Forecasting Short-Term Demand for Empty Containers: A Case Study

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Issues related to the modeling and estimation of short-term demand for empty containers for subsequent movements on international shipping lines are explored. The study is part of a larger research effort directed toward the development of models, methods, and integrated planning tools to address typical problems related to the management of the land distribution and transportation of containers. The study is based on actual operational data coming from a large international maritime shipping company. The information and the extensive manipulations required to obtain a suitable data set for statistical analyses are described, including analyses of both daily and weekly demand for various combinations of container category and customer aggregation. The difficulties and requirements associated with forecasting short-term demand for containers are discussed.

A study aimed at the modeling and estimation of short-term demand for empty containers within the land networks of international shipping lines is presented. The study is part of a larger research effort directed toward the development of models, methods, and integrated planning tools to address typical problems encountered by international shipping companies, which operate large-scale maritime and land networks, in the management of their container fleet and their land distribution and transportation operations.

The planning of these operations is an extremely complex activity, especially if the aim is to simultaneously optimize the cost and service aspects of the company's operations in a competitive environment. Crainic et al. (*1*) describe the various operations and planning issues involved and present the methodological framework that we propose to address them. To facilitate understanding of the context of the demand study, we present a brief overview of operations and the proposed methodology.

Arriving ships carry containers, which come in several sizes and types and are loaded with imported goods, and empty containers returning from previous exports. Loaded containers are moved to their final destinations (import customers), and the empty containers are dispatched wherever they are needed for subsequent exports. Once unloaded, empty containers at the customer's site return either to the port of origin or to another depot. On the other hand, exporting customers require empty containers. Once loaded, containers are transported to the port and loaded on ships together with empty containers sent abroad to cope with the worldwide supply-demand imbalance. Note the importance of empty-container movements. First, every commercial (profitable) movement of a loaded container generates, almost automatically, a nonprofitable empty-container movement. Second, significant regional imbalances between imports and exports result in empty containers being moved over relatively long distances, usually directly between depots. Thus, up to 40 percent of land container traffic is made up of movements of empty containers, which represent a significant portion of the total system cost (*2,3*).

The methodology proposed to improve the management of empty-container movements is based on an integrated multilevel approach, which reflects the observed hierarchy in the decision process and the flow of information. Its first main component is a strategic-tactical model, formulated as a multimode, multicommodity location-distribution problem with interdepot balancing requirements [(*4*); see Crainic et al. (*1*) for references concerning algorithms developed for this model]. The output of this model consists of the set of depots to be used for the duration of the planning horizon (several months to a year), the customer-to-depot allocation rules, and the main interdepot empty-container balancing flows.

The second component of our method corresponds to the level of the operational (day-to-day) planning of the company's activities. At this level, demand must be satisfied and the most effective routes and means of transportation must be selected and used. Two models are used: an empty-container allocation model and an empty- and loaded-container routing model. The allocation model aims to determine the "best" distribution of empty containers that satisfies known and forecast customer demands at lowest total system cost; it is formulated as a stochastic, dynamic network model (*5*). The routing model strives to minimize the overall transportation cost of the loaded and empty containers from their origin to their destination while ensuring on-time delivery (*6*).

Demand data, especially short-term forecasts, are essential for these operational models because, besides regular customers with sufficiently well-known behavior (and possible long-term contracts), a significant part of the total service requests come from irregular customers, who order rarely, or at irregular intervals, or both. Yet, to our knowledge, there does not exist any model with which short-term (daily or

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weekly) container demand can be estimated. Hence, we have initiated an empirical investigation aimed at determining possible formulas for the average demand and the associated probability distributions. Ultimately, we look for models that may help forecast demand by container type and geographical zone, for a very short horizon. This paper gives an account of the first phase of this study, which was dedicated to the exploration of the available information, the construction of a reliable data set, and its statistical analysis. The plan of the paper parallels this sequence.

AVAILABLE DATA

The initial data available for this study come from a company operating worldwide maritime shipping lines to and from some 20 major European ports while servicing customers throughout most of Western Europe. The data correspond to the land distribution and transportation operations of the company for 1986. We concentrate on a network covering France, parts of Germany (corresponding to the former Federal Republic), the Netherlands, Belgium, and Luxemburg. This area corresponds to about 80 percent of the total container movements the company performed in Europe in that particular year.

The 224,374 records of the data file stand for as many land movements of one or several loaded or empty containers. Among the various pieces of information recorded for each movement, the most significant for the demand study are the following:

- Transportation mode identifies the actual mode used for transportation and the type of movement. The two main transportation means are private trucking and railways, including multimodal truck-rail combinations. Movements may be import or export, loaded or empty, and commercial or technical (balancing flows, movements of damaged or rented containers, etc.).
- Commercial mode specifies the type of contract between company and customer. Two modes are prevalent: carrier haulage (70 percent of the performed movements), in which the company manages and pays for the transportation of the containers; and merchant haulage (about 20 percent of the performed movements), in which the customer is entirely in charge of moving the containers and only the loaded movements are registered (with zero cost) in the company's records. The remaining traffic moves under mixed mode agreements, in which the company and the customer are each responsible for a part of the trip.
- The container category used for a given movement is identified by a combination of size and type characteristics. In 1986, the company used containers of 20 different categories (see Table 1). Note that, with the exception of the "bulk" and $9m^3$ containers, the company used exclusively 20′ and 40′ containers (in Europe, a truck is 20′ or 40′ long, whereas a rail car measures 60′). Distinctions among these containers are then induced by the particular usage (shipping line or operational characteristics) they are intended for.

Several manipulations of this initial information had to be performed to obtain a data set suitable for demand analyses (7). After cleaning up the file, we identified the origins and destinations of movements as customers or depots. We then determined a customer (depot) zone for each customer (depot) by selecting some 300 points where container traffic is most intense and building zones around these points that are consistent both geographically and commercially. Thus, because no aggregation of records has been performed, we ensure that, in most cases, a meaningful number of occurrences (observations) for each possible movement type are available for statistical analyses. The next step consists in estimating the daily supply of and demand for empty containers, for each customer zone and container category.

TABLE 1 DESCRIPTION OF CONTAINER CATEGORIES

Size	Type	Designation	Particularities
05	00	$9m^3$ containers	one 20' = 3 $9m^3$
20	00	20' general	All heights
22	00	20' general	8'6 height (Zeebruge)
43	00	40' general	
20	51	20' open top	
40	51	40' open top	
20	60	20' flat	
45	00	40' flat	
20	40	20' isotherm	Not allowed on French Caribbean lines
42	40	40' isotherm	Not allowed on French Caribbean lines
22	49	20' isotherm	Dedicated to French Caribbean lines
42	49	40' isotherm	Dedicated to French Caribbean lines
22	32	20' refrigerated	
43	32	40' refrigerated	
20	72	20' tanker	
41	CT	40' tanker	
49	RW	ACL trailer	ACL shipping line
VR		bulk	
NU		empty trailer	Truck movement without a container
22	80	20' special bulk	
22	02	20' open side	

Two approaches may be used to estimate the supply of and demand for empty containers. The first approach counts the empty containers that arrive (the empty customer demand) at and leave (the empty customer supply) each customer zone. This approach cannot be applied to movements performed under the merchant haulage commercial arrangement. The second method is based on the fact that each time a customer ships a loaded container, the company first had to deliver an empty one and, symmetrically, each loaded container delivered to a customer has to be picked up later on and moved away empty. Thus, the second approach counts the loaded containers that leave (the empty customer demand) and arrive (the empty customer supply) at each customer site.

Table 2 gives the results of the two methods for our data set. Both methods yield approximately the same figures. Yet, the total supply-demand is higher when the loaded method is used, which indicates that not all empty movements have been originally recorded in the company's data base. Consequently, we based our demand study on the daily estimates obtained by using this approach.

There are two sources of potential difficulties in the analysis of data and the interpretation of results. First, as emphasized by the yearly figures given in Table 2, not all container types are equally used. In fact, some are rarely called for. Consequently, 1 year's data may not be sufficient to obtain statistically significant results for some container types. Second, the available data do not reflect demand but rather the actual operations: the performed movements of loaded containers and some of the empty ones. Hence, the date of the request for a given movement is not recorded in the available data, and we miss the refused demand, as well as the container

TABLE 2 SUPPLY-DEMAND EVALUATIONS

Category	Carrier Haulage and Mixed Mode				Merchant Haulage	
	Empty		Loaded		Loaded	
	Demand	Supply	Supply	Demand	Demand	Supply
0500	29	8	8	27	12	505
2000	14183	6414	11361	18302	4674	13478
2040	410	2478	2920	416	628	193
2051	1004	482	520	1024	19	478
2060	223	90	93	242	80	439
2072	351	438	440	352	303	149
2200	3102	2732	3463	2931	549	1803
2232	1066	836	855	1080	378	1502
2249	6229	4568	6734	7181	14446	4320
2280	9	0	0	0	0	0
4051	1029	174	208	1013	10	157
41CT	3	11	11	3	1	0
4240	120	38	47	114	18	5
4249	1564	974	1346	1649	1950	746
4300	6465	2666	4117	8132	1137	2589
4332	1214	876	1015	1348	31	303
4500	581	56	36	560	7	1021
49RW	115	40	43	117	0	0

substitutions the company had to make to satisfy demand when the particular container category requested was not available. Furthermore, it has not been possible to establish exactly the meaning of the temporal information recorded with each movement. (At that time, the company was contracting out all its computer-related operations and was not using or validating in detail its past operational data.) On the basis of discussions with the company's management, we assumed that it indicates the date when the movement took place. This hypothesis is corroborated by the statistical analyses we performed. However, it may also indicate, at least for some movements, the date when the operation was recorded, thus introducing a certain level of uncertainty in our analysis.

In spite of these problems, it was decided to perform the analyses on the movement data, interpreting movements as demand, because this is the only information available. Furthermore, this is the type of data likely to continue to be available, because the planned management information system of the company was still meant to record the actual performed movements.

STATISTICAL ANALYSES

In spite of the aforementioned uncertainties regarding the exact timing of customer requests for empty containers, statistical analyses were performed on the final demand data set. They included analyses of both daily and weekly demand for various combinations of container categories (also called "product" in this section) and customer aggregation.

Daily Demand Analyses

These analyses were motivated by the fact that, in many fields of freight transportation, demand follows weekly cyclic patterns (*8*). More specifically, we were interested in determining whether a model of the following form could be fitted to the observed data:

$$D^p_{aw} = D^p_w \theta^p_d$$

where

D^p_{aw} = demand for Product p on Day d of Week w,
D^p_w = demand of Product p in Week w, and
θ^p_d = day-of-the-week adjustment factor for Product p and Day d.

Plotting demands for every day of the week over the 52 weeks of the year did not yield any clear pattern, whether aggregate demands for a product or demands for a specific container category–customer zone combination were considered, apart from the fact that observed values for Saturdays and Sundays were much lower.

To further investigate the impact of the day of the week on daily demands, linear regressions with dummy variables associated with the days of the week were performed on the data streams with the largest observed values (i.e., the aggregate demands per product and the demands for 24 product-zone pairs). In these regressions, the Saturday and Sunday values of each week were added together, yielding six observations per week for each data stream. The general form of the resulting regression equations was

$$D = aX_1 + bX_2 + cX_3 + dX_4 + eX_5 + f$$

where D is the daily demand for a given product or product-zone pair; X_i is 1 if the demand occurs on the ith day of the week and 0 otherwise; and a, b, c, d, e and f are the regression coefficients to be estimated.

The results of these regressions are summarized in Tables 3 and 4. For Table 3, it must be pointed out that for Product 0500 none of the independent variables X_i was sufficiently correlated with the dependent variable D to pass the tolerance tests of the stepwise regression method; thus in this case the regression is not significant. For the other products, the F-ratios indicate that the regressions are globally significant (the last column of the table gives the probability that the regression as a whole is not significant), but the R^2 coefficients, which correspond to the proportion of the total variation explained by the model, are not large. For the product-zone pairs (Table 4), though almost all regressions can be considered as significant, the R^2 coefficients are even smaller, which indicates a fairly poor fit.

TABLE 3 REGRESSION RESULTS ON UNNORMALIZED AGGREGATE DATA

Category	R^2	F-ratio	Probability
0500			
2000	41%	32.49	0.0000
2040	10%	7.18	0.0000
2051	4%	13.13	0.0003
2060	1%	4.63	0.0323
2072	14%	9.87	0.0000
2200	29%	24.86	0.0000
2232	9%	15.43	0.0000
2249	55%	76.54	0.0000
4051	16%	12.05	0.0000
4240	2%	7.21	0.0076
4249	39%	38.57	0.0000
4300	47%	53.61	0.0000
4332	20%	19.02	0.0000
4500	11%	7.89	0.0000
49RW	7%	7.70	0.0001

TABLE 4 REGRESSION RESULTS ON UNNORMALIZED DISAGGREGATE DATA

Category	Zone	R^2	F-ratio	Probability
2000	105	8%	5.54	0.0001
2000	107	13%	9.32	0.0000
2000	140	9%	6.47	0.0001
2000	154	6%	3.55	0.0039
2000	155	6%	3.81	0.0023
2000	210	8%	5.12	0.0002
2000	220	4%	2.27	0.0472
2000	222	4%	2.80	0.0268
2000	224	6%	3.85	0.0022
2000	237	17%	12.54	0.0000
2000	239	7%	4.84	0.0003
2232	208	12%	7.80	0.0000
2249	9	2%	1.60	0.1753
2249	140	23%	17.64	0.0000
2249	172	17%	12.49	0.0000
2249	192	8%	5.34	0.0001
2249	237	20%	15.27	0.0000
2249	274	33%	29.04	0.0000
2249	275	11%	7.59	0.0000
4300	107	7%	4.84	0.0003
4300	140	15%	10.69	0.0000
4300	208	21%	16.32	0.0000
4300	210	13%	9.13	0.0000
4300	239	2%	0.93	0.4586

Obviously, seasonal patterns could occur; if such was the case, they would probably be responsible for the large amount of unexplained variation. To account for such patterns, new data were created by dividing daily demands by weekly demands (the new observations thus represent the proportion of weekly demand taking place on a given day). The corresponding regression equation is then

$$\frac{D}{D_w} = a'X_1 + b'X_2 + c'X_3 + d'X_4 + e'$$

where D_w is the weekly demand and $D, X_1 \ldots, X_4$ are defined as before. (One independent variable had to be eliminated, because the observed values for every week now sum to 1.)

The results of these regressions for the global demands per product are given in Table 5. Surprisingly, the normalization of daily demands does not produce much larger R^2 values overall, and there are now two container categories for which the regressions are not significant (0500 and 4240).

TABLE 5 REGRESSION RESULTS ON NORMALIZED AGGREGATE DATA

Category	R^2	F-ratio	Probability
0500			
2000	42%	43.66	0.0000
2040	11%	7.42	0.0000
2051	16%	11.86	0.0000
2060	4%	5.89	0.0031
2072	13%	9.32	0.0000
2200	33%	29.99	0.0000
2232	17%	12.29	0.0000
2249	54%	73.41	0.0000
4051	15%	18.58	0.0000
4240			
4249	39%	39.84	0.0000
4300	50%	61.46	0.0000
4332	34%	31.30	0.0000
4500	12%	8.65	0.0000
49RW	8%	13.06	0.0000

It was pointed out earlier that demands on Saturdays and Sundays are, not unexpectedly, much lower. Because this could have had an impact on the previous analyses, it was decided to discard these observations and to perform a new series of regressions similar to the first one for the global demands per container category (i.e., with unnormalized values). These regressions yielded much lower R^2 coefficients (for instance, for Product 2000 the R^2 goes down from 41 to 18 percent and for Product 2249 from 55 to 17 percent). This confirmed that, apart from the difference between working days and weekends, the day-of-the-week effect is not important. This led us to abandon the model initially proposed and to focus our attention on weekly demands.

Weekly Demand Analyses

Whereas our analyses of daily demands were aimed at the identification of repetitive cyclic patterns, a different approach had to be used for weekly demands. For one thing, the available data (1 year) are clearly insufficient to provide any insight into possible seasonal patterns in any of the data streams. Furthermore, preliminary analyses of the aggregate demands per container category indicated that, if seasonal patterns were indeed present, these would be different from one product to another, thus making it useless to try to identify a general pattern for all categories. On the other hand, the observed variations in the demands may simply correspond to plain randomness in the underlying processes. To test this hypothesis, we first tried to fit normal and Poisson distributions to the demands per container category. The parameters used for the postulated distributions were the sample mean and standard deviation for the normal and sample mean for the Poisson. The goodness-of-fit test was the Kolmogorov-Smirnov test, which compares the observed cumulative distribution with the postulated cumulative distribution on the basis of the most extreme absolute difference (MEAD) between them. In fact, in this test, the MEAD is transformed into a standard normal statistic (Z value), from which the probability that the observed data follow the postulated distribution can be derived.

The results of these tests (see Tables 6 and 7) indicate that the normal distribution provides a good fit for four products (2000, 2200, 2249, and 4300) and a reasonable fit for two (2072 and 4051), whereas the demands for Container Categories 0500 and 4249 are approximately Poisson. It is interesting to note that the four container categories for which a good fit was obtained with the normal distribution are those with the largest sample means; there is thus a high level of aggregation of individual demands for these products and, therefore, this result could be expected.

The Kolmogorov-Smirnov test considers all observations as a static sample, neglecting any serial autocorrelation within the data streams. This is important because the presence of significant autocorrelations would invalidate the assumption of plain randomness. When we computed the autocorrelations and the partial autocorrelations for the 16 series, we found that there were no significant autocorrelations for 9 (Products 2000, 2051, 2060, 2072, 2232, 2249, 4051, 4240, and 49RW). It is thus possible to conclude that the series corresponding to Container Categories 2000, 2072, 2249, and 4051 are indeed

TABLE 6 KOLMOGOROV-SMIRNOV TEST: NORMAL DISTRIBUTION

Category	Mean	Standard Deviation	MEAD	Kolmogorov Smirnov Z	Probability
0500	0.53	1.03	0.364	2.597	0.000
2000	354.10	58.30	0.053	0.381	0.999
2040	8.08	5.11	0.153	1.094	0.182
2051	19.75	11.46	0.159	1.136	0.151
2060	4.51	4.91	0.205	1.467	0.027
2072	6.84	3.82	0.106	0.760	0.610
2200	57.18	20.90	0.066	0.469	0.980
2232	20.84	7.83	0.139	0.993	0.277
2249	138.69	23.12	0.076	0.541	0.932
4051	19.67	7.50	0.099	0.709	0.696
4240	2.18	2.46	0.215	1.534	0.018
4249	32.08	8.01	0.143	1.019	0.250
4300	158.27	27.57	0.069	0.494	0.968
4332	26.18	13.79	0.176	1.255	0.086
4500	10.82	6.29	0.116	0.830	0.496
49RW	2.27	2.59	0.218	1.556	0.016

TABLE 7 KOLMOGOROV-SMIRNOV TEST: POISSON DISTRIBUTION

Category	Mean	MEAD	Kolmogorov Smirnov Z	Probability
0500	0.53	0.078	0.555	0.918
2000	354.10	0.290	2.072	0.000
2040	8.08	0.136	0.973	0.300
2051	19.75	0.231	1.648	0.009
2060	4.51	0.253	1.808	0.003
2072	6.84	0.143	1.022	0.247
2200	57.18	0.263	1.878	0.002
2232	20.84	0.182	1.298	0.069
2249	138.69	0.186	1.330	0.058
4051	19.67	0.168	1.203	0.111
4240	2.18	0.169	1.207	0.108
4249	32.08	0.078	0.558	0.915
4300	158.27	0.226	1.617	0.011
4332	26.18	0.358	2.569	0.000
4500	10.82	0.198	1.414	0.037
49RW	2.27	0.193	1.376	0.045

"white noise" (i.e., sequences of independent identically distributed normal random variables).

Further analysis was required for the seven other container categories. This was done by using the well-known Box-Jenkins method, which allows characterization of sequential dependencies in time series through autoregressive integrated moving average (ARIMA) models (*9*). For two of the container categories (2040 and 4300), it was impossible to identify satisfactory models. Models were identified for the five remaining products, but they all displayed a high residual variance-to-mean ratio, which would make them almost useless in practice for predictive purposes (*7*).

We also applied the Box-Jenkins method to the disaggregate series (i.e., the series for the container category–customer zone pairs). For practical reasons, this analysis was restricted to the 24 pairs with annual demand larger than 300 containers. For these disaggregate series, the Box-Jenkins method yielded the following results (*7*):

- For 10 series, no ARIMA model could be identified.
- Four series displayed no significant autocorrelations, and it was possible to fit a normal distribution for three of them and a Poisson for the other.
- ARIMA models were identified and fitted for the other 10 series; however, these models were quite different from one another and, in most cases, the residual variances were large.

Overall, the results obtained for the disaggregate series confirm what could be suspected after the analysis of the aggregate series: the processes underlying the demand for empty containers are complex and their combined effect cannot be easily characterized in statistical terms, except when the level of aggregation is very high (that would be the case in the global demands for Products 2000, 2072, 2249, and 4051).

Discussion of Results

Several general remarks are in order. First, with only one year of data, it is not possible to detect any overall trend in the demands or to identify any seasonal patterns. Second, container categories with low traffic display high coefficients of variation, even for the weekly demands. This may suggest the use of different probability distributions, such as the negative binomial or the gamma, to represent the demand in these cases. Third, some external factors have an important effect on observed demands. For one thing, demands for empties are certainly driven to some extent by ship schedules, because a request for a container probably occurs a few days before the departure date of the ship on which it will sail. With regard to daily variations in demand, legal holidays and "traditional" vacation periods (such as most of July and August in most of Western Europe) must be taken into account. When we plotted the daily demands, we were easily able to pick up the dates of all major holidays on the graphs: in each case, there was a significant dip in demand. Given the large number of such holidays in the countries covered by the study, this in itself may have been sufficient to throw off the time series analyses.

CONCLUSIONS

The objective of the empirical study described in this paper was to gain some insight into the short-term demand process for empty containers and, if possible, to derive demand forecasting models.

We were successful in constructing a data set on demand for empties by using recorded information on loaded container movements. This data set, though not perfect, was adequate to allow for statistical analyses of demand.

The analyses indicated that predicting short-term demand for empty containers is extremely difficult. This confirms the conclusions of similar studies performed for the rail mode (*10,11*). However, when traffic is consistently large, we were able to fit probability distributions for the demand of specific container categories. The distributions can certainly be directly used in short-term planning models.

The situation is different for container categories with low traffic. For them, the available data were not sufficient to estimate distributions by using straightforward statistical techniques. Good predictions require more than 1 year of data, and all elements that may significantly affect the demand process in the specific case under study must be taken into account: ship schedules, holidays, vacations, substitution rules, and so forth. Note, however, that the lack of reliable demand distributions for these container categories is not a critical issue in short-term planning. This is because conservative estimates of buffer stocks at depots can be derived from the means and variances of observed demand. Moreover, given the low level of demands (and stocks) for these containers, the inventory costs associated with overestimating demand form a small portion of total system costs.

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