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SURVEY
METAHEURISTIC APPROACHES FOR THE BERTH ALLOCATION PROBLEM

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Abstract: Berth Allocation Problem incorporates some of the most important decisions that have to be made in order to achieve maximum efficiency in a port. Terminal manager of a port has to assign incoming vessels to the available berths, which need to be loaded/unloaded in such a way that some objective function is optimized. It is well known that even simpler variants of Berth Allocation Problem are NP-hard, and thus, metaheuristic approaches are more convenient than exact methods since they provide high quality solutions in reasonable computational time. Metaheuristics are general frameworks used to build heuristic algorithms for hard optimization problems. In this paper, an overview of promising and widely used metaheuristic methods in solving different variants of Berth Allocation Problem is presented.

Keywords: Container Terminal, Assignment of Vessels, Heuristic Optimization, High Quality sub-optimal Solutions.

MSC: 90-02, 90B80, 68W20.

1. INTRODUCTION

In global optimization problems, an emphasis is given to finding global optimum over all input variables for some set of functions under a given set of constraints. Combinatorial optimization is a branch of global optimization where the examined set of objects is finite. Let D denote the set of feasible solutions, defined by the constraints, for some optimization problem. Then, the global optimization problem can be expressed as:

$$\min\{f(s) : s \in D\} \tag{1}$$

where $f(s)$ is a function to be minimized and s is a feasible solution of the optimization problem. A solution $s^* \in D$ is optimal if

$$(\forall s \in D)(f(s^*) \leq f(s)). \tag{2}$$

Maximization problem can be defined in analogous way. Unlike the exact algorithm which finds the optimal solution s^*, a heuristic algorithm finds $s' \in D$, a solution that is near to the optimal one in short processing time. Metaheuristics are general techniques used for developing heuristic algorithms to solve real life problems. Metaheuristic algorithms started to be the point of interest in operational research at the time when simulated annealing was developed [48] and proposed as a technique that allowed to escape local minima trap. Detailed overview of metaheuristics and their classification can be found in [7, 79].

There are very few exact approaches for solving BAP, are mostly based on mixed-integer programming, using mainly CPLEX as solver [37, 39, 83]. Combinatorial model implemented in [49, 50] is based on branch-and-bound and lookahead techniques; exact branch-and-price algorithms are implemented in [86, 70]; combinatorial benders' cuts algorithm is developed in [9]. In general case, exact solvers can handle instances with 5-40 vessels [9, 83, 86] allocated to 3-30 berths [83, 86]. Generated test instances may become too complicated for exact solvers even for smaller dimensions, and especially when many vessels are to be allocated to the same berth and/or at the same time unit. These cases may yield the inefficiency of exact solver, which may require huge CPU time, or may not be able even to find the first feasible solution.

Having in mind the limitations of exact methods when solving large dimension instances, metaheuristic methods are natural choice as solution approaches for BAP. The main goal of this paper is to survey metaheuristic approaches to different variants of BAP in recent literature. This survey may not be exhaustive, even though several databases were searched, such as ScienceDirect, SpringerLink, IEEE Explorer, Web of Science, GoogleScholar, etc. The rest of this paper is organized as follows. The definition and classification of Berth Allocation Problems is given in Section 2. Metaheuristics applied to BAPs are reviewed in Section 3 and classified in Section 4. Future trends and perspectives are indicated in Section 5, while Section 6 contains concluding remarks.

2. BERTH ALLOCATION PROBLEM

The Berth Allocation Problem (BAP) assumes that berth layout of a port is given, along with a set of vessels that are to be served within a considered planned horizon (Fig. 1). Each berth in a given port is identified by its unique number, called *berth index*. Vessels are represented by a set of data, such as: expected arrival time, the size, anticipated handling time, preferred berth in the port, and many others, depending on considered variant of BAP. The goal of BAP is to allocate each vessel to a berth index and a time interval so that the given objective function value is optimized. Objective function can be defined as minimization of the total cost of the allocation, minimization of vessels' waiting times (time that vessels must wait for a berth due to port congestion) and handling times (time used for loading/unloading vessels), minimization of earliness and tardiness (lateness of vessels against their desired departure time), minimization of fuel consumption, maximization of profit, maximization of quay cranes (QC) utilization, etc. BAP is proved to be NP-hard by Lim [61].

Detailed classification scheme for BAP formulations is given in Bierwirth and Meisel [5] and is summarized here in Table 1. This table describes attributes and their abbreviations used in BAP classification. Four attributes influence the classification of BAPs: spatial, temporal, handling time, and performance measure.

According to the spatial attribute, BAPs can be *discrete*, *continuous*, *hybrid* or *draft*. In the discrete case, a quay is partitioned into a number of sections - berths, whereas each berth can serve one vessel at a time. In addition, a given time horizon could also be partitioned into discrete units, which enables integer arithmetic for calculating the objective function value. In the continuous case, a calling vessel can be placed at any position if it does not overlap with other vessels' possiton. Different combinations of discrete and continuous layout in the BAP formulation lead to various types of hybrid layouts [5, 6]. Discrete, continuous, and hybrid layouts, as well as the special case, named indented berth, when quay cranes are enabled to unload and load containers from both sides of the vessel, are illustrated in Fig. 1. BAP can be classified as *draft* if vessels' berthing positions are influenced with their draft.

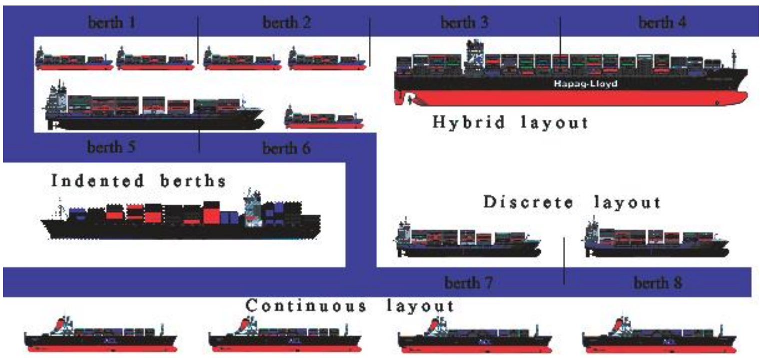


Figure 1: Variants of port layouts

The most common BAP models with respect to the temporal attribute are *static* and *dynamic*. In the static BAP, the arrival times are either not specified, or they impose soft constraints on the berthing times. The first case assumes that vessels are already waiting at the port and can berth immediately. The second case means that a vessel can be speeded up or slowed down at a certain cost. If the arrival times of the vessels are fixed and the vessel cannot berth before the expected arrival time, the corresponding BAP is classified as dynamic. In the case of cyclic BAP, vessels have to be served at terminals repeatedly in fixed time intervals. When vessels arrival times are defined by stochastic parameters and random distribution, BAP is described as *stoch*. Temporal attribute *due* is used when the departure of a vessel is influenced by its due date or if a maximum waiting time for the vessel is predetermined before the service starts.

Based on the handling time attribute, BAPs are classified in five categories: BAPs with fixed handling times, with handling times depending on the berthing position, on the assignment of QCs, on a QC operation schedule, or on stochastic parameters. The last attribute (performance measure) actually corresponds to the objective function of a considered BAP. The value of the objective function can depend on waiting time of a vessel, handling time of a vessel, completion time of a vessel, speedup of a vessel to reach the terminal before the expected arrival time, tardiness of a vessel against the given due date, berthing of a vessel apart from its desired berthing position, and some other factors.

Table 1: Notations for different type of BAP

Spatial attribute		**Temporal attribute**		**Handling time attribute**	
Abbreviation	*Attribute*	*Abbreviation*	*Attribute*	*Abbreviation*	*Attribute*
disc	discrete	*stat*	static	*fix*	fixed times
cont	continuous	*dyn*	dynamic	*pos*	position dependent
hybr	hybrid	*cycl*	cyclic	*QCAP*	QC assignment
draft	vessel draft	*stoch*	stochastic	*QCSP*	QC scheduling
		due	due dates	*stoch*	stochastic

3. METAHEURISTICS IN BAP

In practice, it is important to have a powerful decision support system that helps the container terminal manager to efficiently balance between quick service of vessels and economic use of allocated berths. Having in mind that both container vessels and port resources are very expensive, it is desirable to utilize them as efficiently as possible. Container terminal is highly dynamic system and usually terminal manager has to make the decision in short time periods [32, 45, 85]. Situation in the port is sometimes changing on a minute basis, and therefore, seconds can be crucial in making the right decision. For this reason, it is important to develop an efficient optimization algorithm that will provide terminal manager with necessary data. In the following subsections, we give an overview of metaheuristic methods proposed to BAP in the literature.

3.1. Tabu Search

Tabu Search (TS) is a metaheuristic that guides a heuristic local search procedure in such a way that local optimum can be escaped. TS is originally proposed by Glover [25]. It is usually used in solving combinatorial optimization problems. TS is based on the idea of incorporating adaptive memory and responsive exploration. The algorithm overview and some recent trends in its applications can be found in [23].

In Cordeau et al. [14], TS is used to solve dynamic discrete case of BAP and is extended to continuous BAP. In their model objective function minimizes the sum of the service times for vessels, i.e., the difference between the completion time and the arrival time for each vessel. In order to generate initial solution, authors use *Random Greedy* and *First Come-First Serve* procedures. The initial solution is then modified by the reallocation of the vessel from current berth to the newly selected one. These reallocations produce the neighborhood of the current solution. After a vessel is removed from the current berth, its reinsertion in that berth is forbidden in the next iterations by assigning a tabu status to the attribute. Their study is extended in the paper of Lalla-Ruiz et al. [54], where an elite set of solutions is created with an idea to improve the effectiveness and efficiency of the tabu search. Also, an additional neighborhood (based on swapping) is developed, according to which vessels allocated to either the same or different berths can exchange their temporal and/or spatial position. New starting point for TS is generated by path relinking algorithm. Procedure based on path relinking is iteratively used to bring initially generated solution closer to the elite solution. The elite set of solutions is updated if new best solution is found.

The Tactical Berth Allocation Problem (TBAP) aims to allocate incoming ships to berthing positions and to assign quay crane profiles to them. Quay crane profiles represent the number of quay cranes operating on the vessel during the working shifts associated to the allocated handling time. Housekeeping incorporates containers movement before the arrival of the outgoing vessel from their current yard positions to the new ones, which are closer to the outgoing berth. Giallombardo et al. [24] solve discrete TBAP with the aim to minimize the housekeeping costs generated by transshipment flows between ships and to maximize the total value of chosen quay crane profiles. The problem is solved in two phases: identification of QC profiles of the vessels followed by berth allocation based on a given QC assignment. Authors also adapt TS presented in Cordeau et al. [14] by forming a new procedure where the yard-related housekeeping costs, generated by the flows of containers exchanged between vessels, have to be minimized. TS presented in paper by Lee et al. [58] is applied to large container transshipment hub with multiple terminals where the aim is to minimize total intra-terminal and inter-terminal container flow handling cost. Authors provide hierarchial solution of the terminal and yard allocation problem. TS is integrated in the heuristic procedure used to determine container flow in storage yards. Storage area is observed as a two dimensional network with limited capacity. The TS algorithm determines an appropriate loading sequence onto the network. The disruption management problem of berth allocation is also successfully solved by TS. Some unforseen problems can make impact on planned schedules and thus, the initial plan becomes infeasible and needs to be modified. Zeng et al. [90] combined TS with local rescheduling method to solve problems locally where unwanted effect occurred, first in small time and space window, and afterwards, in extended windows until the entire planning horizon was considered.

3.2. *Greedy Randomized Adaptive Search Procedure*

Greedy Randomized Adaptive Search Procedure (GRASP) is a metaheuristic algorithm that consists of two phases: Greedy Randomized Adaptive phase where solution is generated and local search used to improve generated solution. Those two phases alternate until stopping condition is fulfilled. GRASP is introduced by Feo and Resende [21]. In the first phase, greedy algorithm is used to make the decision about the next step in solution construction. Algorithm always chooses actions that look best at the moment, resulting in solution close to the optimal one. Detailed algorithm description, its extensions and applications can be found in Resende and Ribeiro [69].

Two versions of GRASP are developed in Lee et al. [56] for dynamic continuous BAP, aiming to minimize the total weighted flow time, i.e. to minimize the sum of weighted turnaround times for each incoming vessel, where weight indicates the degree of vessel's importance. The first one constructs the initial solution based on *first-come-first-pack* rule, while the second has no limitations. In the first version of GRASP, two local search procedures are implemented, the first, based on swapping adjacent vessels in the list, and the second, involves A^* like tree search procedure. The second version of GRASP exploits the same idea, but allows that any two vessels can be swaped. The authors of Salido et al. [74] developed an integrated approach based on GRASP for container stacking problem and BAP independently, in which objective function minimizes waiting time of vessels. In Salido et al. [75], authors proposed a decision support system for container terminals. They additionally considered the Quay Crane Assignment Problem (QCAP) by integrating it with BAP, and proposed a GRASP technique as a solution approach. BAP and QCAP that minimize total waiting time of vessels is considered in Rodriguez-Molins et al. [72]. A *dispatching rule* prioritizes all the jobs (vessels) that are awaiting for processing on a machine (berth). The authors designed GRASP that constructs initial valid solution by randomly choosing vessels from the restricted candidate list (obtained by taking into account greedy function value and random degree parameter value). Local search procedure is guided by dispatching rule based on the order of the vessels according to their berthing times. The neighbor of current schedule is obtained by interchanging two randomly selected vessels in the dispatching rule.

3.3. *Squeaky Wheel Optimization*

Squeaky Wheel Optimization (SWO) was proposed in Joslin and Clements [43] as a nonsystematic search technique for solving a wide range of optimization problems. SWO uses greedy techniques to construct an initial solution. This phase is followed by inspection of produced solution for promising points where the initial solution can be possibly improved, such that objective function value is improved. Detected points are used to define priorities and order of constructive moves for the next step of the greedy algorithm.

Simultaneous optimization of tactical BAP and QCAP for transshipment hubs is presented in Zhen et al. [92]. Authors use SWO to solve large-scale realistic instances. Since SWO obtains new solution from the previous one by swapping only adjacent vessels and thus, moving high-cost value vessels to the front of the lists, the idea of Zhen et al. [92] is to combine SWO with *critical-shaking neighborhood search*. This method chose predefined number of vessels with the highest cost value and randomly shakes the priority of them to help sequences escape from the local optimum. Following earlier study on integrated BAP [63], the QCAP and the Quay Crane Scheduling Problem (QCSP) are considered in Meisel and Bierwirth [64]. The authors incorporate SWO in the phase of berth allocation and crane capacity assignment since it gave better results than TS.

SWO is also used to tackle dynamic hybrid BAP [84]. The initial solution for berthing assignment is obtained by the *first come-first served* ordering of the calling vessels. At the end of iteration, new priority is calculated based on current service time of vessels. The vessel with particular priority is allocated to the berths that minimize total service and waiting time of vessels after all vessels with higher priority have already been allocated. Algorithm moves vessels with larger total service and waiting time to the start of priority list enabling improvement of their service. Extensive experiments based on real bulk port data showed that heuristic method used in [84] can find near optimal solutions for larger problem instances.

3.4. Variable Neighborhood Search

Variable Neighborhood Search (VNS) is a simple and effective metaheuristic method based on local search procedure [35, 65]. The basic idea of VNS is the systematic change of neighborhoods within a descent phase to find a local optimum, and also in the perturbation phase to escape from the corresponding valley. VNS has been widely used to address combinatorial and global optimization problems [35].

VNS has been applied to minimum cost discrete BAP in Hansen et al. [36]. The deterministic variant of VNS, called Variable Neighborhood Descent (VND), is used as a local search, and it uses three neighborhoods. *Or opt* neighborhood selects one, two or three vessels and inserts them between any two other vessels handled at the same berth. The second neighborhood exchanges the schedule of two ships served at different berths, while the third removes the selected vessel from the berth and tries to insert it somewhere else. Two nested neighborhoods are used in shaking phase. In the first one, for two randomly selected vessels, their berths and order of arrival are interchanged. In the second, a randomly selected vessel is removed from the set of handling vessels on current berth, and it is added to the set of vessels of the randomly selected berth in the most appropriate order. VNS from Hansen et al. [36] showed good results on all test instances and almost always reached optimum. It also outperformed genetic algorithm and memetic algorithm on the given set of instances.

Minimum cost hybrid BAP is considered in Davidović et al. [16] and solved by VND. Three types of neighborhoods, based on *sequence pair* solution representation, are used in VND environment. Sequence pair involves two types of permutations to describe vessels positions in space-time diagram. Based on the obtained initial solution, algorithm identifies a group of vessels that are not allocated to preferred berthing positions, and tries to find better allocation for each vessel from that group. In this phase, three neighborhoods are examined: changing position of the vessel in the first permutation, changing position of the vessel in the second permutation and finally, all possible rearrangements in both permutations.

3.5. *Simulated Annealing*

Annealing of solids is a natural process that occurs when solids are heated and then slowly cooled. Simulated Annealing (SA) algorithm developed by Kirkpatrick et al. [48] simulates small movement of atoms with resulting energy change. SA efficiency depends on a few parameters such as initial temperature, cooling rate and temperature length which usually represents the size of neighborhood of a solution. A comprehensive review of SA-based optimization algorithms is given in Suman and Kumar [77].

Kim and Moon [47] studied continuous BAP where cost of the non-optimal berthing location and cost of tardiness have to be minimized. They use so called *x-clusters* and *y-clusters* (set of vessels-rectangles whose vertical or horizontal sides are in contact) and define them as *stable* if the cluster can not be moved along x-axis or y-axis. Stability of the cluster is used to improve the quality of the generated solution. Dynamic discrete BAP is solved in de Oliveira et al. [18] by combining *clustering search* method and SA for solutions generation, where the objective function minimizes the weighted sum of service times. At each temperature, current solution is sent to the clustering search. Three different rearrangements of vessels are used to define the neighborhood of the solution: the *reorder ships*, *reallocate ships*, and *change ships*. In order to ensure good diversity among the generated consecutive solutions, vessels are chosen randomly, and one of the three reallocation types is applied. The uncertainty of vessel arrival delay (due to weather conditions, adverse sea, delays at previous port, etc.) and handling time is taken into account in the paper of Xu et al. [87], resulting in so-called continuous *robust BAP*. Authors described useful properties of the optimal solution and used them to reduce the solution space. The solution space is divided in subsets and each one is represented by a sequence of vessels. In each subset, *branch & bound* technique is applied to decode the optimal solution of the subset, while SA is used to efficiently explore the sequence space. Zhen et al. [93] studied deviation of vessels' arrival time and operation time as uncertainty factors. The objective is to minimize the cost of the tactical BAP and the expected value of the recovery costs. Integrated dynamic continuous BAP with water dept constraints and QCSP is solved in Elwany et al. [20]. Authors define vessels priority list to determine the order in which they should be allocated. Higher priority is given to large vessels and to those with larger expected finishing time values. SA is used to explore the space of priority lists where the neighborhood is created by interchanging two randomly chosen adjacent vessels in the priority list. When feasible solution is constructed, *spatial and temporal shifts* are applied with the aim to produce better quality solutions.

3.6. Particle Swarm Optimization

Kennedy and Eberhart [46] proposed Particle Swarm Optimization (PSO) as a global optimization technique, based on bird flocking phenomenon. PSO starts with an initial pool of particles which are distributed over some search space. Each particle calculates objective function value at its current position, and has to choose a new position in the search space, based on the current position and on its previous best positions. The movement is also influenced by positions of one or more members of a pool, and may undergone some random perturbations. Detailed survey on modifications, hybridizations, and applications of PSO can be found in Zhang et al. [91].

PSO was used for the first time as a solution approach to BAP in Ting et al. [82]. Authors investigated dynamic discrete BAP and treated it as vehicle routing problem with time windows. In their representation, berths are considered as vehicles, vessels are observed as customers, while a berthing sequence at a particular berth corresponds to a vehicle route. PSO is used to search through the solution space and after each PSO iteration, local search procedure is applied only to the best found particle, due to the time complexity of the LS procedure. Solution of BAP is represented as array of cells, with the length that is equal to the number of vessels. Each cell contains real number from a uniform distribution in the interval of $(0, NumberOfBerths)$ which guarantees that the decision variables are in the feasible region.

3.7. Bee Colony Optimization

Bee Colony Optimization (BCO) is a population based optimization technique inspired by the foraging principles of honey bees. Detailed description of the BCO algorithm steps can be found in Davidović et al. [17]. BCO is capable to efficiently solve hard combinatorial optimization problems and it has been applied to the variety of transportation, location and scheduling problems [80].

The only study in the literature that applies BCO to BAP is Kovač [51]. The author considers static Minimum Cost Hybrid BAP with the aim to minimize costs of positioning, speeding up or waiting, and tardiness of completion for all vessels. To enhance the performance of the constructive variant of the BCO algorithm, three improvement techniques are proposed. The first is applied to each complete solution obtained after an iteration of the algorithm is completed. The second and the third improvement techniques are applied several times through the algorithm's run only on the current global best solution. The results presented in Kovač [51] showed that the developed improvement techniques have huge impact on the performance of the proposed algorithm.

3.8. Ant Colony Optimization

Ant Colony Optimization (ACO) is a metaheuristic technique proposed by Colorni et al. [13] and it follows the behavior of ants in their attempt to find optimal path from nest to food source. The probability that ant chooses one path depends on pheromone level laid on that path. To increase search randomness and exploration of new regions it is assumed that pheromone is evaporating over time. Algorithm overview and the recent advances can be found in [19].

A multi-objective multi-colony ant algorithm is used in Cheong and Tan [11] to solve BAP, where total service time of vessels and total delay in the departure of vessels are minimized. Groups of ants are used to search for a single solution and each ant is responsible for the schedule of one berth in the solution. ACO minimizes total service time and total tardiness of vessels. Elitist strategy is employed in this ACO to intensify search around best found solutions. In addition, algorithm use more heterogenous ant colonies which differs in pheromone matrix and in some other ACO parameters.

3.9. Evolutionary Algorithms

Evolutionary algorithms (EA) are generic population-based metaheuristic optimization algorithms based on some nature phenomenons, such as recombination, selection, mutation, and reproduction [2]. Each EA solution is mapped onto a chromosome which consists of genes. Chromosomes quality is evaluated and the fittest are selected to survive in the next generation. More details about EA can be found in [89].

Cheong et al. [10] develop multi-objective EA (MOEA) to solve variant of multi-objective BAP with the aim to fulfill both interests of port and ship operators by concurrently minimizing three conflicting objectives of makespan, number of crossings and waiting time. Waiting time is reduced for each ship in such a way that it is as closest as possible to the first-come-first-serve policy. MOEA uses fixed length individuals and crossover as well as mutation operator. Decoding scheme is based on assignment order instead of mostly used berth order, in cases when ships can berth only at the same time or later than preceding ships. Authors showed effectiveness of assignment order (ships are placed in the feasible leftmost berthing space with earliest berthing time) in optimizing the usage of berth space.

In Cheong et al. [12], a multi-objective EA that incorporates the concept of Pareto optimality is applied to the multi-objective BAP. Minimization of the port makespan, the total waiting time incurred by vessels and degree of deviation from a predetermined priority schedule are considered. To solve this problem, the EA incorporates local search, a hybrid solution decoding scheme, and an optimal berth insertion procedure. A fixed-length chromosome representation with length equal to the number of berths is used. A list of served vessels on berth is associated to each berth. Local search involves sorting of vessels on randomly selected berth based on vessels' priority. The set of obtained solutions is decoded and ranked based on the Pareto ranking scheme, and the poorly ranked solutions are removed from the population. To decode a solution, authors used two different decoding schemes: berthing order and assignment order, and examined their impact on solution quality. Crossover operation randomly selects berths in both parents and exchanges their associated vessel lists. In that process, some vessels can be missing, and thus, they have to be inserted on randomly chosen berth. The probability that a ship is inserted into a particular berth is inversely proportional to the handling time of the ship at the berth.

Karafa et al. [44] treated dynamic discrete BAP with stochastic vessel handling times and known probability distributions. The objective is to minimize risk and total service time. Authors proposed calculation of risk measure for a given berth schedule based on probability distributions. They adopt a multi-population EA with integer chromosome representation and four mutation operators: insert, swap, scramble, and inversion. EA is combined with Post-Pareto simulation used to select one non-dominated solution from the Pareto front solutions. The selected solution represents the schedule to be implemented. Applied Post-Pareto simulation is based on simple Monte Carlo procedure.

In Kovač et al. [52], an EA-based optimization method is developed for solving the static Minimum Cost Hybrid Berth Allocation Problem (MCHBAP) with fixed handling times of vessels. The main problem one faces when dealing with the MCHBAP is a large number of infeasible solutions. In order to overcome this problem, the EA implementation proposed in Kovač et al. [52] is adapted to the problem and involves four types of mutation operator but no crossover operator. Two different optimizations where developed for the chosen individuals: the first one allows changing the associated berth of a vessel, while the second performs local search within berth and allows only perturbations of the vessels' order within the chosen berth.

3.10. Genetic Algorithms

GA is an adaptive, global search technique that utilizes concepts of natural adaptation and selective breeding of organisms [38]. GA works with a population of individuals, each representing a possible solution to a given problem. Each individual is represented by a genetic code, a string of characters (genes) from some alphabet. After decoding, a fitness value is assigned to each individual, which measures the individual's quality in the population. Genetic operators: selection, crossover, and mutation are iteratively applied until a certain stopping criterion is satisfied and the best individual of the last generation is reported as the final solution to the considered problem. An overview of basic and advanced GA techniques for solving various NP-hard optimization problems can be found in Bäck et al. [3, 4], Reeves [68], Talbi [79].

Golias et al. [26] use the concept of time windows to solve dynamic discrete BAP by GA. The objective is to simultaneously minimize the cost from late vessels departure and maximize the benefits from vessels departure before and within the requested time window. To make problem more realistic, handling time is influenced by the berthing position. Theofanis et al. [81] proposed GA for medium to large instances of dynamic discrete BAP that is independent from the objective function. They applied the proposed GA to minimize the total weighted service time when vessels may have various service priorities. GA from Theofanis et al. [81] does not use crossover because of large number of produced infeasible individuals. Before selecting the next generation, internal optimization phase is applied to the randomly selected number of feasible individuals. Branch and bound algorithm reassigns ships allocated to each berth while minimizing the total weighted service time for each ship. However, optimization phase is time consuming if the number of berths is larger than 5.

Imai et al. [42] showed that genetic algorithm outperforms the implemented subgradient optimization in the case of two-objective BAP that minimizes weighted delay in ships departure and total service time. These two objectives are conflicting, and GA is used to identify non-inferior solutions. GA showed dominance especially in congested terminal situations with a frequent ship calling and long ship handling time.

Multi-user container terminal with indented berths for fast handling of mega-container ships is addressed in the paper of Imai et al. [41]. It is assumed, that several small ships can be served simultaneously at a berth. Authors showed that the indented terminal serves the mega-ship faster than the conventional terminal. On the other hand, the total service time for all ships was longer than the one in the conventional terminal. In the developed GA, each chromosome is represented as a string of characters with the *short string representation* equal to the number of vessels enlarged by the number of berths minus 1. A chromosome representation simply defines the relationship among berth-ship-service order. The considered model minimizes total service time, but instead of classical fitness function, defined as the reciprocal of the objective function, authors use sigmoidal function and experimentally confirm that it gives better results.

Han et al. [33] considered a variant of BAP with the aim to minimize the total turnaround time (i.e. the time it takes between the arrival of a vessel and its departure from a port) and to improve the terminal operation efficiency. Metropolis sampling process is incorporated in GA instead of mutation operator, and it is applied to each individual. The role of Metropolis sampling process is to avoid local optimum trap and to enlarge search space. It avoids the difficulty of selecting mutating probability and results in better search behavior. One-point crossover is applied to randomly selected individual and on the current best individual. Infeasible offspring may be produced, which implies that adjustment of produced new offspring has to be performed.

In Arango et al. [1], GA is combined with simulation technique and applied to discrete BAP in the case of Seville port. The proposed hybrid system uses first-come-first-served allocation strategy for vessels. GA is used to minimize the total service time of vessels. 20% of individuals in current population is affected by mutation while the rest of 80% is influenced by crossover operator. The results of the case study showed that the proposed hybrid system improved performance of the Seville port and reduced averige handling times by 14%, while the maximum handling times are reduced by 21%. The minimization of the berthing location deviation, total penalty and energy consumption of quay cranes is studied in Chang et al. [8]. Combination of BAP and QCAP is presented and solved by hybrid parallel GA. Initial population is generated by heuristic algorithm, while GA is used to find sub-optimal solution for BAP and QCAP. Liang et al. [59] introduced quay crane dynamic assignment in BAP and proposed a multi-objective hybrid GA approach with a priority-based encoding method.

Objective functions minimize waiting and delay time of vessels, handling time of containers and crane movements. GA is performed in four stages: creating a ship sequence (based on vessels priority), allocating ships to berths, assigning quay cranes to ships, and designing berth and quay cranes scheduling. A hybrid multistage operation-based GA with a priority-based encoding method is studied in Liang et al. [60]. The proposed GA is dealing with ship-to-ship transshipment and tries to minimize the sum of the handling and waiting time of ships, tardiness, and the waiting time of transshipment (it occurs when the arrival interval between the two ships is too long). Algorithm starts with procedure that decides whether or not direct transshipment service should be made between ship pairs, and it is followed by the four-stage algorithm presented in Liang et al. [59].

Golias et al. [27] formulated discrete and dynamic BAP as a multi-objective mixed integer optimization problem. The length of individual is equal to the product of the number of berths and the number of vessels. To preserve a diversity of different solutions in the Pareto Front, a multi-population multi-selection GA approach is used. Mutated population is copied into two sets at each iteration. Based on the Pareto Front optimal set, first duplicate is used to select parents for the next generation. Second duplicate represents elitist set used to obtain improved values of each objective function within the Pareto Front. Next generation of individuals is obtained by combining both obtained sets.

In the case of dynamic discrete BAP, Golias and Haralambides [29] concurrently minimize vessels' tardiness and waiting time and maximize the premium from vessels' early departure. To solve this model, authors used GA previously presented in Golias et al. [31]. Integer representation of individuals with two layers is used. First layer consists of arrival times, while the second one describes service order of vessels at each berth. In each iteration, all four mutation operators (insert, swap, scramble, invert) are applied, but in later generations, weight is shifted from the invert and scramble to the insert and swap mutations. By this strategy, large jumps are allowed in the initial iterations, followed by intensive search of smaller regions.

Hierarchial optimization approach for dynamic discrete BAP is studied in Saharidis et al. [73]. Two conflicting objective functions are used to define two levels of hierarchy and the set of the decision variables is split in two subsets. To solve this problem, authors designed GA based on the *k-th best algorithm* for the case where multi-objective functions are considered in the upper level. Upper level of hierarchy is solved only once by GA, instead of sequentially together with lower level in each algorithm iteration. Obtained GA solutions are sorted according to their quality, and sent to the lower level one by one, without solving the upper level problem again. Similar approach is studied in Song et al. [76] by bi-level programming model. BAP is solved by GA, as upper level, while QCAP is resolved to the optimality by *branch & bound* method in the lower level.

Zhou et al. [95] and Zhou and Kang [94] deal with dynamic discrete BAP, which minimizes total waiting time of calling vessels, in which arrival times and handling times of vessels are considered as stochastic parameters that follow normal distribution. Based on the characteristics of the optimal solution, *reduced* *search space* GA is developed. Individual is represented with two sub-strings. The number of considered vessels determines the length of sub-strings. The first sub-string holds information about the assigned berth while the second one defines orders for each ship at each berth. Individuals are encoded based on vessels' arrival time and an Order Limit Number. By this encoding method, reduced search space is obtained. A lamda-optimal based heuristic for dynamic discrete BAP is used to guarantee local optimality at a predefined neighborhood in paper of Golias et al. [28]. The authors propose GA for solving medium to large scale instances in order to reduce CPU time. The quality of GA solution is examined on two often-used berthing demands: the minimum service time and the minimum weighted service time. Fitness function value is inversely proportional to the calculated objective function value of the produced chromosome. Authors combine elitism and semi-greedy strategy by incorporating roulette wheel selection.

Nested loop-based evolutionary algorithm is developed in Yang et al. [88] with the aim to investigate interaction between BAP and the QCAP and the feedback of both sub-problems. Two inner loops and one outer loop are used in the algorithm. Inner loops are implemented as GAs and they produce feasible BAP solutions and corresponding QCAP, respectively. Transfer of values of interfering variables is implemented through outer loop. Outer loop returns produced output as a new input for the first inner loop.

Simultaneous robust BAP and QCSP is studied in Han et al. [34]. Opposite to study of Zhou and Kang [94], authors used probability density distribution to describe stochastic feature of the problem. GA is used to find robust solutions to the problem. A simulation based procedure with Monte Carlo sampling is evaluating the quality of each chromosome. Bi-objective optimization model for robust BAP is defined in Golias et al. [30], in the case of uncertain vessel arrival and handling times. Two objective functions are minimized: average total vessel service time and the range of the total service time. Initial population is created by *first come first served with early start* and *first come first served with early finish* strategies. Objective function of each individual is calculated with minimum search and maximum search heuristics. On each chromosome from the current Pareto front, four mutation operators are applied, producing four offspring. One point crossover operator is also applied to a randomly chosen chromosome from the current Pareto front. All produced offspring is used to create a new Pareto front.

Robust dynamic continuous BAP and QCSP are studied in Rodriguez-Molins et al. [71]. To introduce robustness within BAP, authors use buffer times, that are maximized to absorb possible incidences or breakdowns, while the total service time of the incoming vessels is minimized.

Tactical BAP is studied in Lalla-Ruiz et al. [53] and a *biased random key* GA is proposed as solution approach. Chromosomes are vectors whose length is twice the number of vessels. Vessels' berthing order is defined by the first part of the chromosome. Second part holds information on assignment of quay crane profiles to the vessels. Random keys are integrated in GA to cope with infeasibility of the offspring. Random key is a real number from the interval [0,1) and each gene in chromosome consists of one random key value. By using biased random key, GA population is divided in two sub-sets: elite set and non-elite set. Crossover operator selects one parent from each subset and they exchange genetic material. Offspring will have greater probability of inheriting the keys from its elite parent.

Continuous BAP is efficiently solved by GA in [22]. Authors used integer representation of individuals with the length of chromosome equal twice the number of vessels. The first half of a chromosome represents handling times while the second half shows vessels' berthing locations. One point crossover operator is applied to randomly chosen parent individuals until the number of generated offspring is 90% of the current population. Mutation is used on 9% of individuals of the current population.

3.11. Memetic Algorithms

Premature convergence is inherent characteristic of GA. Memetic Algorithm (MA) is designed in such a way to avoid that unwanted property. It is presented by Moscato and Norman [66] and it applies operators such as combinations and local improvements on a set of initial solutions to create new solutions. Basically, MA explores the neighborhood of a given solution. Each MA generation consist of four sequential steps: selection of parents, combination of parents for offspring generation, local improvement of offspring, and the update of the population. Various aspects of MA, algorithm description and detailed overview can be found in [67].

Continuous BAP is solved in Mauri et al. [62] by MA, while SA is used as a local search technique. Mutation operator in proposed MA is based on three procedures: *Re-order vessel* (swap two randomly selected vessels from the same berth), *Re-allocate vessel* (randomly selected vessel from a berth is inserted on random position at another berth), and *Swap vessels* (two randomly selected vessels from randomly selected berths swap their positions). One randomly selected mutation procedure is also used in SA. Computational results show that MA produced solutions with small gaps from the best-known values in low computational times.

In Lee and Jin [57], MA is successfully applied to BAP for cyclically visiting feeders, and allocating storage yard space to the transshipment flows between mother vessels and feeders. The aim is to minimize the total moving distance of all flows between the quayside and storage yard and to minimize the gap between the highest and the lowest workload. The authors proposed MA as a combination of GA and TS. The offspring is created by genetic operators on randomly generated initial population. TS procedure is used to optimize offspring generated by GA operators. Based on the solution quality, selection operator chooses individuals from the current population and the post-optimized offspring to enter the next generation.

3.12. Partial Optimization Metaheuristic Under Special Intensification Conditions

Partial Optimization Metaheuristic Under Special Intensification Conditions (POPMUSIC) is based on the idea that problem can be divided into smaller subproblems which can be solved to the local optimum. That is why the POPMUSIC can be seen as a local search algorithm used in the specific large neighborhood. It is proposed by Taillard and Voss [78] as a method suitable for solving large combinatorial problems.

Lalla-Ruiz and Voß [55] use POPMUSIC in the environment of dynamic discrete BAP aiming to minimize the sum of service times. Random-greedy method is applied to obtain an initial solution, which is divided into number of parts equal to the number of berths. A sub-problem is constructed based on randomly chosen part and its nearest parts. The obtained sub-problems are modelled as a *Generalized Set-Partitioning Problem* and solved by using CPLEX.

4. SOLUTION APPROACHES SUMMARY AND DISCUSSION

BAP and its variants are recognized as one of the most investigated themes related to the marine transportation. This paper classifies 53 relevant papers from recent literature, published after 2003. From Fig. 2, it can be seen that BAP is constantly in the focus of the researchers, and that there is emerging trend in the number of published papers per year.

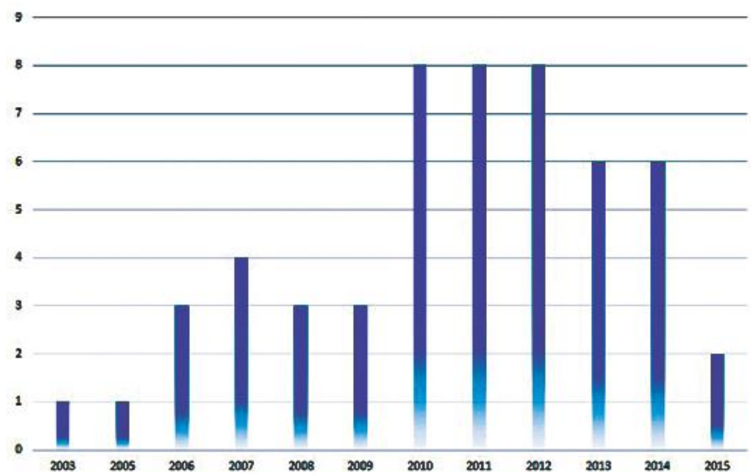
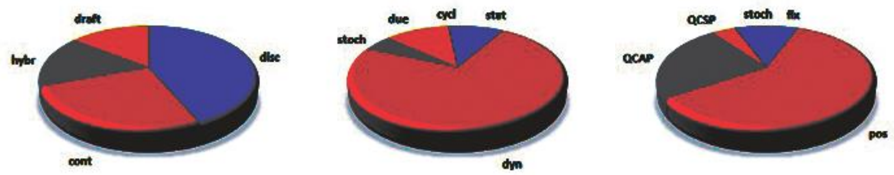


Figure 2: Number of BAP related papers per year of publication

Table 2 summarizes the examined BAP papers, their classification and some of the most relevant BAP parameters. In the first column, the variants of BAPs studied in the papers, labelled in Meisel's notation, are given. Although, this notation includes performance measure as the fourth parameter, it is omitted from Table 2. This is due to the fact that objective functions are described in previous sections. In addition, in this way, better visibility of groups with similar papers is achieved. The second column shows the reference to the investigated paper, while metaheuristic algorithm used as a solution approach to BAP is listed in the third column. The last three columns describe BAP dimensions in term of the number of vessels, number of berths, and the length of the time horizon, respectively. Some entries related to the number of vessels are denoted by ”inter arrival time”, which means that the group of vessels is arriving during the unit of time and their number is usually determined by exponential distribution. In the case of continuous BAP, the number of berths is not defined, and therefore, the data in the corresponding column of Table 2 (represented in meters) denote the length of quays. If some of the BAP’s parameter is not clearly stated in the corresponding paper, it is marked with * in Table 2.

A variety of BAP versions may be noticed from Table 2. In general, BAP is hard to solve and very often even metaheuristics may struggle to find a good solution in acceptable CPU time. Objective function plays significant role in defining complexity of the BAP, as well as the classification parameters listed in the first column. For example, it is hard to compare complexity of discrete and hybrid BAP. Discrete BAP may have some symmetries because vessels can occupy only one berth, and thus, vessels may be easily reallocated from one berth to another. Also, already scheduled vessels may be exchanged between two neighboring berths, while it is not likely to be possible in hybrid BAP. That is the reason for diversity in the number of considered vessels, berths and length of the time horizon, as it can be seen from Table 2. As the number of vessels grows and other port dimensions stay fixed, the density of allocated vessels also grows, which results in the huge number of infeasible solutions. Therefore, when defining the parameter domain sets, the authors have to negotiate between the requirements of real-life instances and good algorithm’s performance.

Many different models are used in the literature to present practical features of BAP. As it is already mentioned, models can be classified and described by spatial, temporal, and handling time attributes [5]. Distribution of these parameters based on the frequency of occurrence in the recent relevant papers is presented in Fig. 3.



Spatial attribute Temporal attribute Handling time attribute

Figure 3: Frequency of BAP variants in the recent literature

Regarding spatial attribute, majority of used models are discrete (44%), followed by continuous layouts (26%), while hybrid and draft layouts are considered in remaining 30% of the examined literature. Even greater difference occurs in temporal attribute, where 73% of papers are concentrated on dynamic vessel arrival, while only 8% of models incorporate static vessel arrival. The latest liter-

Table 2: Metaheursitic solution algorithms for BAP

			Problem dimension		
Problem	*Article*	*Solution algorithm*	*# of vessels*	*# of berths*	*Time horizon*
disc | stat | pos,QCSP	Arango et al. [1]	GA	52	2	1 month
	Song et al. [76]	GA	6	3	*
disc | dyn | QCAP	Liang et al. [59]	GA	11	4	24 h
	Liang et al. [60]	GA	11	4	*
	Lalla-Ruiz et al. [53]	GA	10 to 50	3 to 8	56 h to 108 h
	Giallombardo et al. [24]	TS	10 to 60	3 to 13	1 to 2 weeks
disc | dyn | pos	Golias et al. [27]	GA	40 to 80	5 to 10	1 to 2 weeks
	Golias and Haralambides [29]	GA	inter arrival time	5	1 week
	Saharidis et al. [73]	GA	50	5 to 10	1 to 2 weeks
	Golias et al. [30]	GA	inter arrival time	4 to 5	1 week
	Ting et al. [82]	PSO	25 to 60	5 to 13	*
	[54]	TS	25 to 60	5 to 13	600 time units
	Golias et al. [28]	GA	40 to 80	5	1 to 2 weeks
	Golias et al. [31]	GA	inter arrival time	5	*
	Hansen et al. [36]	VNS	10 to 200	10 to 20	*
	Theofanis et al. [81]	GA	20-25 per week	5	1 to 2 weeks
	Golias et al. [26]	GA	9	2	*
	Imai et al. [42]	GA	24	4	1 week
disc | dyn | pos, stoch	Karafa et al. [44]	EA	inter arrival time	5	1 week
disc | dyn,due | pos	Lalla-Ruiz and Voß [55]	POPMUSIC	40 to 55	5 to 7	600 time units
	Cordeau et al. [14]	TS	25 to 35	5 to 10	*
disc | dyn, due | pos	de Oliveira et al. [18]	SA	60	13	*
disc | dyn, due | f ix	Lee and Jin [57]	MA	15 to 40	3 to 8	*
disc, draft | stoch | QCAP, stoch	Han et al. [34]	GA	34 to 88	4 to 5	*
disc, draft | stoch, due | QCAP, stoch	Zhou and Kang [94]	GA	25 to 100	4	*
disc, draft | dyn | pos	Han et al. [33]	GA	7	2	*
disc, draft | dyn, due | pos	Zhou et al. [95]	GA	25, 50, 75, 100	5 to 8	*
cont | dyn | QCAP	Chang et al. [8]	GA	40	4	*
	Yang et al. [88]	GA	inter arrival time	800 m to 1600 m	1 week
	Rodriguez-Molins et al. [71]	GA	5 to 20	700 m	*
	Salido et al. [74]	GRASP	20	*	*
	Salido et al. [75]	GRASP	5 to 20	*	*
	Zeng et al. [90]	TS	26	1202 m	7 days
cont | dyn | pos	Ganji et al. [22]	GA	3 to 30	250 m to 3500 m	*
cont | dyn | pos,QCAP	Meisel and Bierwirth [63]	SWO	20 to 40	1000 m	1 week
	Meisel and Bierwirth [64]	SWO	40	1000 m	168 h
cont | dyn | QCAP,QCSP	Rodriguez-Molins et al. [72]	GRASP	5 to 20	700 m	*
cont | dyn | fix	Kim and Moon [47]	SA	7 to 40	1200 m	72 h
	Xu et al. [87]	SA	16 to 30	1200 m	2016 time units
	Lee et al. [56]	GRASP	5 to 200	80 m to 100 m	*
cont | stoch | stoch	Zhen et al. [93]	SA	8 to 40	*	*
cont, draft | dyn | pos,QCAP	Elwany et al. [20]	SA	20 to 40	1000 m	168 h
cont | cycl, due | QCAP	Zhen et al. [92]	SWO	15 to 60	500 m to 2000 m	1 week
hybr | stat | fix	Kovač et al. [52]	EA	21 to 35	8	112 h
	Kovač [51]	BCO	21 to 35	8	112 h
	Davidović et al. [16]	VNS	21 to 35	8	112 h
hybr | dyn | pos	Mauri et al. [62]	MA	60	13	*
	Lee et al. [58]	TS	15 to 40	3 to 4	6 to 21 time units
	Imai et al. [41]	GA	*	2	*
hybr, draft | dyn | pos	Cheong et al. [12]	EA	100 to 200	5 to 10	*
	Cheong and Tan [11]	ACO	100	5	*
	Umang et al. [84]	SWO	10 to 40	10 to 30	150 h
	Cheong et al. [10]	EA	100	5	*

ature introduced cyclic and stochastic arrival of vessels. Cyclic arrival assumes that vessels are coming in the port periodically, in fixed time intervals, while in the stochastic case, arrival times are based on some stochastic parameter. Handling time is mainly shaped by the assigned berthing position (60%). On the other hand, quay crane resources (QCAP+QCSP) influence vessels' handling times in 28% of the examined papers. Stochastic attribute in handling time is newly introduced and appears in 6% in recent papers. The simplest case involving fixed handling times is considered only in 6% of models.

Since BAP is proven to be NP-hard problem, it is expected that algorithms based on metaheuristic approaches dominate in the literature. The left side of Fig. 4 shows metaheuristics that are applied most frequently to BAP and its variants. On the right side of Fig. 4, those metaheuristics are grouped based on their main characteristic. Genetic algorithms take part in 43% of BAP related papers, followed by 8% of evolutionary algorithms. Tabu search and simulated annealing are included in 18% of solution approaches. Surprisingly, swarm intelligence is rarely used, i.e., in only 6% of algorithms. Evolutionary algorithms dominate with more than 55%. Approaches based on local search are proposed in 32% of BAP related papers.

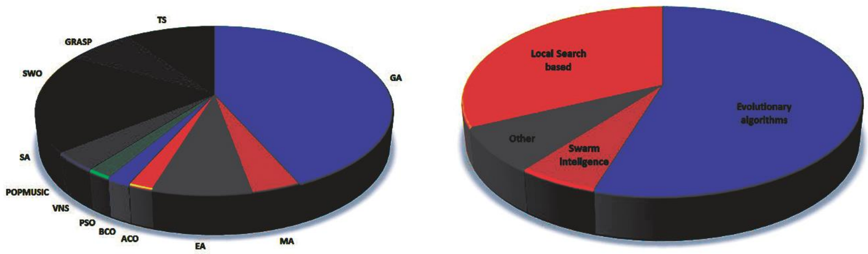


Figure 4: Metaheuristic methods for solving BAP

5. FUTURE TRENDS AND PERSPECTIVE

There are many topics that could be addressed by future research mainly arising from the variety of BAP models. Metaheutistic algorithms are promising tools as they can handle various features of the problem with a great degree of flexibility. On the other hand, it is difficult to make a systematic evaluation of these algorithms due to the strong heterogeneity of BAP models. However, a comparative analysis of algorithms is needed to assess general suitability of different approaches to BAP. To make this process easier, it is necessary to create commonly accepted BAP benchmark instances that will enable authors to evaluate their approaches. Unfortunately, the current benchmarks are either too general, or they are only used in small segments of research field. Defining benchmark instances for general berth allocation problems, that will meet all required criteria for good benchmark set is one of the many open topics in this research area.

The literature overview revealed diversity in mathematical models and formulations for different variants of BAP, thus the comparison of these models with each other becomes indispensable. Models assessment is necessary to identify the most convenient features to be addressed in the forthcoming literature. Majority of the models applied to BAP related literature consider deterministic parameters, while stochastic and uncertain cases are more realistic. Future research should incorporate stochastic parameters in solution methods and robust optimization models.

Even if it is obvious that metaheuristic approaches are necessary when solving BAP, exact methods, especially those based on combinatorial optimization and on sophisticated optimization techniques, are fruitful field for research. It seems to be the promising direction to integrate some bounding techniques in the existing exact and relaxation methods into integer programming. BAP is a highly dynamic system that has influence on other stages of loading/unloading containers and other weights in the port. That is why even small deviations from optimal vessel allocation can dramatically raise transportation cost and negatively affect port economy, implying that developing of exact methods is still important.

Metaheuristics may fail in producing good quality solutions or solutions in acceptable CPU time in the cases of large-size BAP instances. Therefore, hybrid techniques, especially hybrid metaheuristics can provide solution for these instances. Also, hybridization of metaheuristics with exact solvers can still attract more interest. One hybridization strategy is that metaheuristic is used to quickly give good starting solution for the exact method. On the other hand, an exact method may be used as a tool to accurately solve some parts of complex BAP problem, especially in the case when a problem can be decomposed into smaller subproblems.

The literature overview made it clear that GA is a dominating metaheuristic with good results in various BAP cases. Swarm intelligence based algorithms were not in focus of researchers until now, but it seems that they can be easily adapted to efficiently solve BAP, particularly due to their property to be better controlled than GA. Implementation of the solution approaches to BAP can be naturally parallelized, especially in the case of the discrete layout, because berths serve vessels independently to each other. Also, in many cases, BAP can be decomposed into smaller problems, which may be solved concurrently. In this light and due to the previously described BAP characteristics, it is evident that parallelization of metaheuristics could be a promising direction for future research.

6. CONCLUSION

The speed of finding high-quality solution is of crucial importance in designing an efficient and reliable decision support system in container terminal. Berth allocation problem (BAP), the Quay Crane Assignment Problem (QCAP), and the Quay Crane Scheduling Problem (QCSP) are highly interrelated and have the largest impact on container terminal efficiency [15, 22, 40]. Due to this fact, BAP is one of the most treated optimization problem in operations and transportation research literature. In the last decade, the number of scientific papers from this field has evidently been increasing.

This paper gives an overview of the most prominent literature related to the BAP emphasizing papers that propose metaheuristic approaches to BAP. There are very few exact solution methods to BAP, and they can deal only with small size instances. Due to the fact that BAP is proven to be NP-hard, it is reasonable to use metaheuristic methods to solve BAP to near optimality in short computational time. Variety of metaheuristic techniques are applied to different types of BAP, but the majority of authors prefers genetic algorithm. GA gives good results in almost all cases of BAP. Its popularity and advantage over other methods probably come from the fact that GA is easy to implement and can be competently applied to the container terminal optimization problems.

The absence of objective method for comparing solutions quality of metaheuristic techniques is apparent, and thus, benchmark instances that cover different types of BAP are needed. For further enhancement of metaheuristic methods, their parallelization, hybridization, and combination with exact methods seem to give encouraging signs.

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