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MULTI-OBJECTIVE SHIP'S CARGO HANDLING MODEL

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Abstract. This paper proposes a new optimization model for ship's cargo handling operations which solution gives the structure of cargo handling resources required, along with attaining the minimum total 'in-port' costs and the minimum of time required for completion of cargo operations. Due to complexity of the model which consists of composite multi-objective functions together with several decision variables and constraints, the solution has been sought by utilization of an adapted genetic algorithm combined with a hybrid algorithm. Testing of the model on real world data yielded acceptable results in a short time. In the course of decision making, the ship's operator can, on the basis of the proposed model and taking into consideration shipping market data, choose appropriate variation of the returned solution, which incorporates minimum costs, minimum of operational time and related cargo handling resources.

Keywords: ship; optimization; cargo handling; genetic algorithm; seaport.

Introduction

Cargo and cargo units carried on or under ship's deck shall be so loaded, stowed and secured as to prevent, as far as, is practicable, throughout the voyage, damages or hazard to the ship and the persons on board, and loss of cargo overboard. These cargo handling operations, as well as, cargo separation are linked processes onboard ship during its stay in the port. Service time of ship's cargo cranes, forklifts and longshoremen, as well as, sequence of cargo units' arrival alongside the ship follow certain probability distributions (Van Asperen *et al.* 2003; Hess, S., Hess, M. 2010; Hess, M., Hess, S. 2011). In this paper the general cargo ship is defined as a multichannel, multiphase mass service system, where the input flow of general cargo passes through the four phases in the process of cargo handling (Hess, S., Hess, M. 2009). When making business decisions related to these processes (Hess *et al.* 2007, 2008; Machuca *et al.* 2007), it is essential for the ship's operator to achieve the minimum transhipment costs and costs of the ship's stay in port together with minimum service time.

Due to the problem complexity, a multi-objective optimization model is set up which consists of two objective functions. The first one addresses the minimum total cost of services and waiting time and the second one addresses the minimum service time. Decision variables are: number of ship's cargo cranes, number of forklifts, number of workers engaged on cargo securing, and workers engaged on cargo separation and marking.

The problem in developing and solving such models lies in their complexity and steep procedure of finding the space of optimal solutions for both functions simultaneously (Tijms 1995). Furthermore, there is the complexity of the objective functions' forms containing several unknown variables (decision variables) along with constraints in the space of possible solutions. Therefore, in this paper process of solving is based on adapted genetic optimization algorithm that is combined, for purpose of achieving more precise solutions (Deb 2009; Koza 1992; Liu *et al.* 2008), with hybrid optimization algorithm. It should be emphasized here that the process starts with completely different assumptions in optimization modelling than the classical mathematical procedures that can be found in operating research literature (Kleinrock 1975; Jensen, Bard 2002).

In the next part description of the problem is given, after which follows the mathematical model and the process of solution search. Model has been tested on the real world example with general cargo ship with five holds and five cargo cranes that loads 700 cargo units by ship's cranes.

1. The Problem

Organization of cargo handling operations and optimal utilization of the existing port and shipboard resources, i.e. ship's cranes, forklifts and workers, with the objective of minimizing the total operational costs (Hess, S., Hess, M. 2009) may prove to be a hard task.

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Furthermore, the added complexity arises if the ship's operator considers such costs confronted to total earnings in the broader context of business making, in time period that extends ship's stay at port.

An example is related to costs and gain through complete ship's voyage, from the first loading port to the last discharging port according to concerning chartering agreement. Minimizing total operating costs related to cargo handling in port doesn't necessarily lead to the maximal gain on the observed voyage. In reality, the minimum of mentioned costs can be achieved by slower operations of cargo handling, especially in ports with lower port dues and high tariffs for overtime work. Effect of longer ship's stay at a port, on the other hand, leads to postponed signing of the next chartering agreement and in turn fewer earnings in longer period of time. Hence, apart from finding the solution for minimal total operating costs of cargo handling in the port, it is essential at the same time to determine minimal time of ship's stay at port (Van Asperen *et al.* 2003).

The goal of this paper is to determine simultaneously minimal costs and minimal ship's service time, as well as, quantifying resources needed for cargo operations (ship's cargo cranes, forklifts, workers). Here, for the sake of problem simplicity, the process of cargo handling is limited to loading operations only. However, analogically, process of cargo discharging or combination of loading/discharging can be observed.

To acquire the solution of the problem thus formulated, it is essential to define two objective functions, one for the minimum costs and the second for the minimum service time, with constraints regarding the resources for loading operations. For that reason, a mathematical model of multi-objective optimization with constraints in the space of input variables is set up (Tijms 1995; Zimmermann *et al.* 2002).

2. Mathematical Dependences

As highlighted in the paper by Hess, S. and Hess, M. (2009) ship can be defined as a mass servicing system where the arrival rate of units, parameter λ, represents the average number of general cargo units arrived alongside the ship during an observed time unit (e.g. during a year, month or day). The average number of general cargo units that can be served at the ship in a time unit is service rate μ. According to the queuing systems' classification (Kleinrock 1975; Jensen, Bard 2002), cargo handling operations on the ship can be observed as the queuing system with more than one service place and unlimited number of cargo entities in queue.

Onboard cargo handling process consists of four main operations that can be represented as a multi-phase queuing system. Each of the phases corresponds to a separate queuing system with different service places. In the first phase the arrival rate is total cargo units that is to be loaded on the ship, and service places are ship's cranes. In the second phase, arrival rate is the same as in the former phase, while service places are forklifts manipulating cargo units in ship's holds. Once the cargo is stowed in the holds as per cargo plan, the third phase – cargo securing – may begin. In the fourth phase the secured cargo is separated and marked for different recipients, where the service places are represented with another groups of workers. Output from the former phase is input to the consecutive phase of the multi-phase queuing system, i.e. all four phases have equal arrival rate λ ('equivalence property' of multi-phase queuing system). Furthermore, valid assumption for all the four phases of queuing system is that the arrival rate has Poisson and the service time exponential distribution, where μ_i is the service rate of the phase i; $i = 1, 2, 3, 4$. Service rates for all service places of the same phase are assumed to be equal.

The model set up in the paper by Hess, S. and Hess, M. (2009) for estimation of the optimal number of service places in each phase consists of one objective function minimizing sum of expected total costs:

$$\min C = \min\left(C_s + C_W\right), \tag{1}$$

where C_s is expected total service cost:

$$C_s = S_1 \cdot C_1 + S_2 \cdot C_2 + S_3 \cdot C_3 + S_4 \cdot C_4 = \sum_{i=1}^{4} C_i \cdot S_i, \tag{2}$$

while C_W is expected total waiting cost:

$$C_W = \sum_{i=1}^{4}\left(C_{wi} \cdot L_i - \sum_{n=0}^{S_i} n \cdot p_{ni}\right) - \sum_{i=1}^{4}\left(C_{wi} \cdot \frac{S_i^{S_i}}{(S_i - 1)!} \cdot p_{0i} \cdot \frac{\psi_i^{S_i+1}}{1-\psi_i}\right), \tag{3}$$

with notation:

- C_i – service cost per time period for each service place of the phase i, $i = 1, 2, 3, 4$;
- C_{wi} – expected waiting costs per time period for each cargo unit, at phases $i = 1, 2, 3, 4$;
- S_i – number of the service places of the phase i, $i = 1, 2, 3, 4$;
- ρ_i – traffic rate of the service place of the phase i, $i = 1, 2, 3, 4$; $\rho_i = \lambda/\mu_I$;
- $\psi_i = \rho_i/S_i$ – coefficient of the system occupancy; condition of queuing system stability (statistical equilibrium) follows: $\psi_I < 1$, $i = 1, 2, 3, 4$;
- p_{0i} – probability of no units waiting on the phase i, $i = 1, 2, 3, 4$;
- p_{ni} – probability of n units waiting on the phase i, $i = 1, 2, 3, 4$;
- L_{qi} – average number of units waiting in the line on service in the phase i, $i = 1, 2, 3, 4$;
- L – average number of units in the queuing system in the phase i, $i = 1, 2, 3, 4$.

However, considering the problem extension in this paper, another objective function is introduced that minimizes total service time W_{ser} in all four phases. Thus, the model becomes multi-objective optimization model in the form:

$$\min C = \min\left(\sum_{i=1}^{4} C_i \cdot S_i + \sum_{i=1}^{4}\left(C_{wi} \cdot L_i - \sum_{n=0}^{S_i} n \cdot p_{ni}\right) - \sum_{i=1}^{4}\left(C_{wi} \cdot \frac{S_i^{S_i}}{(S_i-1)!} \cdot p_{0i} \cdot \frac{\psi_i^{S_i+1}}{1-\psi_i}\right)\right); \quad (4)$$

$$\min W_{ser} = \min \beta \cdot Q \cdot \sum_{i=1}^{4} w_{ser_i} = \min \beta \cdot Q \cdot \sum_{i=1}^{4} \frac{1}{\mu_i \cdot S_i}, \quad (5)$$

with constraints:

$$S_i \le s_{ui}\,;\ s_{ui} \text{ – integer; } i = 1, 2, 3, 4, \quad (6)$$

where:

- W_{ser} – total time duration of handling given cargo units;
- w_{ser_i} – time duration of the cargo operations in phase i;
- β – coefficient of the phase overlapping in the multiphase mass servicing system;
- Q – total number of units in the cargo handling process;
- s_{li} – lower limit of S_i;
- s_{ui} – upper limit of S_i.

Input variables in the model are: $\lambda, \mu_1, \ldots, \mu_4, C_1, \ldots, C_4, C_{w1}, \ldots, C_{w4}$, and decision variables: $S_1, \ldots, S_4$.

Due to the complexity of computational procedure (Powell 1983; Censor 1977), the approach taken here to find the solution, in the first part applies genetic optimization algorithm (GA) adapted to the problem structure in order to reach solution area close to the optimum in a fewer number of iterations, followed by the application of hybrid optimization algorithm (GHA) that leads to the final solution area.

3. Problem Solution

In order to attain a practical solutions for the given model (Hess, M., Hess, S. 2011) we have formulated the problem as multi-objective, since a single objective one with several constraints would not adequately represent the problem. Hence, there is a vector of minimization objectives, $F(x) = [F_1(x), F_2(x)]$ that is subject of a number of constraints:

$$\min_{x \in R^n} F(x), \text{ subject to}$$
$$G_i(x) = 0, i = 1, \ldots, k_e;\ G_i(x) \le 0\,;$$
$$i = k_e + 1, \ldots, k;\ l \le x \le u. \quad (7)$$

Note that because $F(x)$ is a vector, if any of the components of $F(x)$ are competing, there is no unique solution to this problem. Instead, the concept of noninferiority (Pareto optimality) is used to characterize the objectives (Censor 1977). A noninferior solution is one in which an improvement in one objective requires a degradation of another. We started from a feasible region Ω in the parameter space, x is an element of the n-dimensional real numbers $x \in R^n$ that satisfies all the constraints, i.e., $\Omega = \{x \in R^n\}$. This allows definition of the corresponding feasible region for the objective function space Λ:

$$\Lambda = \{y \in R^m : y = F(x), x \in \Omega\}. \quad (8)$$

The vector $F(x)$ maps parameter space into objective function space. A noninferior solution point can now be defined as follows: Point $x^* \in \Omega$ is a noninferior solution if for some neighbourhood of x^* there does not exist a Δx such that $(x^* + \Delta x) \in \Omega$ and

$$F_i(x^* + \Delta x) \le F_i(x^*),\ i = 1, \ldots, m \text{ and}$$
$$F_j(x^* + \Delta x) < F_j(x^*) \text{ for at least one } j. \quad (9)$$

On Fig. 1, the set of noninferior solutions lies on the curve between C and D. Points A and B represent specific noninferior points. A and B are clearly noninferior solution points because an improvement in one objective, $F_1(x)$, requires a degradation in the other objective, $F_2(x)$, i.e., $F_1(B) < F_1(A)$, $F_2(B) > F_2(A)$.

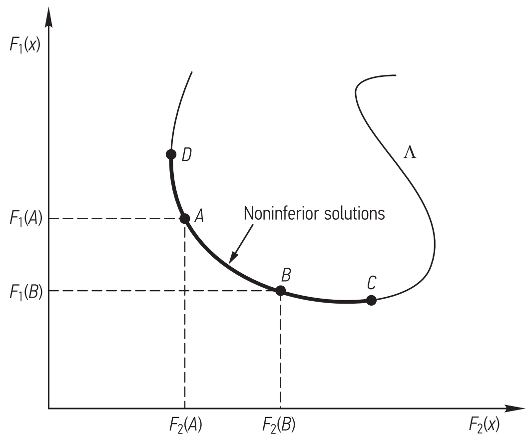

Fig. 1. Set of noninferior solutions

Multi-objective optimization generates and selects noninferior solution points since any point in Ω that is an inferior point represents a point in which improvement can be attained in all the objectives. The goal in this optimization is constructing the Pareto optima and the algorithm used in process calculation is described in (Deb 2009). The relative importance of these objectives and the system's best capabilities are determined and tradeoffs between the objectives fully traced. Thus, set up of the multi-objective design strategy here enabled a natural problem formulation to be expressed. For the purpose of finding practical solutions *Matlab* has been used.

Our approach finds a local Pareto front for multiple objective functions, each of four decision variables, using the genetic algorithm followed by hybrid function. We also impose bound constraints on the decision variables as noted in model formulation. We have provided a fitness function, the number of variables, and bound constraints in the problem. The initial assignment of values to the decision variables is generated randomly. The next generation of the population is computed using the non-dominated rank and a distance measure of the each individual decision variable (individuals) in the current generation. A non-dominated rank is assigned to each individual using the relative fitness. Individual *p* dominates *q* (*p* has a lower rank than *q*) if *p* is strictly better than *q* in at least one objective and *p* is no worse than *q* in all objectives. Two individuals *p* and *q* are considered to have equal ranks if neither dominates the other. The distance measure of an individual is used to compare individuals with equal rank.

The multi-objective GA function employed here uses a controlled elitist genetic algorithm, which always favours individuals with better fitness rank and favours individuals that can help increase the diversity of the population even if they have a lower fitness value. It is very important to maintain the diversity of population to achieve convergence to an optimal Pareto front. This is done by controlling the elite members of the population as the algorithm progresses by specifying the fraction of the population on the best Pareto frontier to be kept during the optimization and computation of distance measures of individuals. The crowding distance measure function calculates distance in design space. In the first stage we set the Pareto fraction to value of 0.4, so the current population size on Pareto front shrunk to 40% of the population size.

At this stage the number of points on the Pareto front was 23. The average distance measure of the solutions on the Pareto front was 0.1002. The spread measure of the Pareto front was 0.3805.

A smaller average distance measure indicates that the solutions on the Pareto front are evenly distributed. The default initial population is created using a random number generator in a default range of [0;1]. The default population size used is 95 that will clearly identify the eventually disconnected Pareto front. The algorithm uses three different criteria to determine when to stop the process of calculation. It stops when the maximum number of generations (120) is reached. It also stops if the average change in the spread of the Pareto front is less than tolerance specified (0.02). The third criterion is the maximum time limit in seconds (10).

At the second stage the number of points on the Pareto front was 34. The average distance measure of the solutions on the Pareto front was 0.0882. The spread measure of the Pareto front was 0.4105.

Search for better precision of final solution employs multi-objective GA hybrid function. A hybrid scheme is used to find an optimal Pareto front for our multi-objective problem. GA can reach the region near an optimal Pareto front relatively quickly, but it can take many function evaluations to achieve convergence, so GA is run for a small number of generations to get near an optimum front. Then the solution from GA is used as an initial point for another optimization method that is faster and more efficient for a local search. The Fgoalattain-algorithm from *Matlab* is used as the hybrid method to spot the goal attainment problem.

In multi-objective GA the hybrid algorithm starts at all the points on the Pareto front returned by GA. The new individuals returned by the GHA are combined with the existing population and a new Pareto front is obtained. GHA provides a vector specifying the goal for each objective as the extreme points from the Pareto front found so far.

At the third stage the number of points on the Pareto front was 30. The average distance measure of the solutions on the Pareto front was 0.0702. The spread measure of the Pareto front was 0.4769.

Furthermore, the random number generators are also reset so that the results with the previous run (without the hybrid function) can be compared.

At the fourth stage, on initial iteration the number of points on the Pareto front was 31. The average distance measure of the solutions on the Pareto front was 0.0921. The spread measure of the Pareto front was 0.5017.

If the Pareto fronts obtained by GA alone and by using the hybrid function were close, they are compared using the spread and the average distance measures. The average distance of the solutions on the Pareto front has now been improved by using the hybrid function. The spread here is a measure of the change in two fronts and was higher when hybrid function was used. This indicates that the front has changed considerably from that obtained by GA with no hybrid function. In this stage, the indices showed higher value of the average distance measure and the spread of the front, meaning the diversity of the solution has been partially lost.

To preserve the diversity, at the fifth stage, the GA was run again with the final population returned in the last run. Here, the hybrid function is removed. The number of points on the Pareto front was 31. The average distance measure of the solutions on the Pareto front was 0.0396. The spread measure of the Pareto front was 0.2932.

Processing time required to reach the final results (Table 1) was less than 2 seconds on processor Intel Core Duo 3600 MHz. Since, this approach in multi-objective optimization generates and selects noninferior solution points in which improvements are attained in all the objectives, the method proved suitable for solving a practical problem and is tested in the following part.

Table 1. GA and GHA input controls and output parameters

	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5
tolerance	0.02	0.02	0.02	0.01	0.02
time limit (s)	10	10	10	10	10
max number of generations	202	136	148	20	2
number of points on Pareto front	23	34	30	31	31
average dist. measure of solutions Pareto front	0.1002	0.0882	0.0702	0.0921	0.0396
spread measure of Pareto front	0.3805	0.4105	0.4769	0.5017	0.2932

4. Practical Example and Results Analysis

The model has been tested on the real world example, using hold's capacity and cargo handling data for general cargo ship 'Hever Castle', with five holds and fitted with five cargo cranes, which loads 700 cargo units in port of Trieste. The cargo to be loaded is handled from wharf and/or trucks alongside the ship into ship's cargo holds by ship's cranes. After selection and validation of collected historical data for the port all variables have been made available for entering into the model. The selection and validation of port's data have been made in consultation with port's experts and ships' agents and after discussion with the domain experts.

Therefore, input variables in the model are: Q = 700 units, λ = 40 units/h, μ_1 = 14 units/h, μ_2 = 21 units/h, μ_3 = 8 units/h, μ_4 = 14 units/h, C_1 = 582 m.u./h, C_2 = 270 m.u./h, C_3 = 3.95 m.u./h, C_4 = 3.54 m.u./h, C_{wi} = 4.99 m.u./h. Coefficient of the phase overlapping in the multiphase mass servicing system, β is in range of [0.33;0.46], subject to the number of service places engaged in each phase. The number of service places of phase i are decision variables $S_1, \ldots, S_4$, which, in this example, have the following constraints:

$$S_1 \leq 5; \;\; S_2 \leq 6; \;\; S_3 \leq 18; \;\; S_4 \leq 12. \qquad (10)$$

The final results for loading of 700 cargo units of general cargo are obtained in form of points on Pareto front, Fig. 2, which coordinates are positioned in the space of optimal results that satisfy minimum of objective functions. That means each point represents minimum of costs and associated minimum of the operational time, reached along with specific combination of S_i, number of service places by phase.

Since there is no unique optimal result, ship's operator will be able, taking into consideration the real case, take decision on how long the cargo operations will last and get the amount of the associated costs, and vice versa.

Port dues, port operating costs and costs of the port in idle state, contained in the total cost C, vary from port to port. Similar applies to the ship's operating costs related to the transhipment of cargo in the port, which vary from ship to ship, affected for example, by type, size and age of the ship, the ship's transhipment equipment, and the operational policy of ship's operator.

If the operating costs per hour are high, ship's operator tries to reduce them in a way to reduce the number of service places per phase, thus extending the service time and stay of ship in the port. This is true in the case when the cost of the ship's stay in port is relatively low and the situation on the shipping market is unfavourable so it is worth to keep the ship for an extended period in port, resulting in higher realized gain in longer period. In the case when the cost of the ship's stay in port is high or in the case when the freight rates are high, ship's operator may opt for a shorter service time in the port, which entails a greater number of service places and higher operating costs per hour (Hess, S., Hess, M. 2010; Juan *et al.* 2012).

The lesser service places per phase the longer service time and ship's stay in port. In this case operating costs per hour are smaller; however, total costs of the ship in port may be higher depending on total service time. Ship's operator may select such operational option if the port dues are low or state of the shipping market is unfavourable. It is important to emphasize here, that in some ports ship's operator is not in position to make such selection or he is bounded by offered options (Chang *et al.* 2012).

Fig. 2 shows that in the first part (up to 16 h) curve quickly descend which may be explained by the fact that the ship's service time grows inversely proportional to the number of service places per phase, resulting in almost linear decrease of costs per hour. The second part of curve falls considerably slower and asymptotically approaches specific cost value. Extreme right points on the Pareto front mark minimal savings in costs per hour considering the extension of the duration of the service time. This can be interpreted through the introduction of increased certain port taxes and increased port/service-places operational costs after a certain time the ship spends in port. By such measures, ports often tries to discourage retention of the ship in port beyond a specified time limit in order to free up berth and port capacities to accept new ships. Such a port policy is expected particularly in the ports with higher volume of ships' traffic.

Rows of the Table 2 show some of the iterations of costs and service time calculations on Pareto front along with numbers of service places in each phase.

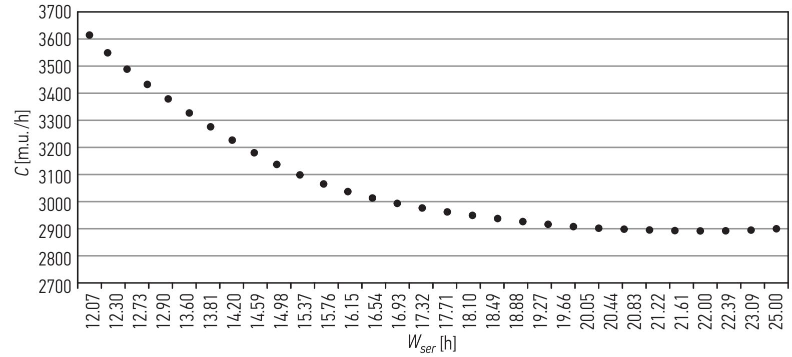

Fig. 2. Pareto front of costs C and service time W_{ser}

The results match the perception and expected experience in performing loading operations on board. For example, if ship's operator, in the area of optimal solutions, decides for a solution obtained in the iteration 14, the operational cost will amount to 2988.06 m.u./h, while the time required for their execution will be 16.93 h. In this case, in the first phase three cranes work on four cargo holds, in the second phase four forklifts are distributed in four holds. Furthermore, nine workers are needed for cargo securing and two workers for cargo marking and separation.

Ship's operator, on the basis of data from the Table 2, can accurately determine the total costs related to the transhipment in the port, and duration of transhipment along with the resources needed per phase. Moreover, taking into consideration the current state of the shipping market and the rates and terms of ports, ship's operator takes optimal business decision.

Table 2. Values of objective functions and decision variables for some points on Pareto front

Iteration	C [m.u./h]	W_{ser} [h]	S_1	S_2	S_3	S_4
11	3031.42	16.15	4	4	12	7
28	3011.57	16.54	4	3	10	5
14	2988.06	16.93	3	4	9	2
•	•	•	•	•	•	•
•	•	•	•	•	•	•
•	•	•	•	•	•	•
31	2895.52	21.61	3	2	8	3
23	2896.98	25.00	2	2	6	3

Conclusions

Cargo loading by ship's cranes, cargo stowing, securing and separation onboard a general cargo ship should be well planned and coordinated throughout the operational plans in order to achieve minimum total operational costs along with minimal service time. Because of a multiphase service system with two objective functions, to find a solution of the problem multi-objective optimization model has been suggested which is able to quantify necessary resources in each operational phase along with satisfaction of target functions given certain limitations. Analogy could be drawn to observe the process of unloading, or a combination of cargo loading/unloading, in which case phases would be arranged differently, which, may be the subject of further research.

Given the complexity of the model with multi-objective functions, several decision variables and constrained solution space, the approach taken here to search for solution is based upon an adapted genetic optimization algorithm in combination with a hybrid optimization algorithm for the purpose of achieving improved results. In the space of possible solutions (Pareto front) computational process with variations of different methods of crossover and mutation for GA and optimization options for GHA produces results that match the experiences from practice when performing cargo loading operations on general cargo ship.

The advantage of suggested process of solution search manifests itself in obtaining the space of optimal solutions, which provides ship's operator with possibility of selecting one of them in a broader consideration of business making on the shipping market.

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