes	60 (will become 120)
3 Esbjerg	120
England	
4 Hunterston	350
Netherlands	
5 Amsterdam	80
6 Rotterdam	120
Norway	
7 Narvik	250
West Germany	
8 Emden	80
9 Hamburg	90 (will become 120)
10 Weserport	80
11 Wilhelmshafen	95
Sweden	
12 Landskrona	20
13 Oxelösund	65

Fig. 1

unloaded, combined with the use of small ships for the transport from the central port to the ultimate destination.

This strategy makes trans-shipment necessary. On the routes from Australia and South Africa to Europe, however, the benefits of low freight rates will outweigh the trans-shipment costs.

The strategy increases the number of shipments in the North Sea area. A new system of maritime transport could be used for the transport of the additional shipments. The project group SHI [1] launched the idea of introducing a system of sea-going barges and tugs. The seagoing barges are engineless ships which are pushed forward by separate vessels. The main advantage of the system is that barges stay in port to be loaded instead of expensive ships, including their crew. Where the system contains more barges than tugs, barges can be loaded while tugs are on their way with other barges.

The system has been proven to function well on rivers in North West Europe. The feasibility of a tug-barge system in the North Sea area can be determined by studying the ship movements in this area. Predictions of maritime imports and exports of bulk goods can be used.

The study is complicated, mainly because of the many ports involved (Fig. 1). For that reason a model has been developed that enables the simulation of ship movements between ports, on a computer. The model remained too complicated to allow for the analysis of the results without the aid of special analysis techniques.

This article illustrates the use of simulation models in combination with statistical analysis techniques, like experimental design, regression analysis, and factor screening.

2. Transport and Distribution

In North West Europe the port of Rotterdam is the most conveniently situated trans-shipment port. Moreover the port is already accessible to ships of 250,000 DWT. Energy coal will be transshipped from carriers of 250,000 DWT into carriers of say 40,000 DWT. The latter will be used for the transport of coal from Rotterdam to import terminals in Denmark, North West Germany and Sweden.

The maritime transport of energy coal in North West Europe may be combined with the transport of iron ore. Iron ore is transported from the mining area in Scandinavia to steel industries in Belgium, West Germany, the United Kingdom and The Netherlands.

For the distribution of the above mentioned bulk goods sea barges may be used. Sea barges are engineless vessels which are pushed forward by pusher boats. The system is similar to the tug-barge system that is in use on the rivers in North West Europe. The essential requirement for the employment of a tug-barge system is that port times are a substantial part of the total transport times. The above mentioned shipments of coal and iron ore meet this requirement.

2.1 Sea Barges and Tugs

The first pusher boat sailed in the year 1840 in the state of Ohio, USA. This vessel was designed especially to push other vessels. The first tug-barge combination in Europe was put into service in the year 1952 on the river Wolga.

Sea-going barges appeared for the first time in 1970. In that year two Belgian barges were put into service, with a deadweight capacity of 14,000 DWT each. The barges were shaped to have a concave notch at their stern end.

The bow part of the pusher boat was connected to the stern portion of the barge by means of a transverse horizontal pin. The end of the transverse horizontal pin, extended from either side of the pusher, was fixed to a pin-end receiving means (skeg) mounted on the corresponding sidewall of the concave or notch. The pusher and barge were rope connected in such a manner as to form something like a single watercraft with an articulation at it's sternend (Figs. 2 and 3).

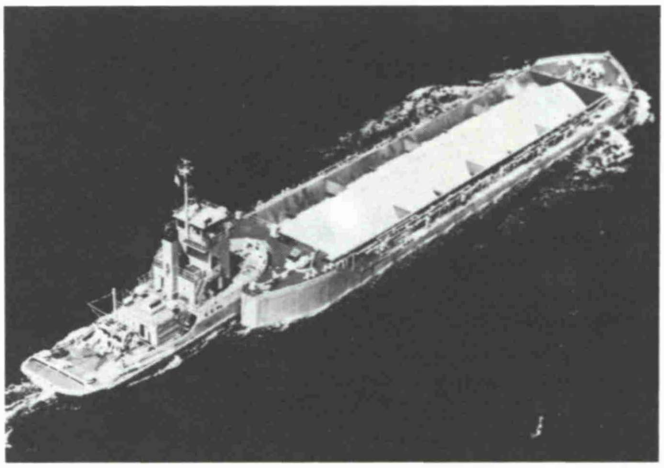

Fig. 2

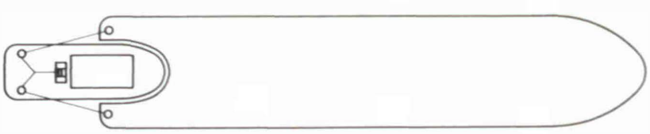

Fig. 3

The tug-barge combination has economic advantages in the following areas, when compared to conventional ships:

a) construction costs: Barges are cheaper to build than equivalent conventional ships (Table 4).

Table 4: Investment in conventional ships and pushers/barges in 10^6 DFL [1]

TYPE OF VESSEL	PRICE
Conventional ship	
40,000 DWT	51
Sea barge	
30,000 DWT	16
40,000 DWT	19
Pusher boat for	
30,000 DWT sea barges	31
40,000 DWT sea barges	35

b) crew costs: The pusher boat pushes a preloaded barge of say 40,000 DWT as an integrated system and she spends virtually no time in port. Typically one barge is being discharged/reloaded at either end of the voyage whilst the third is in transit. Crew costs for a tug-barge system of one tug and three barges are lower than for three equivalent conventional vessels.

c) Shorter yard time for repairs: The tugs or barges not under repair can continue to be used.

Table 5: Transport and ballast routes
Quantities in 10^6 ton/year

Coal and Iron ore			
Route Number	From	To	Quantity
1	5	4	1.0
2	6	2	1.0
3	6	3	2.0
4	6	8	1.0
5	6	9	3.0
6	6	10	2.0
7	6	11	2.0
8	6	12	4.0
9	7	1	3.0
10	7	4	2.0
11	7	6	4.0
12	7	9	2.0
13	13	8	1.5
			29.5
Ballast			
Route Number	From	To	Quantity
14	1	6	3.0
15	2	7	1.0
16	3	7	2.0
17	4	7	3.0
18	8	6	2.5
19	9	5	1.0
20	9	6	1.5
21	9	7	3.5
22	10	6	2.0
23	11	6	2.0
24	12	7	2.5
25	12	13	1.5
			25.5

The economics of push/tow have led to numerous types of tug-barge connections. The conventional rope system is far from satisfactory for steady navigation in open sea, where lengths of waves are comparable to the ship's length or more (heavy tension, which the ropes are subject to; incessant shocks and vibration; great number of crew members who are indispensable for connecting work and have no work during navigation). Barges are either equipped with adjustable or with selectable skegs, in order to deal with changes of draft and trim. Some systems can automatically complete the docking of the tug into the barge and also operate in a reverse manner to effect separation when unplugging (ARTUBAR, ARTICOUPLE). In order to implement the policy of fast turn-around times of pusher boats in port, the oil/fuel required for the voyage may be carried in the barges. This means that the barges may be bunkered while in port and that the tug need not be thereby delayed. The fuel is transferred to the tug's tanks as necessary while on passage.

2.2 Ports

In every port involved in a tug-barge system, ships and tug-barge combinations will arrive. The processes of ships and tug-barge combinations are similar apart from a few dif-

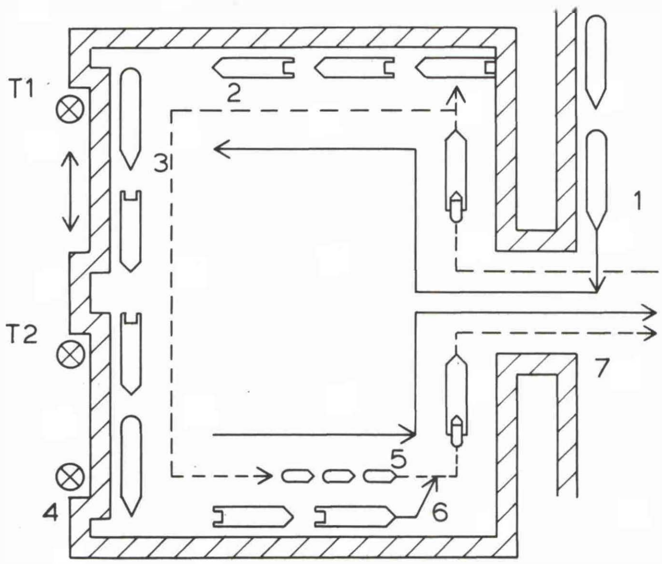

Fig. 4

ferences (see Fig. 4). If the required quay length in the terminal is available then the ships will sail in and dock, otherwise they wait outside the port. Barges, however, will usually wait in a special mooring area inside the port. As soon as quay length is available the barges are transferred from this "waiting room" to the terminal.

After completion of the loading or discharging process, the ships will leave to a destination, which may be outside the system. Barges will be transferred to the mooring area again and wait there until a pusher boat arrives. Pusher boats need not wait until the loading or discharging process of the barge is completed. A pusher of an arriving tug-barge combination can be disconnected from the arriving barge and connected to another barge, which is ready to leave.

The port times of tugs and barges are determined by a number of factors:

a) The approach channel of the terminal:
The approach channel may be blocked by other ships which are leaving the port.

b) The number of jetties of the terminal:
If a jetty is free then an arriving tug-barge combination may moor at the quay directly. As soon as the combination has moored, the tug may be disconnected from the barge.

c) The number of cranes and their average capacity:
Usually as many cranes as possible are assigned to one ship or barge, in order to minimise the turnaround times of the vessels. Usually ships and barges will have to wait at the quay until cranes are available.

d) The number of ships, which must be loaded or discharged and their sizes:
The waiting time of ships is more expensive than the waiting time of barges. Therefore ships should always have higher priority than barges.

e) The time that is required to connect and disconnect a barge to a tug:
For a rope-connected pusher barge about 15 minutes is needed to connect a tug-barge combination. Automatic coupler systems reduce the connecting and disconnecting times to only a few seconds.

Because of the reduced port times less tugs are needed in comparison with equivalent conventional ships. Barges, however, will have to wait when they are ready to leave until they are picked up by an arriving pusher boat. Therefore more barges will be needed in comparison with conventional ships of the same size.

To determine which is more attractive, a pusher barge system or conventional ships, the influence of the number of tugs and barges in the system on the transport capacity must be measured.

For this reason a simulation model has been developed which allows for simulation of movements of tugs and barges between ports, as well as for the simulation of conventional ships.

3. Simulation Model

A model of the system has been developed, using the simulation package 'SOLE' (Simulation of Logistics Elements). [2]. Thirteen ports in North West Europe are assumed to be involved in the tug-barge system (see Fig. 1). A number of cargo flows between these ports must be maintained by a fleet of distribution carriers. The average yearly cargo flow between two ports is assumed to be fixed. However, the yearly number of shipments between two ports is a random quantity that is determined by many factors. Therefore the actual yearly cargo flow between two ports may differ from the fixed value with an amount equal to a few ship loads.

The return voyages of discharged vessels do not necessarily have to equal the inverted transport voyages. In some cases a return cargo may be present for a different export harbour in the system. In other cases the vessels will have to depart in the ballasted state to an export harbour of their choice. The latter is implemented in the simulation model by adding special routes to the net of transport routes, so called ballast routes. The ballast routes are selected in such a way that the total distance of all ballast voyages in a year is minimal. This has been achieved by making use of Linear Programming Techniques [3].

All routes and the quantities that should be transported on these routes each year are displayed in Table 5, including the selected ballast voyages. During a simulation run, data are collected concerning the actually transported quantities in order to determine whether the transport capacity of the distribution fleet is satisfactory.

The ports that are involved in the system are modelled as follows (see Fig. 4). At most two terminals of each port are modelled: the main import terminal and/or the main export terminal (Fig. 4: T_1 and T_2). In every port, ships from outside the system may arrive (Fig. 4: 1). These ships wait outside the port until enough quay length is available. As soon as quay length is available and the approach channel (7) is free the ship sails in and docks (3). At the quay the ship usually has to wait until cranes (4) are available before the loading or discharging process can be started. When the loading or discharging process is completed the ship leaves the quay and sails out of the port through the channel. Leaving ships waiting at the channel have a higer priority than arriving ships. As soon as a ship has left the port it leaves the system and its processing terminates.

Arriving tug-barge combinations sail through the channel into the port. A tug disengages out of the barge and waits until a barge is ready to leave (5). The tug re-engages into the leaving barge and sets course to the next destination of the barge. An arriving barge waits until quay length is available (2). As soon as quay length is available and no ships are waiting to dock the barge is transferred to the terminal. When the loading or discharging process of a barge is completed it is transferred to a waiting area (6) again, where it waits until a pusher boat arrives.

The simulation model requires the following input data for every port:

a) The width of the approach channel, and the time that is needed to sail through the channel.
b) The number of jetties of every terminal.
c) The number of cranes of every terminal and their average capacity.
d) The time that is needed to dock and to leave the quay and the time that is needed to transfer a barge to, or from, a waiting area.
e) The yearly amount of cargo that is imported or exported by ships, and the expected minimum and maximum size of these ships. It is assumed that the sizes of arriving ships are uniformly distributed between these values.
   The model calculates the mean inter-arrival time of the ships from the input data. It is assumed that an Erlang-distribution with two degrees of freedom holds for these inter-arrival times.
f) The distances to all relevant other ports are listed, as well as the frequencies of voyages to these ports. Departing barges select their next destination from this list in a fixed sequence. This mechanism assures a correct distribution of cargo between the ports, provided that the transport capacity of the distribution fleet is satisfactory.

The following input data must also be specified:

a) The number of tugs in the system and, for each tug, the port where it is initially located.
b) The number of barges and, for each barge, the port where it is initially located.
c) The capacity of the barges.

It is assumed that a tug on her own has no complete seaworthiness and maneuvrability, so it must be locked into the stern notch of a barge during ocean operations. This condition has the following consequence: An arriving tug always adds a barge to the number of barges in the port and a leaving tug always removes a barge from the port. Therefore the number of extra barges in a port will never change. The more barges in a given port, the greater chance that one of them is ready to leave at the moment a pusher boat arrives, so the shorter the port time of pusher boats. However, to prevent barges from being idle, waiting for a pusher boat most of their time, the number of extra barges in the ports should be selected carefully.

The simulation model has been used to measure the influence on the transport capacity of the number of tugs in the system and the number of barges in every port. Regression analysis techniques assist in the estimation of these influences. The results were used to determine which combinations of numbers of tugs and barges are able to maintain the desired cargo flows.

4. Experiments and Regression Analysis

Simulation can be applied in the study of many practical problems, but unfortunately the results of a simulation experiment are valid only for the specific parameter values and mathematical relationships of the executed simulation program. If the user wishes to know the effects of changing a parameter or relationship then the simulation program must be run again. Experimental design helps in the efficient exploration of the great many system variants that could be simulated.

Insight into the behaviour of the simulation model might be gained by using a so-called metamodel. This metamodel is a linear regression model, that explains how the simulation output (y, e. g. the transport capacity of a tug-barge system) reacts to changes in the model's parameters ($x \ldots x_k$, e. g. the number of tugs, the number of barges and so on). The factors can be selected such that either the output is optimized or a satisfying value of the output is obtained, i. e., which input values yield fixed desired output values. The latter is the objective in this particular case.

The simplest linear regression metamodel the analyst may postulate is the first oder metamodel (see also Note 1):

$$y_i = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} + u_i \quad (i = 1 \ldots n) \quad (1)$$

In Eq. (1) y_i is the response of simulation run i, x_{ij} is the value of factor x_j in run i and u_i is a stochastic noise.

The number of factors is k and the number of simulation runs is n. Metamodelling also applies to deterministic simulation in which case u_i vanishes.

Equation (1) is equivalent to:

$$y = X \cdot \beta + u \quad (2)$$

In Eq. (2) y, β and u are vectors and X is a matrix.

X contains the values of the input parameters of all experiments. X is called the design matrix. Which combinations of input parameters should be simulated is an experimental design problem. Experimental design theory has been widely applied in agricultural and technical experiments. In a simulation model all factors are completely under control so that experimental design theory becomes highly relevant.

In many simulation models, only a few input variables have a significant effect on the output. By identifying those variables in some reasonable way the model could be made simpler, more efficient and easier to analyse (e. g. if the number of extra barges in a given port has no effect on the transport capacity of the system, then all extra barges can be removed from this port). Factor screening methods attempt to identify the more important variables. The most effective screening methods are based on non-standard experimental designs. Experimental designs generally employ only a small number of factor levels. Usually two levels, designated high (+1) and low (−1) of each factor are sufficient to detect which factors have major effects. Consequently most screening methods are based on two-level designs. Besides, two-level designs are more economical than multi-level designs.

A review of all studied factors and their high and low levels is displayed in Table 6. A first order metamodel is assumed to be valid. The original metamodel Eq. (1), however, is replaced by:

$$y_i^* = \beta_0 + \beta_1 x_{i1}^* + \ldots + \beta_k x_{ik}^* + u_i \quad (i = 1 \ldots n) \quad (3)$$

In (3) y_i^* and x_{ij}^* are transformations of y_i and x_{ij}:

$$y_i^* = \log y_i \text{ and } x_{ij}^* = \log x_{ij}.$$

This transformation is very popular in econometrics. The coefficients β_j represent elasticity coefficients. Although the model is not linear in its variables x_{ij} and y_i, it remains linear in its coefficients β_j.

Table 6: Review of input factors

Port independent factors				
			minimal	maximal
Number of tugs			8	12
Capacity of a barge (10^3 DWT)			30	40
Required transportation capacity (10^9 ton km/year)			40.6	63.0
Port dependent factors				
Port	Number of extra barges in port		Loading/discharging capacity (ton/hour)	
	minimal	maximal	minimal	maximal
1	0	2	2,400	2,800
2	0	2	1,300	1,800
3	0	2	1,500	2,000
4	0	2	2,000	2,400
5	0	2	3,500	4,000
6	0	5	7,000	8,000
7	0	5	5,000	6,000
8	0	2	1,200	1,600
9	0	3	3,000	3,500
10	0	2	1,500	2,000
11	0	2	1,200	1,600
12	0	2	3,500	4,000
13	0	2	2,000	2,400

An experimental design would require more runs than are acceptable. Therefore, a two-stage screening is applied. The first stage is based on a group screening design and the second-stage on a classical design. In group screening designs the factors are partitioned into groups of suitable sizes. The original factors are grouped into a much smaller number of groups (Table 7). Under mild assumptions (Note 2), a group will be significant if and only if that group contains one or more important original factors. Eight group factors are introduced, each one representing the combined effect of all factors within the group (Table 7). The groups are tested by considering each as a single factor. Because the number of groups is much smaller than the original number of factors, the group factors can be examined in a standard experimental design. The group factors are treated as qualitative on/off variables. Hence a group factor x_j ($j = 1 \ldots 8$) has the level —1 if all the group's members are at their low level, and when all members are at their high level then $x_j = +1$.

Note that the group factors are not to be transformed, since they are treated as qualitative factors.

Table 7: Grouping of input factors

Group factor	Group contents	Number of factors in group
x_1	Required transportation capacity	1
x_2	Number of tugs	1
x_3	Capacity of a barge	1
x_4	Number of barges in port 3, 6, 7, 8, 9, 11, 12	7
x_5	Number of barges in port 1, 2, 4, 5, 10, 13	6
x_6	Loading/discharging capacity in port 6, 7, 9	3
x_7	Loading/discharging capacity in port 3, 11, 12	3
x_8	Loading/discharging capacity in port 1, 2, 4, 5, 8, 9, 13	7

The proposed metamodel is:

$$y_i^* = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_k x_{ik} + u_i \quad (i = 1 \ldots n) \quad (4)$$

The factor level combinations of the eight group factors, which should be simulated, are displayed in Table 3 (see also Note 3). Executing the corresponding simulation runs yields the sixteen simulation responses y_i plus the corresponding standard errors s_i (Note 4).

To judge the importance of a parameter, the coefficients β_j must be estimated. The Ordinary Last Squares (OLS) estimators are well-known (Note 5). However, typical for simulation is that the covariance matrix of y (say Ω_y) is usually a diagonal matrix D (which implies that all experiments are independent) with elements $\sigma_i^2 = E(s_i^2)$. Therefore, OLS may be replaced by Estimated Weighted Least Squares (EWLS), where observation y_i is weighted with its estimated variance s_i^2. EWLS is a special case of the Generalized Least Squares approach (GLS, see Note 5).

Analytically the variances of the estimators for β can be derived only for known D or for large sample sizes. Monte Carlo experiments [4], show that if the σ^2_i are estimated from at least five observations (e. g. five subruns, see Note 4) then an estimator $\hat{D}$, with elements s_i^2, can be used. The EWLS estimators give more accurate estimators of β, provided the σ_i^2 differ by a factor, say, ten. Then significant parameters can be detected more frequently.

Whatever model the analyst starts out with, he has to test this model's validity. The following procedure is recommended:

a) postulate a metamodel
b) estimate the parameters β_j in this metamodel
c) validate the estimated regression model following the traditional scientific procedure, i. e., use the model to forecast the response y at a *new* setting of the simulation factors, say x_{n+1}:

$$\hat{y}_{n+1} = x'_{n+1} \cdot \hat{\beta} \quad (5)$$

Compare the metamodels prediction (5) to the actual simulation response y_{n+1} (Note 6). If the metamodel's prediction deviates significantly from the simulation model's result, the estimated metamodel is rejected.

Table 8: Experimental design (R-IV) for the first screening stage

Combination	x_1	x_2	x_3	x_4	$x_5 = x_1 x_3$	$x_6 = x_2 x_4$	$x_7 = x_3 x_4$	$x_8 = x_2 x_3 x_4$
1	1	−1	−1	−1	1	1	1	−1
2	1	1	−1	−1	−1	−1	1	1
3	1	−1	1	−1	−1	1	−1	1
4	1	1	1	−1	1	−1	−1	1
5	1	−1	−1	−1	1	−1	−1	1
6	1	1	−1	1	−1	1	−1	−1
7	1	−1	1	1	−1	−1	1	−1
8	1	1	1	1	1	1	1	1
9	−1	1	1	1	−1	−1	−1	1
10	−1	−1	1	1	1	1	−1	−1
11	−1	1	−1	1	1	−1	1	−1
12	−1	−1	−1	1	−1	1	1	1
13	−1	1	1	−1	−1	1	1	−1
14	−1	−1	1	−1	1	−1	1	1
15	−1	1	−1	−1	1	1	−1	1
16	−1	−1	−1	−1	−1	−1	−1	−1

The following scheme has been used to obtain as many validation runs as possible: One run i is removed from the sixteen available simulation runs. β is estimated from the remaining fifteen observations, assuming a non-singular matrix, say $X_{(i)}$, remains. The resulting estimator $\hat{\beta}_{(i)}$ is used to predict the simulation response of the removed run. The prediction $\hat{y}_i$ is compared with the (removed) actual response y_i, using the statistic of Note 6. Next a different run i' may be removed and the previously removed run i is added. This permutation procedure (called cross-validation) results in sixteen statistics. The model should be rejected if any of the sixteen values of the statistic (Note 6) is significant. The test results are displayed in Table 9.

The "experiment-wise error rate" is $\alpha_E = 30\%$, so the "per comparison error rate" is approximately equal to $\alpha = 0.01$ (Note 6), which results in a significance level of 2.33. Since none of the statistics (Table 9, Column 5) is significant the GLS regression model has been accepted. The OLS model has been rejected (not in tables). The estimated variances $(s_i^*)^2$ however, vary drastically, namely between 0.003 and 0.50 (Table 9, Column 3), so the common variance assumption of the OLS approach does not seem to be realistic in this case. Only the GLS results are given, because the GLS model is expected to yield more reliable results.

After the model has been validated, all sixteen simulation runs are used to estimate the coefficients β (Table 10). A second test is used to judge the significance of these coefficients (Note 7). The significance level follows from an error rate of 5% and equals 1.96. The groups 1, 5, 7 and 8 appear to be not significant (Table 10, Column 3), therefore all factors within these four groups are ignored from now on.

Table 9: Cross validation of the group factor metamodel

GLS	1	2	3	4	5
Removed run i	y_i^*	$\hat{y}_i^*$	$(s_i^*)^2$	$x_i' \Omega_{\hat{\beta}} x_i$	t-value
1	6.95	6.47	0.015	0.082	1.54
2	7.70	7.96	0.034	0.057	−0.86
3	7.26	6.95	0.015	0.19	0.69
4	7.88	8.05	0.034	0.061	−0.56
5	6.05	6.20	0.50	0.015	−0.20
6	6.08	6.02	0.015	0.042	0.25
7	6.49	6.53	0.18	0.019	−0.09
8	5.90	6.15	0.086	0.020	−0.76
9	7.20	6.71	0.068	0.029	1.54
10	5.82	6.08	0.043	0.047	−0.86
11	6.77	6.46	0.018	0.023	0.69
12	5.71	5.89	0.048	0.047	−0.56
13	7.54	7.69	0.003	0.55	−0.29
14	7.70	7.64	0.025	0.032	0.25
15	7.21	7.25	0.007	0.20	−0.09
16	7.62	7.87	0.007	0.10	−0.76

1 $y_i^* = \log y_i$

2 $\hat{y}_i^* = \frac{1}{m} \sum_{j=1}^{m} \log \bar{y}_j^*$ (Note 4)

3 s_i^* = standard error of y_i^* (Note 4)

4 $x_i' \Omega_{\hat{\beta}} x_i$ = estimated variance of $\hat{y}_i^*$ (Note 6)

5 resulting statistic (Note 6)

Table 10: Coefficients estimation and significance test of groups

GLS	1	2	3
group j	$\hat{\beta}_j$	$\hat{var}(\hat{\beta}_j)$	t-value
0	6.868	0.054	126.5**
1	−0.027	0.038	− 0.7
2	0.133	0.038	3.5*
3	0.109	0.038	2.9*
4	−0.621	0.047	− 13.0**
5	−0.064	0.039	− 1.7
6	−0.271	0.041	− 6.6**
7	0.016	0.039	− 0.4
8	−0.009	0.038	− 0.2

1 $\hat{\beta}_j$ = estimate of coefficient β_j

2 $\hat{var}(\hat{\beta}_j)$ = estimate of the variance of $\hat{\beta}_j$ (diagonal element of $\Omega_{\hat{\beta}}$, see Note 5).

3 resulting statistic

* significant at $\alpha = 0.025$

** significant at any $\alpha > 0.000001$

The second screening stage is based on a R-III design, so a first order metamodel is assumed to be valid (no interactions between the remaining factors are permitted, see also Note 5). The twelve remaining factors are displayed in Table 11 and the corresponding experimental design in Table 12 (in Table 12 the columns of the standard design are permuted). Since the standard errors s_i^* vary between $\sqrt{0.236} = 0.485$ and $\sqrt{0.004} = 0.063$, only GLS is applied (Table 13, Column 3). Table 13 shows that the GLS regression model need not be rejected, since the maximum of the sixteen statistics is 1.17 (Table 13, Column 5, validation 13), whereas the significance level is 2.33 for $\alpha = (0.30/16)/2 = \pm 0.01$.

After accepting the model all sixteen runs are used to re-estimate β. Some parameter estimates were found insignificant. Next these insignificant parameters were set to zero (removed from the metamodel) and the remaining β were again re-estimated. This procedure is called "backwards elimination". The coefficients of the simplest metamodel that is still valid are presented in Table 14.

Next the number of tugs in the system is set to a certain value. The port times of these tugs are reduced by placing extra barges in the ports that are found significant. The metamodel has been used to determine the optimal number of barges in each port. By changing the number of tugs in the system and repeating this procedure, all possible

Table 11: Remaining input factors in the second screening stage.

Factor		minimal	maximal
x_1	number of tugs	8	12
x_2	capacity of a barge (10^4 DWT)	3	4
x_3	loading/discharging capacity port 6 (10^3 ton/hour)	7	8
x_4	loading/discharging capacity port 7 (10^3 ton/hour)	5	6
x_5	loading/discharging capacity port 9 (10^3 ton/hour)	3	3.5
x_6	number of extra barges in port 3	1	2
x_7	id. port 6	1	5
x_8	id. port 7	1	5
x_9	id. port 8	1	2
x_{10}	id. port 9	1	3
x_{11}	id. port 11	1	2
x_{12}	id. port 12	1	2

Table 13: Cross-validation of the ultimate metamodel (1, 2, 3, 4, 5: see Table 9).

GLS	1	2	3	4	5
Removed run i	y_i^*	$\hat{y}_i^*$	$(s_i^*)^2$	$x_i' \Omega_{\hat{\beta}} x_i$	t-value
1	7.183	7.125	0.034	0.060	0.19
2	7.169	7.030	0.046	0.045	0.46
3	7.255	7.384	0.056	0.067	−0.36
4	7.147	7.236	0.034	0.046	−0.31
5	6.141	6.383	0.236	0.056	−0.45
6	6.855	6.860	0.032	0.039	−0.01
7	7.211	7.155	0.069	0.049	0.16
8	5.792	5.751	0.038	0.059	0.13
9	7.288	7.133	0.058	0.050	0.47
10	7.153	7.112	0.023	0.056	0.15
11	7.278	7.417	0.079	0.059	−0.37
12	7.208	7.277	0.021	0.052	−0.26
13	7.063	6.583	0.070	0.596	1.17
14	7.389	7.252	0.004	0.061	0.54
15	7.628	7.846	0.029	0.057	−0.74
16	6.188	6.411	0.045	0.045	−0.74

Table 12: Experimental design for the second screening stage (R-III)

Combination	x_1	x_2 $(= x_1 x_5)$	x_3	x_4	x_5	x_6 $(= x_3 x_4)$	x_7 $(= x_3 x_5)$	x_8 $(= x_1 x_3)$	x_9 $(= x_4 x_5)$	x_{10} $(= x_1 x_4)$	x_{11} $(= x_1 x_4 x_5)$	x_{12} $(= x_3 x_4 x_5)$
1	−1	1	−1	−1	−1	1	1	1	1	1	−1	−1
2	−1	1	1	−1	−1	−1	−1	−1	1	1	−1	1
3	−1	1	−1	1	−1	−1	1	1	−1	−1	1	1
4	−1	1	1	1	−1	1	−1	−1	−1	−1	1	−1
5	−1	−1	−1	−1	1	1	−1	1	−1	1	1	1
6	−1	−1	1	−1	1	−1	1	−1	−1	1	1	1
7	−1	−1	−1	1	1	−1	−1	1	1	−1	−1	−1
8	−1	−1	1	1	1	1	1	−1	1	−1	−1	1
9	1	−1	−1	−1	−1	1	1	−1	1	−1	1	−1
10	1	−1	1	−1	−1	−1	−1	1	1	−1	1	1
11	1	−1	−1	1	−1	−1	1	−1	−1	1	−1	1
12	1	−1	1	1	−1	1	−1	1	−1	1	−1	−1
13	1	1	−1	−1	1	1	−1	−1	−1	−1	−1	1
14	1	1	1	−1	1	−1	1	1	−1	−1	−1	−1
15	1	1	−1	1	1	−1	−1	−1	1	1	1	−1
16	1	1	1	1	1	1	1	1	1	1	1	1

Table 14: Coefficients estimation and significance test of the remaining factors

GLS	1	2	3
group j	$\hat{\beta}_j$	$\hat{var}(\hat{\beta}_j)$	t-value
0	15.957	28.04	5.56**
1	0.698	0.24	2.91*
2	0.838	0.34	2.47*
3	−2.859	1.13	−2.54*
4	−2.254	0.59	−3.80*
7	−0.309	0.06	−5.04**
8	−0.289	0.07	−435**
10	−0.157	0.09	−1.70
12	−0.173	0.15	−1.12

* Significant at $\alpha = 0.025$
** Significant at any $\alpha > 0.000001$
1, 2, 3: See table 10

combinations of tugs and barges can be found that are able to realise the desired cargo flows. Finally the tugs and barges in the model are replaced by conventional ships of the same size. A few experiments using this model were carried out to determine how many conventional ships would be needed to maintain the desired cargo flows. The optimal combination of numbers of tugs and barges has been compared with the fleet of equivalent conventional ships.

5. Results

The metamodel described in the previous section allows for the variation of decision factors (number of tugs, number of barges in each port), as well as environmental factors. Environmental factors are not controllable but they do effect the output.

The environmental factors are:

a) The cargo flows that must be realized.

b) The loading/discharging capacity of the terminals.

Finally, the sensitivity of the results to changes in the capacity of the barges were investigated.

The minimal numbers of tugs and barges in four alternative situations are displayed in Fig. 5. These combinations are able to realise the desired cargo flows, provided that the extra barges are optimally spread over the ports in the system.

The four pusher barge systems have been compared to three cases in which pusher boats and barges were replaced by conventional ships (The capacity of the ships is assumed to be 40,000 DWT in all cases, see also Table 15).

The Net Present Value of the investment and operating costs of the tug-barge system are presented in Fig. 6. From Fig. 6 the optimal combinations of tugs and barges can be obtained. Some results of a control simulation of the optimal pusher barge system in the base case are displayed in Table 16. The optimal system contains 9 tugs (Fig. 6) and 18 barges (Fig. 5).

Table 15: Number and costs of conventional ships that are needed to realize the desired cargo flows in different cases (see also Figs. 4 and 5).

Studied case	Number of needed conventional ships of 40,000 DWT	NPV of the total costs (10^6 DFL)
1 Base case	14	933
2 Increased loading/ discharging capacities of the terminals	11	764
3 Increased yearly cargo flows	21	1406

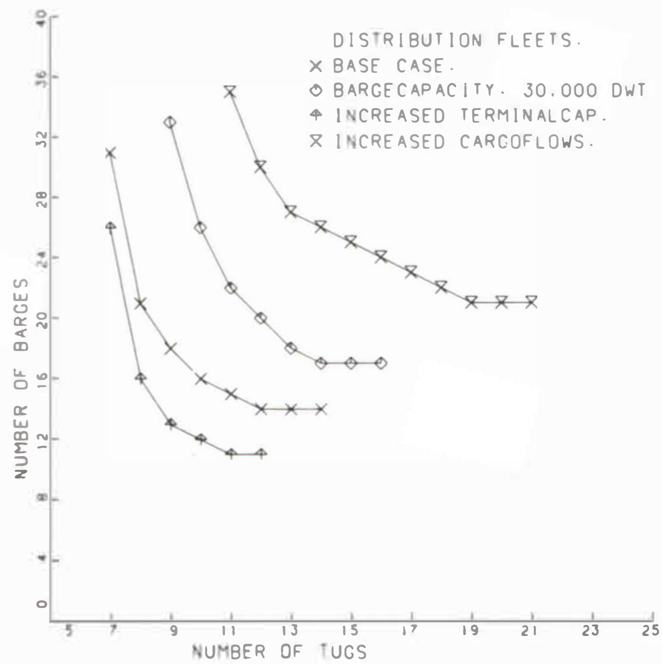

Fig. 5

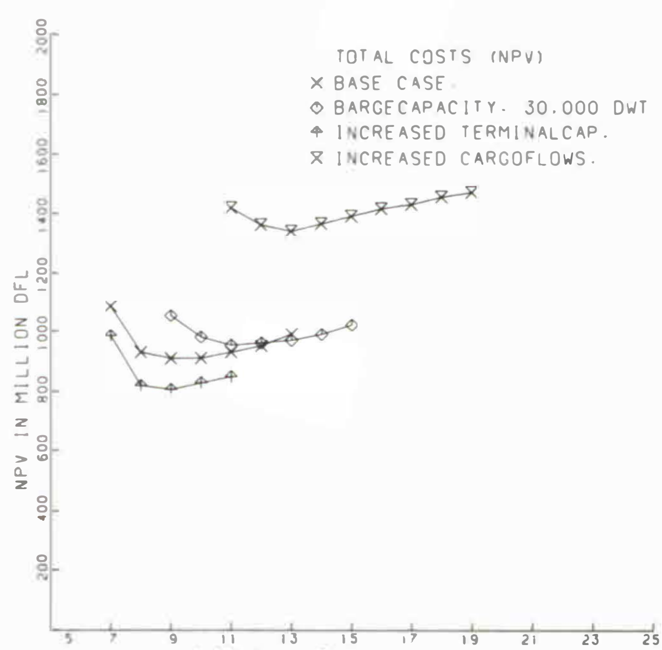

Fig. 6

Table 16: Some results of a simulation of a system with 9 pusher boats and 18 barges (columns 1, 3, 4, 5) and a simulation of a fleet of 14 conventional ships (columns 1,2).

Port 1	Average port time conventional ships (hour) 2	Average port time pusher boats (hour) 3	Number of extra barges in port 4	Average port time barges (hour) 5
6	49.2	15.1	2	57.1
7	71.0	25.3	2	102.7
9	40.6	4.3	2	140.0
13	29.3	6.4	1	66.9

The port times of conventional ships (Table 16, Column 2) have been obtained from an equivalent simulation of a fleet of 14 conventional ships (Table 15: base case).

It can be noted that due to the influence of extra barges for example in port 9, the port times of tugs have been reduced from 40.6 hours in the case of conventional ships (Column 2) to 4.3 hours (Column 3). The amount of cargo distributed between the ports in this simulation experiment was found satisfactory, so the results obtained from the metamodel seem to be reliable.

6. Conclusions

The simulation model of the pusher-barge system enables an accurate quantitative analysis of the system. However, special statistical analysis techniques are indispensable, because of the many parameters. The simplifications that are introduced by the superpositioned linear regression metamodel seem to be justified, according to statistical tests and control simulations. In other words, inside the experimental area, the metamodel is a valid model of the real system. Because of its simplicity it is a useful tool for calculations and predictions.

The optimal fleet of pusher boats and barges consists of twice as many barges as pusher boats. Instead or fourteen conventional ships, only nine pusher boats are needed.

Unfortunately, comparison of the costs of the tug-barge system with the costs of conventional ships (Fig. 5, Table 15) shows that the tug-barge system yields only a minor profit in the base case, which vanishes when the capacity of the barges is reduced, or when the capacity of the terminals is increased. Therefore it seems unwise to introduce a large scale pusher barge system in the studied situation.

Nevertheless, the same method of analysis can be applied in similar situations that seem to be more profitable.

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Appendix

Note 1

A more general metamodel postulates that the effect of factor j also depends on the values of the other factors j' ($j' \neq j$). This can be formalized as in the following equation where for illustration purposes $k = 2$:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_{12} x_{i1} x_{i2} + u_i \quad (i = 1 \ldots n)$$

Here the coefficient β_{12} denotes the interaction between the factors 1 and 2.

Note 2

To avoid a possible cancellation of important factors, the groups of a group screening design must satisfy two conditions:

a) The signs of all effects of the members of a group should be the same: Consider two factors which have effects that are negatives or near negatives of each other. If these two factors are the only important factors in a group, their effects may be masked by experimental error. Thus the group-factor would not test significant. If a few individual factors have unknown signs, however, then these factors can be placed in groups of size one (individually examined).

b) No interactions should exist between factors of different groups: If the metamodel includes two-factor interactions between factors of different groups then the group-factors may be investigated in a special design.

Neither assumption a) nor b) are very restrictive.

Note 3

Two simple classical experimental designs have been used.

a) Resolution-III-designs

Suppose three factors are investigated, so that $k = 3$. Each factor is studied at only two levels. Hence all 2^3 factor level combinations might be simulated. However, if the analyst assumes, that the first order model of Equation (1) is valid, then he can save 50% of his simulation runs.

The value of the third factor can be equal to the value of the (nonsignificant) interaction of the first two factors: $x_{i3} = x_{i1} \cdot x_{i2}$, so that four runs suffice:

combination	x_{i1}	x_{i2}	$x_{i3} = x_{i1} \cdot x_{i2}$
1	−1	−1	1
2	1	−1	−1
3	−1	1	−1
4	1	1	1

In general, Resolution III (R-III) designs assume that a first-order model with k parameters holds, and permits the estimation of $k + 1$ effects (including the mean value of y) in only $n = |k + 1|$ runs (where $|k + 1|$ means that $k + 1$ is rounded upwards to the next multiple of four). If n is a power of 2 then a 2^{k-p} design can be used. If n is not a power of 2 then the trick of identifying first-order effects with interactions does not work. Instead a table of so called Placket-Burman designs has to be consulted, which specifies X [5].

b) Resolution-IV-designs

If all factors are qualitative, then R-IV-designs permit the unbiased estimation of all first-order effects even if two-factor interactions are important. At the same time these designs provide estimators of certain sums of interactions. Technically R-IV-designs can be constructed very simply: once a R-III-design is available, it can be duplicated with reversed signs, i. e., in the lower part of the design $x_{ij} = -x_{i'j}$ (if $k = 7$ then $i' = 1 \ldots 7$ and $i = 8 \ldots 16$). So a R-IV design requires twice as many runs as a R-III design. Once a R-IV design has been selected, cross-products $x_j x_j'$ are also fixed (this also holds for R-III designs).

Note 4

Each run i is cut into, say m nearly independent subruns of fixed length. The subrun averages are treated as m independent observations. The underlying idea is that although the first few observations of a subrun still depend on the last observations of the preceding subrun, the subrun averages are practically speaking independent, if the subruns are long enough. The standard error after m subruns is:

$$s_i = \left(\sum_{j=1}^{m} (\bar{y}_j - y_i)^2 / (m - 1) \right)^{1/2}$$

The simulation response y_i is assumed to be equal to the average of the subrun averages:

$$y_i = \frac{1}{m} \sum_{j=1}^{m} \bar{y}_j$$

Note 5

Ordinary Least Squares (OLS) uses a strictly mathematical, i. e. nonstatistical, criterion: minimize the sum of squared deviations. The resulting estimator is [6]:

$$\hat{\beta} = (X' \cdot X)^{-1} X' \cdot y$$

If the assumptions of normally and independently distributed errors u_i with constant variance σ^2 and zero expectation hold, then the OLS estimator is known to be the best linear unbiased estimator (best meaning minimum variance):

$E(u'u) = \sigma^2 I_n$ is the unit matrix of size n
$E(u) = 0$ 0 is the null vector

The covariance matrix of $\hat{\beta}$ is:

$$\Omega_{\hat{\beta}} = \sigma^2 (x' x)^{-1}$$

Usually the common variance σ^2 is estimated from the Mean Squared Residuals:

$$\text{MSR} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 / n\text{-}k\text{-}1),$$

where k denotes the number of estimated parameters, and $\hat{y}_i$ is the predicted value:

$$\hat{y} = X \cdot \hat{\beta}$$

If the standard assumptions do not hold, then the covariance matrix of y does not equal $\sigma^2 I_n$. A best linear unbiased estimator results when GLS is applied:

$$\hat{\beta} = (X' \cdot \Omega_y^{-1} \cdot X)^{-1} X' \cdot \Omega_y^{-1} \cdot y,$$

where Ω_y denotes the covariance matrix of u (or equivalently y). If the individual simulation runs are independent, then Ω_y becomes a diagonal matrix D with elements σ_i^2.

The covariance matrix of the GLS estimator is:

$$\Omega_{\hat{\beta}} = (X' \cdot X \cdot X\, \Omega_y (C \cdot X' \cdot X)^{-1} \cdot X')^{-1}$$

Since Ω_y in practice is usually unknown, the estimator and its covariance matrix may be derived from:

$$\hat{\beta} = (X' \cdot \hat{D}^{-1} \cdot X)^{-1} X' \cdot \hat{D}^{-1} \cdot y$$

and

$$\Omega_{\hat{\beta}} = (X' \cdot \hat{D}^{-1} \cdot X)^{-1}$$

where $\hat{D}$ is an estimator of D, with elements s_i^2.

GLS is simplified to weighted least squares, the weight for observation y_i being inversely proportional to its variance σ_i^2.

Note 6

A predicted value of the response of simulation run $n + 1$ can be compared to the acutal response. Let y_{n+1} be the response and $\hat{y}_{n+1}$ the estimated prediction, then an appropriate statistic is:

$$t_{n+1} = (y_{n+1} - \hat{y}_{n+1}) / \left(s_{n+1}^2 + x'_{n+1}\, \Omega_{\hat{\beta}} \cdot x_{n+1}\right)^{1/2}$$

where x_{n+1} is the setting of the factors x_j in run $n + 1$ and $\Omega_{\hat{\beta}}$ is the estimated covariance of $\hat{\beta}$ (Note 5).

The statistic may be approximated by a standard normal variable $N(0,1)$ [4]. More than one run may be carried out to test the metamodel's validity, resulting in more than one statistic. In case of a cross validation, n statistics are obtained, where n is the number of experiments.

The proper significance level is based on the Bonferroni inequality, i. e., the model is rejected if any of the values of the statistics is significant:

$$\max_{1 \leq i \leq n} |t_i| > t^{\alpha'} \text{ with } \alpha' = (\alpha_E / n)/2,$$

where α_E is the "experiment-wise error rate", say 20%, α' is the "per comparison error rate" and the factor 2 is needed because a two sided test is appropriate.

Note 7

The significance of an estimated parameter $\hat{\beta}_j$ can be tested by the Student t-test:

$$t_d = (\hat{\beta}_j - \beta_j^0 / \sqrt{\hat{var}(\hat{\beta}_j)}$$

Here β_j^0 is the hypothesized value, usually zero.

The denominator follows from the main diagonal of $\Omega_{\hat{\beta}}$. The index d denotes the degrees of freedom of t. In simulation s_i^2 has so many d. f. that the t-distribution can be replaced by the standard normal distribution.

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