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A Decision Support System for Integrated Berth and Ship Un - loader Allocation in Bulk Material Handling port

Abstract:

Berth allocation and material handling problems in ports are generally solved independently. This article provides a framework for aligning allocation decisions of berth and ship un-loader in an integrative manner. The ultimate goal of these decisions is to minimize the waiting time, operating time and ships priority deviation. As the sojourn time of a ship in port is costly, and given the scale and the complexity of the problem, a Decision Support System (DSS) is developed for the port authority. Two different approaches have been considered in this paper: 1) Solving the problem sequentially by decomposing the problem into two sub-problems- the berth allocation and the dynamic allocation of ship un-loaders in different berths 2) solving the problem by integrating berth allocation and dynamic allocation problem. Controlled Elitist Non - dominated Sorting Genetic Algorithm and Chemical Reaction Optimization are proposed in designing the DSS. Computational experiments are conducted on information provided from an Indian port. Results show that integrating berth and ship un-loader allocation achieves significant cost savings by considerably reducing the ship sojourn time in port.

Keywords: Ship Sequencing; Berth allocation; Ship-unloader allocation; Bulk material handling terminal port; Meta-heuristic.

1. Introduction

Port terminals have gradually played an important role in the world economic system. In 2013, the *UNCTAD and WTO* (2013) reported that the sea trade growth increased by 2.1 % for the world merchandises. The international sea trade service reached 4.7 trillion dollars and 5 % annual growth. This growing economy further empowers the growth of import by exerting more influence on port infrastructure to improve their efficiencies and productivities. In particular, the situation is more critical for bulk material as they have to be carried out through seas. In fact, compared to other freight transportation modes, coastal logistics is the cheapest transport way for bulk materials (coal, oil, iron, etc.). In addressing research questions, most of the researchers focused on container terminal port and addressed the optimization of berth allocation and quay crane scheduling, rather than discussing issues related to handling bulk materials. In fact, in bulk material handling, ships are scheduled from the anchorage base until the empty berth. Ship un-loaders are then assigned to the ship hatches. Unlike quay cranes, one ship can accommodate more than one ship un-loader at a time. The high problem complexity and economic benefits in determining the number of ship un-loaders to assign to a particular ship at a particular time provide motivation for this work. The primary focus is to minimize the delays in bulk material handling operations by considering the optimization of the ship scheduling, the berth allocation and the ship un-loader allocation. In most of the previous works, ship un-loaders were not considered in the problem, while berth allocation and material handling were addressed as two independent problems. This article aims at integrating berth and ship un-loader allocation to achieve high efficiency.

Decisions of berthing and allocation of ship un-loaders to berths in different time periods are usually based on complex priority rules and are not adapted to satisfy the customer needs due to the poor scheduling performance. Because of the complexity of the problem of minimization of priority deviation and waiting and operating times, a decision support system is proposed to solve the problem and provide a near optimal solution satisfying both objectives.

After arriving to the port, ships wait in the anchorage to get berthed. Once they get a call for berthing, they move through a channel towards the berth. Only one vessel can move through the channel at a time. Thus, the problem can be represented as a sequencing problem by giving the ships *order numbers* with which they can cross the channel towards the berth. The methodology proposed in this paper consists of two phases. The phase I focus on deciding on the order numbers based on waiting times and priority deviation minimization. After that the berthing sequence is decided, the port authority manages the contract with the ship owners. Thus they aim to solve the integrated problem sequentially. The phase II focuses on the allocation of ship un-loaders to different berths in different time periods (One time period is the time between two consecutive ships berthing events). This work proposes a novel framework that aims to achieve objectives: minimizing the delay at anchorage, minimizing the waiting time of the ship at the port and minimizing the deviation from customer driven priority. In the literature, the multi objective problem has not been considered in an integrative manner, but has always simplified and decoupled. We also propose an integrated approach of combining both the problems to compare its performance as against the sequential approach as requested by the port authority.

The paper is organized as follows. The second section provides a literature review on the problem considered. The problem formulation of berth allocation and ship-un-loader scheduling is presented in section 3. Section 4 discusses the decision support system developed to solve the problem. Section 5 reports a case study and relates it with the computational experiments. Finally, Section 6 presents the conclusion of work and future research directions.

2. Related Work

Operations in port terminal can be classified into three functional systems: sea side operations, yard operations and landside operations (Golias et al. 2009). In sea side operations, the port operators are assigned from anchorage to berth within a planning horizon.

Ship routing with transshipment and berth allocation have been studied separately in the literature. Ship routing decisions are made by ship liner companies to optimize the overall operations costs and allocate berths by minimizing the loading and unloading costs (Pang and Liu 2014). Christiansen et al. (2004) describes a ship routing and scheduling problem with strategic fleet planning and continue with the tactical and operational fleet planning level. Meisel and Bierwirth (2009) discussed the berth allocation models that minimize the waiting time and the ship handling time. Lin and Ting (2014) proposed two models for the dynamic berth allocation problem: a discrete, and a continuous model and used simulated annealing technique to solve them. Türkoğulları et al. (2014) discussed the berth allocation and quay crane assignment problem in the context of a container terminal describes a problem based on berth allocation and crane assignment to transfer the containers from ship to land within a given planning horizon. Umang et al. (2013) proposed exact solution and heuristics approach to solve a dynamic, hybrid berth allocation problem. They considered to minimize the service time of all vessels at the port.

As the discrete and dynamic berth allocation is NP hard problem (Cordeau 2005), heuristics have used to solve the problem. Ting et al. (2014) considered the discrete and dynamic berth allocation problem by minimizing the total waiting and handling time of berthed ships. Wang et al. (2014) described the liner ship route scheduling problem and determined the arrival and departure times at each port in a given time window. Golias et al. (2014) addressed the robust berth scheduling and used a genetic algorithm based heuristic to minimize the average and range of total operation time required to serve all ships in a port.

Researchers have likewise carried out studies related to yard/quay crane operations. Ng et al. (2005) proposed a branch and bound algorithm to solve the yard crane scheduling problem to address efficiently the loading/unloading operations of conatiners. Gharehgozli et al. (2014) developed a model for yard crane to minimize the crane travel time to carry out containers. Kim et al. (2004) introduced a quay crane scheduling model for a container terminal port. The model determines the sequence of containers unloading/loading to minimize the service operations times. Guan et al. 2009 described a crane scheduling problem for container terminal port and used exact and heuristic approach to solve the problem. Moghaddam et al. (2009) suggested a model for quay cranes scheduling and assignment for a container terminal port.

Some of the authors have considered integrated models of only two among three interconnected problems (berth allocation, yard operation, landside operations). For instance, Robenek et al. (2014) developed a model that integrates the dynamic berth allocation and yard assignment for bulk material handling port. This model optimizes the total service time of ship berthing at the port. Park et al. (2003) considered the berth and quay crane scheduling problem and proposed a two-phase solution, in which they determined berth allocation, service time and number of assigned cranes in the first phase. In the second phase, they determined the schedule of cranes on the basis of the outputs of the first phase. Xu et al. (2012) developed a model for robust berth scheduling and used simulated annealing and branch and bound algorithm. Ursavas (2014) developed a decision support system to determine simultaneously berthing and quay crane allocation decisions. Babu et al. (2014) suggested a model to schedule ships, plan stockyard and rake scheduling to minimize the ship delay at port terminal. However, they have focus on sea side and landside operation, which is beyond the focus of this work.

In this paper, we highlight the port management issue that researchers usually consider, but in a holistic view; specifically, the scenarios based on seaside operations, berth operations and yard operations are considered. In fact we consider into account the interdependences between these operations with the aim to achieve a globally optimized solution for bulk material handling port problem.

3. Mathematical model formulation

In this problem context, we have developed two models, the first model is formulated as two-phase optimization model: berth allocation (Phase I) and ship un-loader allocation (Phase II). Phase I is modeled as a bi-objective problem– minimizing the ships waiting time as a first objective, and the deviation of ships priority of from their berthing orders as a second objective. The berth allocation problem is viewed as a sequencing problem, as the channel allows only one ship to pass at a time. When a berth is available and a ship is waiting in the anchorage, the ship moves through the channel to get berthed according to his *order*. Based on their orders, ships are berthed and the berth allocation problem is then converted to a sequencing problem. As customer priority is port dependent, in this paper we have considered giving priority to ships based on quantity carried in them. Phase 2 is modeled as a single objective problem that minimizes the total operations time (unloading time) of the ships after they are berthed. The ship un-loaders can shift from a berth to another one only when a ship is berthed. The un-loading rate is considered as constant as all the un-loaders are considered with equal capacity. The total operating time is dependent on the number of ship un-loaders used and the duration of their use. In second model, we integrated the phase (I and II) in a single phase (III) problem. The model assumptions are as follows:

Model Assumptions

(1) Berths are discrete and all ship can be berthed. The length of a berth is large enough to accommodate any ships under consideration.
(2) The maximum number of un-loaders that can be assigned to a ship is 2. This assumption complies with the berth length constraint.
(3) In a given berth, only one ship can be served at a time.
(4) The time needed to move a un-loader from a ship to other is negligible.
(5) The estimated arrival time of a ship at the anchorage and the quantity of products are known a largely in advance.
(6) Ship un-loader allocation is a dynamic process where the un-loaders are moved only when ships arrive for berthing.

Notation:

Indices

v is the index of the ship, $v = 1,.., n \in V$

j is the index of the berth, $j = 1,\ldots, b \in B$

Input Parameters

a_v Arrival time of ship v

f_v Priority of ship v

r Unloading Rate (fixed for all ships)

Q_v Quantity of products on ship v

Decision Variable

b_v = Berthing time of ship v

o_v = Berthing order of ship v
d_v = Departure time of ship v
$q_{v,m,j}$ = Number of ship unloaders assigned to ship v, when m^{th} ship is berthed on berth j
p_v = Number of p^{th} ship after ship v is berthed

$$x_{v,j} = \begin{cases} 1 \text{ if ship v is berthed in berth } j \\ 0 \text{ otherwise} \end{cases}$$

$$y_{v,w,j} = \begin{cases} 1 \text{ if ship } v \text{ is berthed in berth } j \text{ before ship } w \\ 0 \text{ otherwise} \end{cases}$$

3.1 Sequential Approach to Berth Allocation and ship-unloader allocation

Model 1(Phase I): Berth allocation

The objective of Phase I is to find the optimal order in which the ships should be allowed to pass through the channel towards the berths. It is assumed that each ship will be assigned 2 ship unloaders to the berth.

Objective Functions

Minimization

$$\sum_{\{v \in V\}} (d_v - a_v) \quad \text{(I)}$$

$$\sum_{\{v \in V\}} |O_v - f_v| \quad \text{(II)}$$

Constraints

$\sum_{\{b\in B\}} x_{v,j} = 1 \qquad \forall\, \mathrm{v} \in \mathrm{V}$ (1)

$b_v \geq a_v \qquad \forall\, \mathrm{v} \in \mathrm{V}$ (2)

$d_v = b_v + \frac{Q_v}{2r} \qquad \forall\, \mathrm{v} \in \mathrm{V}$ (3)

$d_v \geq d_w + \frac{Q_v}{2r} - My_{v,w,j} \qquad \forall v, w \in V, j \in B$ (4)

$d_w \geq d_v + \frac{Q_w}{2r} - M(1 - y_{v,w,j}) \quad \forall v, w \in V, j \in B$ (5)

$y_{v,w,j} + y_{w,v,j} \ = 1 \qquad \forall v, w \in V, j \in B$ (6)

$I(y_{v,w,j})O_v > O_w \qquad \forall v, w \in V, j \in B$ (7)

$x_{v,j},\ y_{v,w,j} = \{0,1\}, d_v, b_v \in R^+ \qquad \forall\, v \in V, \forall\, j \in B$ (8)

The first objective stated in Equation (I) aims to minimize the waiting time. The second objective expressed in Equation (II) aims at minimizing the deviation from customer priority. The customer priority could be based on their loyalty and on the contracts developed in the past. The second objective aims at giving berthing orders to customers in such way that they are close to the priority assigned to them.

Phase II: Ship un-loaders allocation

The objective of Phase II is to find the optimal number of ship unloaders that should be assigned to each ship. The ship unloaders are assigned dynamically.

Model 1(Phase II): Ship un-loader allocation

Objective

$\min \sum_{v\in V}(d_v - b_v)$ (III)

Constraints

$\sum_{\{b\in B\}} x_{v,j} = 1 \qquad \forall\, \mathrm{v} \in \mathrm{V}$ (1)

$b_v \geq a_v \qquad \forall\, \mathrm{v} \in \mathrm{V}$ (2)

$d_v \geq d_w + \frac{Q_v}{2r} - My_{v,w,j} \qquad \forall v, w \in V, j \in B$ (4)

$d_w \geq d_v + \frac{Q_w}{2r} - M(1 - y_{v,w,j}) \quad \forall v, w \in V, j \in B$ (5)

$y_{v,w,j} + y_{w,v,j} \ = 1 \qquad \forall v, w \in V, j \in B$ (6)

$I(y_{v,w,j}) O_v > O_w \qquad \forall v, w \in V, j \in B$ (7)

$x_{v,j},\ y_{v,w,j} = \{0,1\}, d_v, b_v \in R^+ \qquad \forall\ v \in V, \forall\ j \in B$ (8)

$p_v = \ sup_m \ \sum_{m=s}^{p} rq_{s,m,j} x_{v,j} (b_{m+1} - b_m) \ \mid Q_v - \ \sum_{m=s}^{p} rq_{s,m,j} (b_{m+1} - b_m) > 0$ (9)

$d_s \geq b_s + \sum_{m=s}^{p} (b_{m+1} - b_m) + \ {Q_v - sup_m \ \sum_{m=s}^{p} rq_{s,m,j} x_{v,j} (b_{m+1} - b_m)} \Big/ {rq_{s,p,j}} \qquad \forall\ \mathrm{v} \in \mathrm{V}$ (10)

Equation (III) states that the objective function is to minimize the total operations (unloading) time for all ships. Equations (1-10) are explained in phase I.

3.2 Integrated Approach for berth allocation and ship-unloader allocation

Model 2 (Phase III):

Minimization

$\sum_{\{v \in V\}} (d_v - a_v)$ (I)

$\sum_{\{v \in V\}} |O_v - f_v|$ (II)

$\min \sum_{v \in V} (d_v - b_v)$ (III)

Constraints

$\sum_{\{b \in B\}} x_{v,j} = 1 \qquad \forall\ \mathrm{v} \in \mathrm{V}$ (1)

$b_v \geq a_v \qquad \forall\ \mathrm{v} \in \mathrm{V}$ (2)

$d_v = b_v + \ \frac{Q_v}{2r} \qquad \forall\ \mathrm{v} \in \mathrm{V}$ (3)

$d_v \geq d_w + \ \frac{Q_v}{2r} - M y_{v,w,j} \qquad \forall v, w \in V, j \in B$ (4)

$d_w \geq d_v + \ \frac{Q_w}{2r} - M(1 - y_{v,w,j}) \quad \forall v, w \in V, j \in B$ (5)

$y_{v,w,j} + y_{w,v,j} \ = 1 \qquad \forall v, w \in V, j \in B$ (6)

$I(y_{v,w,j}) O_v > O_w \qquad \forall v, w \in V, j \in B$ (7)

$x_{v,j},\ y_{v,w,j} = \{0,1\}, d_v, b_v \in R^+ \qquad \forall\ v \in V, \forall\ j \in B$ (8)

$p_v = \ sup_m \ \sum_{m=s}^{p} rq_{s,m,j} x_{v,j} (b_{m+1} - b_m) \ \mid Q_v - \ \sum_{m=s}^{p} rq_{s,m,j} (b_{m+1} - b_m) > 0$ (9)

$$d_s \geq b_s + \sum_{m=s}^{p}(b_{m+1} - b_m) + \frac{Q_v - sup_m \; \sum_{m=s}^{p} rq_{s,m,j} x_{v,j}(b_{m+1} - b_m)}{rq_{s,p,j}} \quad \forall \, v \in V \qquad (10)$$

Constraint in Equation (1) states that all the ships have to be berthed in only berth. Constraints (2-3) impose that the ship is berthed after its arrival and departs after un-loading. Constraints (4 - 6) illustrate the precedence relationship between two ships where M is a large number. Constraint (7) relates order of a ship to its precedence relation in Equations (4-6) where I (.) is the indicator function. Equation (8) states the domain of the two decision variables. Equation (9) determines the number of ships that get berthed such that the ship v has not been completely unloaded for $v \in V, \forall j \in B$. Constraint (10) determines the departure time of ship $v \in V, \forall j \in B$.

4. Decision Support System (DSS)

The Decision Support System (DSS) is intended to generate the ordering of ships to pass through the channel and manage dynamic allocation of ship un-loaders according to the methodology presented in Figure 1. This problem is multi- objective NP - Hard problem (Cordeau et al., 2005). In phase I, optimal decisions are taken considering the trade-offs between two or more conflicting objectives: Minimizing total waiting time of ships for berthing at the port while maximizing port efficiency and minimizing the customer priority deviation. In Phase II: decisions pertaining to assign the ship unloader to berthed ship and minimizing the total operating time to unload the bulk cargo from the berthed ship at the port.

For a non-trivial multi-objective optimization problem with conflicting objective functions, there does not exist a single solution that simultaneously optimizes each objective. In that case, there exists a (possibly infinite) number of Pareto optimal solutions. A solution is called non-dominated, Pareto optimal, Pareto efficient or non- inferior, if it is not inferior to any other solution in all the different objective value functions. Without additional subjective preference information, all Pareto optimal solutions are considered equally good.

The presence of multiple objectives gives preference to a family of non-dominated or non-inferior solutions, known as a Pareto - optimal solutions (Sarkar and Modak 2005). Since, no solutions in non-dominated set is absolutely better than any other, any one of them can be taken as an acceptable solution based on the decision maker's choice. Therefore, controlled elitist non-dominated sorting genetic algorithm (CENSGA-II) is proposed to solve the problem. In fact, the literature shows that CENSGA-II outperforms most of the multi-objective genetic algorithms, in particular non-dominated sorting genetic algorithm (NSGA-II) (Deb and Goel 2001 and Deb and Pratap 2002) that contributes the most used technique for these types of optimization problems. Phase II, pertaining to ship un-loader allocation problem, is also NP hard in nature. A number of studies suggest that, for this kind of resource allocation problems, chemical reaction optimization (CRO) algorithm is well adapted (Xu et al. 2011 and Xu et al. 2013). In this, CRO gives outperforming result in comparison to other meta-heuristic algorithm. Hence, to solve the problem for model 1 considered, we propose to use CENSGA-II for phase I, and CRO for phase II and for the model 2 (phase III), we propose to use CENSGA-II to solve the tri-objective problem.

<<<<Insert Fig.1>>>>

4.1 Controlled Elitist Non-dominated Sorting Genetic Algorithm (CENSGA II) Phase I

Genetic algorithm is a meta–heuristic which is frequently used to solve the single objective scheduling and resource allocation problem, which generates the near optimal solution for all alternatives. In multi-objective problems, objectives conflict with each other. NSGA-II (Dai et al. 2014) and CENSGA-II (Mohapatra et al. 2014) are generally used to solve such type of multi-objective scheduling and allocation problem and to generate the Pareto-front which gives set of optimal solution. In this phase, the problem has two objectives: 1) minimizing the waiting time of the ships. 2) Minimizing the deviation of the order of berthing with user defined priority. This phase is multi-objective ship scheduling and allocation problem.

Implementation of Controlled Elitist NSGA-II

The detail of the implementation of the algorithm on the berth allocation problem is discussed below.

Chromosome representation

The chromosome is represented as shown in Fig.2. A digit of the chromosome represents the order of a ship with that particular index. The order is the sequence in which the ships are allowed to pass through the channel which connects anchorage to the berths. The heuristics for berth allocation according to the chromosome is described in section 5.1.

Mutation Operation

The chromosome experiences mutation in the form of exchange of the berthing orders as shown in Fig.3. According to figure 3, the ship 12 is given a higher priority in moving through the channel than ship 1 after the mutation operation is performed on the chromosome.

<<<<Insert Fig.2 and Fig. 3>>>>

Crossover Operation

The crossover operation is performed through real number crossover; Random numbers are generated on the interval [0-1] as a binary and sorted such that their orders are the same as the order sequence in the chromosome.

<<<<Insert Fig.4>>>>

Selection in CENSGA-II

In CENSGA-II, the number of individuals to be selected as new parents from the current best non-dominated Pareto front is restricted. The restriction is based on a pre-defined distribution of the number of individuals in each Pareto front using Geometric distribution (deb and goel 2001). The number of individuals in each front is restricted to n_i where the geometric distribution is obtained from Equation (21):

$$n_i = rn_{i-1} \quad (21)$$

Where n_i *is* the maximum number of allowed individuals in front i and r (r <1) is the reduced rate the new population size N. Let k be the number of non-dominated fronts in population. Then, n_i can be defined as (22):

$$n_i = N\frac{1-r}{1-r^K}r^{i-1} \quad (22)$$

Let $n^{(i)}$ denotes the maximum number of individuals from front i. Then,

$$n_i \leq n^{(i)} \tag{23}$$

The selection of n_i individuals from the front i is done by the crowded distance operator (23). The geometric distribution ensures an exponential decrease of the number of solutions. The selection process is shown in Fig.5, where the required number of chromosomes is not taken from the top Pareto but rather following a geometric distribution in order to maintain the diversity.

<<<<Insert Fig.5>>>>

Quality of Pareto

The quality of a Pareto front is defined by the diversity and the number of solutions in it. Examples of poor Pareto fronts are given in Fig.6. Pareto in figure 6(a) presents intermittent solutions. Pareto in figure 6(b) has very few points to be considered as high quality Pareto front.

<<<<Insert Fig.6 (a and b) >>>>

4.2 Chemical Reaction Optimization technique (Phase II)

Chemical Reaction Optimization (CRO) (Li and Pan 2013) is proposed to find the optimal number of ship un-loaders. The problem is considered as dynamic since the number of ship un-loaders available in a particular berth is variable and depends on the number of ships. The dynamic scheduling problem of bulk material handling ship un-loaders is an NP Hard as it comes under nondeterministic polynomial – time hard class of problems. Chemical Reaction Optimization is a meta-heuristics inspired by the nature of chemical reactions (Roy et al. 2014). A chemical reaction is inspired from the natural process of transforming unstable substances into stable ones. In a chemical reaction, molecules interact through a sequence of elementary reactions. The CRO is inspired by the first two laws of thermodynamics – 1) the total energy remains constant, that is, the energy cannot be created nor destroyed but can only be transferred. 2) All reacting systems tend to increase the stability by minimizing their potential energy by attaining equilibrium state. In CRO, it is obtained by converting potential energy into kinetic energy and by transferring energy of the molecules to the surroundings. The energy profile of the reactants is a representation of single energetic pathway, along the reaction co-ordinate and the final product are shown in Fig. 7. A chemical reaction is triggered by collisions which may be inter-molecular or uni-molecular. The uni-molecular collision occurs when a molecule collides with the wall of the container in which the reaction is taking place, which may lead to decomposition of the molecule into smaller molecules. The inter-molecular reaction occurs when the two molecules collide which may lead to the synthesis of a new molecule.

<<<<**Insert Fig.7** >>>>

Implementation of CRO

The CRO is population-based meta–heuristics. The population consists of molecules. The population size may vary based on decomposition or synthesis with iterations. The decomposition and synthesis are controlled by factors α and β respectively. Proper values of α and β balance intensification and diversification. The different attributes of CRO can be explained as:

Molecular structure captures a solution in form of specific format i.e. number, vector, or even a matrix. In this phase of problem, we deal with berth with ship-unloader and store the solution in matrix form as shown in Fig. 8.

<<<<**Insert Fig.8** >>>>

The *Potential Energy PEw* for a molecule w is equal to the fitness function of the molecule. The *Kinetic Energy KEw* is a non-negative number quantifying the tolerance for accepting poorer solution over the current one. *NumHit* is the number of hits a molecule undergoes (collisions). A molecule experiences a change in molecular structure with each hit. *MinStruc* is the molecular structure of a molecule, which has attained minimum potential energy. *MinPE* stores the potential energy stored by *MinStruc. MinHit* is the number of hits a molecule has undergone when it realized its minimum potential energy in *MinStruc. MoleCall* is a parameter set to decide if a molecule undergoes uni-molecular collision or inter-molecular collision. *KELossRate* is the parameter which determines the rate at which the kinetic energy of the molecule is lost. There are four kinds of elementary reactions:

1. *On-wall ineffective collision.*

   In an on-wall ineffective collision, a molecule collides with container or external agents. In this collision, $w->w'$, the molecule undergoes changes. In this process, some amount of *KE* of the transformed molecule is added to the central buffer. The motive is to provide kinetic energy to a new molecule that has less potential energy than the current one. Let $a \in [KELoss, 1]$ be a random number, then:

   $$KE_{w'} = (PE_w + KE_w - PE_{w'}) * a$$

   The remaining energy is transferred to the buffer as shown in Fig.9.

   $$buffer = buffer + (PE_w + KE_w - PE_{w'}) * (1-a)$$

<<<<Insert Fig.9 >>>>

2. *Decomposition*

   In decomposition reaction, the molecules collide with the wall or external agent, $w->w_1' + w_2'$, and in this collision, the molecule decomposes into two molecules. Decomposition allows exploring the search space.

   To increase the possibility of having decomposition, a small amount of energy is provided from buffer. The energy conservation can be seen in Fig.10 and described by the following equations, which state that how energy is taken from the buffer and how it is given to two molecules in the form of kinetic energy. Where, δ_1 and δ_2 are random numbers, ϵ (0, 1).

   $$E = PE_w + KE_w + \delta_1 * \delta_2 * buffer - (PE_{w_1'} + PE_{w_2'})$$

   $$buffer = buffer(1 - \delta_1 * \delta_2)$$

   $KE_{w_1'} = E * \delta_1$ and $KE_{w_2'} = E * \delta_2$

<<<<Insert Fig.10 >>>>

3. *Inter– molecular ineffective collision*

   In inter-molecular collision, $w_1 + w_2 -> w_1' + w_2'$, multiple molecules collide with each other and bounce away. Molecularity remains unchanged. The process is similar to the uni-molecular collision, but since more molecules are involved, the total sum of energy of the molecule sub-system is larger than uni-molecular collision. The molecules have a higher probability of exploring the surroundings. If the potential energy of the new molecules obtained from searching the neighbors follows $E > 0$ where:

$$E = PE_{w_1} + KE_{w_1} + PE_{w_2} + KE_{w_2} - (PE_{w_1'} + PE_{w_2'})$$

then, the energy conservation in the reaction can be stated through the following equations and according to the Fig.11. However, δ_3 and δ_4 are random numbers $\in (0, 1)$.

$$KE_{w_1'} = E * \delta_3 \text{ and } KE_{w_2'} = E * (1 - \delta_4)$$

$$PE_{w_1} = PE_{w_1'} \text{ and } PE_{w_2} = PE_{w_2'}$$

<<<<Insert Fig.11 >>>>

4. *Synthesis*

   In the synthesis, two molecules combine to form a new molecule. $w_1 + w_2 -> w'$ as shown in Fig.12. The resulting molecule has a higher ability to explore regions for new solutions. The kinetic energy of the new molecule is given as follows:

$$KE_{w'} = PE_{w_1} + KE_{w_1} + PE_{w_2} + KE_{w_2} - PE_{w}'$$

<<<<Insert Fig.12 >>>>

The CRO algorithm is shown in Fig.13. Molecules with higher energy move and trigger collisions. A molecule undergoes uni-molecular collision or intermolecular based on a random number b from a uniform distribution on [0, 1]. If b >*MoleColl* then, the molecule undergoes inter-molecular collision. If b <= *MoleColl* then, uni-molecular collision occurs and decomposition criteria are checked for the decomposition reaction or on-wall ineffective collision. If (*NumHit – MinHit)*> *α* then, the molecule undergoes decomposition. If b >*MoleColl*, inter-molecular collision occurs and synthesis criteria are checked for synthesis or inter-molecular ineffective collision. The two molecules are randomly selected. If $KE <= \beta$ for both molecules, synthesis occurs. Otherwise, inter-molecular ineffective collision occurs. The iterations continue for a predetermined number of times and stops when the stopping criteria are met.

<<<<Insert Fig.13 >>>>

4.3 Integration Approach for Ship Scheduling and Ship - unloader Allocation

In the integrated approach, the chromosome is developed such that it includes the ship ordering and ship-unloader allocation. CENSGA II is used to solve the integrated problem. The chromosome is an extension of the chromosome shown in Figure 8 where the chromosome has *n* row and *b+1* columns. The first column is a transpose of the chromosome shown in Figure 2. The rest of chromosome structure is same as in chromosome used for ship un-loader allocation as shown in figure 14. The genetic operations are modified such that the feasibility in the chromosome is maintained. Real number crossover is used in the first column of the chromosome while intermolecular collision operation is used for the rest of the chromosome. Similarly, for mutation, genetic operations are used differently for first column (mutation) and rest of the chromosome (on wall ineffective collision). This ensures the feasibility of the solution.

<<<< Insert Fig.14 >>>>

5. Case Study

In this article, a real life case of a private port located in east coast of India is discussed. The data collected consist of 22 ships with expected anchorage within a fortnight in the month of October. There are 3 berths in the port and 5 ship un-loaders. At any time, there can be at most 3 ships un-loaders in any berth.

The implementation of the case study is carried out using the software MATLAB 2009-A on i7 processors (8.0 GHz) in Windows 8 platform.

5.1. Sequential Approach to Berth Allocation and ship-unloader allocation

Determination of the optimal order of ships

The optimal ships orders are obtained using CENSGA-II. The parameters adopted are: Population size is 100, Mutation probability is equal to 0.1 and crossover probability is equal to 0.65. The quality of the Pareto is characterized by its diversity and its efficient frontier coverage. To show the solution quality with respect to the generations, the Pareto front for CENSGA-II is shown in Fig. 14 (a) to Fig.14 (f). In each figure, ten different runs are used to generate the results. It is observed that the Pareto becomes continuous with the increase of the number of generations (number of solutions in Pareto increases).

<<<<Insert Fig.15 (a) to Fig.15 (d) >>>>

The quality of the solution can be characterized through the average of the objective functions of the Pareto solutions as shown in Fig.15.

The number of iterations is kept at 250 as the quality of Pareto deteriorates after 200 iterations due to the convergence to the same solutions.

The heuristics for allocation of berth based on order of ships is explained as:

Heuristics for Berth Allocation

Initialize $t\ (b) = 0$ for all berths
For $i = 1$ *to* V:
    v = ship with order v
    b = berth with min {t}
    Assign berth b to ship v
    if $t\ (b) < a_v$ then
        $t\ (b) = a_v + a_v/2\mathrm{r}$
    else if $t\ (b) > a_v$ then
        $t\ (b) = t\ (b) + a_v/2\mathrm{r}$
end For

The berth allocation results are shown in Fig. 16. The figure is a schedule of the ships berthing over the period of time considered. The rectangle number is the ship number and the rectangle width shows the operating time of the ship.

<<<<Insert Fig.16 >>>>

Results of the ship un-loader allocation

The optimal ships order is considered to solve the ship un-loader allocation problem. The parameters adopted are: Population size 10, MoleColl 0.12, Buffer 0, KERateLoss 0.2, Alpha 50, Beta 10, Generations = 100.

A comparative study between CRO and Genetic Algorithm (GA) is provided. Fig.17 shows the average objective values of MinPE in each generation. It is observed that as the number of generation's increases, the average value of the MinPE decreases. Fig.18 shows the objective function value using GA. The minimum objective (operating time) value obtained is 375 hours for CRO, improving the GA results by 19 hours from which is very significant in terms of objective value and also the computational complexity as it is obtained at lesser number of iterations and smaller population. The optimal ship un-loader allocation using CRO is shown in Fig.19.

<<<<**Insert Fig.17** >>>>

<<<<**Insert Fig.18** >>>>

<<<<**Insert Fig.19** >>>>

Computational experiments are developed on a number of problem instances as described in table 1. To compare the solutions, the average objective values of waiting time and priority deviation for solutions in efficient frontier are compared with the average objective function values for 100 randomly generated solutions. Regarding operating time, a solution from the center of Pareto is taken to be solved using CRO and the objective function value is compared with the solution provided by GA. In the operating time column, the number inside the brackets represents the number of generations in which the Meta–heuristics converge for the same value. For simplicity reasons, results are presented in integer format.

<<<<**Table .1** >>>>

It is observed that CRO performs better than GA in all the tested cases with respect to the operating time and the number of generations required converging to a final solution. The experimental results show that increasing the number of ship un-loaders is more effective than increasing the number of berths, .i.e. increasing the number of ship unloaders (by one unit) will perform better than increasing the number of berths (by one unit) when the other parameters are unchanged. Practically, it is also easy to use more ship un-loaders than building berths

Integrated Approach for berth allocation and ship-unloader allocation

The optimal sequence of ships and allocation of ship unloaders are obtained using CENSGA-II in an integrated manner. The parameters considered are: Population size is 100, Mutation probability is 0.1 and crossover probability is equal to 0.65. The quality of the Pareto is characterized by its diversity and its efficient frontier coverage. To show the solution quality with respect to the generations, the Pareto front for CENSGA-II is shown in Fig. 21

<<<<**Insert Fig.20 (a and b)** >>>>

The number of iterations is kept at 300 as the quality of Pareto deteriorates after 300 iterations due to the convergence to the same solutions.

Computational experiments are shown on a number of instances as described in table 2. To compare the solutions, the average objective values of waiting time and priority deviation and operation time solutions for sequential approach are compared with integrated approach. For simplicity reasons, results are presented in integer format.

<<<<**Table .2** >>>>

It is observed that sequential approach performs better than integrated approach in all cases with respect to number of generation to finally convergence of solution.

6 Conclusions and future research directions

This work proposes a decision support system to integrate berth allocation and ship un-loader allocation by solving them sequentially. In total, three key considerations to holistically approach the port scheduling problem are considered – minimizing waiting time, minimizing operating time of ships after berthed and minimizing priority deviation of the ships. To solve the problem, two different approaches have been proposed. In the sequential approach, two Meta–heuristics have been proposed – CENSGA-II and CRO. In phase I, the optimal ship order is determined using CENSGA-II. Based on this order, in phase II, CRO is used to find the optimal ship un-loader allocation. A comparative study is done between CRO and GA, where it is observed that CRO performs better than GA, both in terms of solution quality and computational time. The sequential approach is useful for the port authorities to revise their contract with their clients.

Further, an integrated approach is considered to integrate ship sequencing and ship un-loader allocation to mitigate the impact on the optimality the problem may face because of breaking the problem into two stages of ship sequencing and ship un-loader allocation.

The developed model offers reassessment opportunity for the port authorities for their decisions on developing the infrastructure either by employing more ship un-loaders or by increasing the number of berths. The decision support model enables the user to select from a number of optimal solutions based on his final decision. This DSS can also react to the changes in the system by updating the data inputs.

This paper considers that ship un-loaders change from a berth to another only when a ship is ready to get berthed. Future work may consider the occurrence of unexpected situations; The model can also be extended by incorporating stochastic features of ship operations like over delay due to break down maintenance, uncertain loading/unloading time, operating status of ship un-loaders, and uncertainties in stockyard management.

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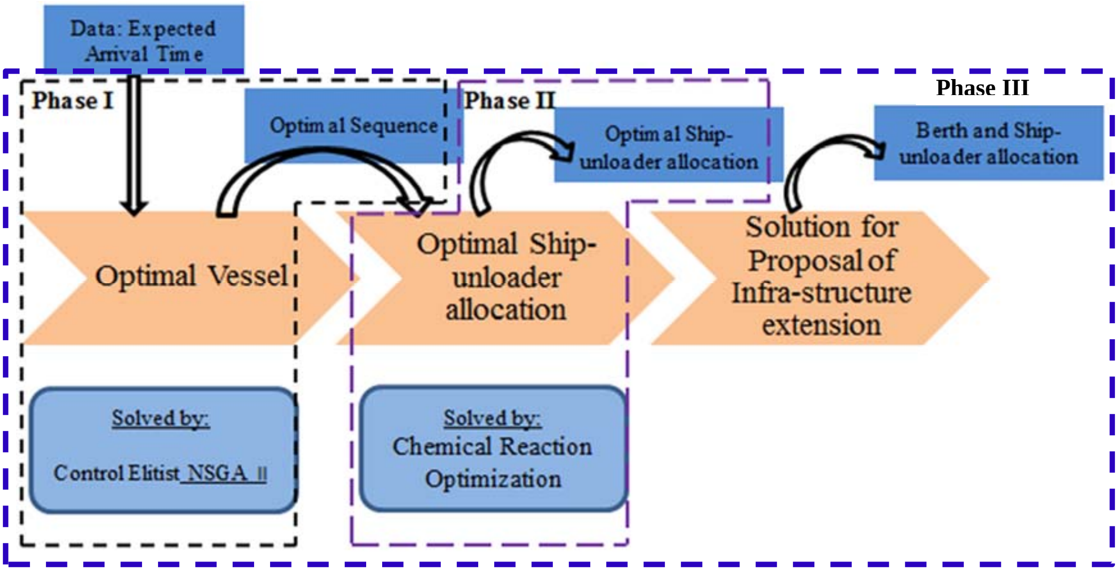

Fig.1 Schematic representation of the proposed methodology

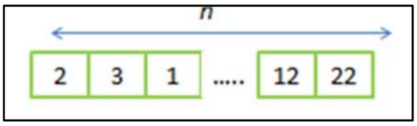

Fig2: Chromosome Encoding

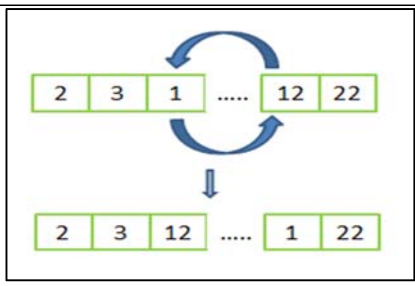

Fig3: Chromosome Mutation

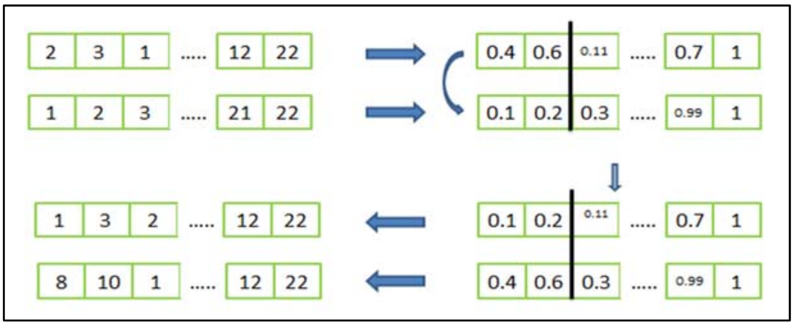

Fig4: Chromosome real number crossover

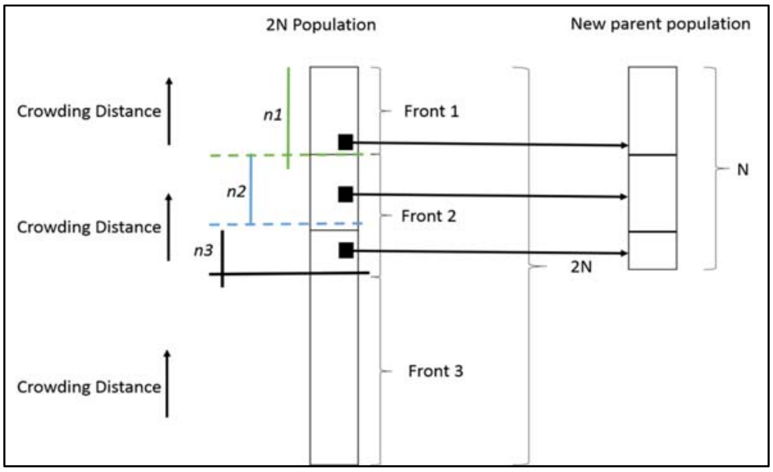

Fig.5: Selection procedure in CENSGA-II

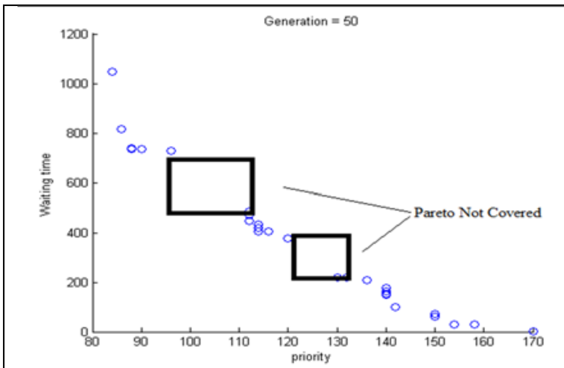

Figure 6 (a): Pareto not covered

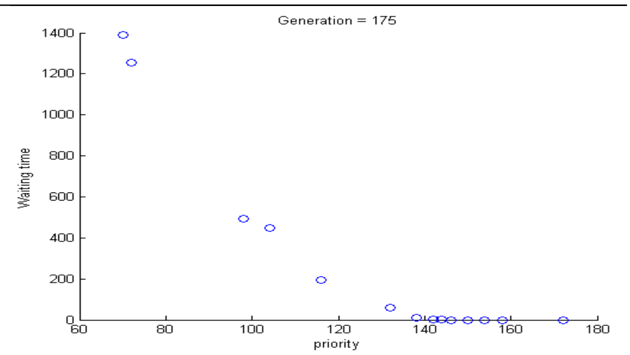

Figure 6 (b): less number of solutions in Pareto

Fig.6: Examples of Poor Pareto

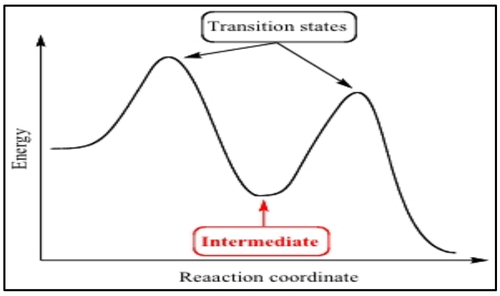

Fig.7: Energy profile of reactants

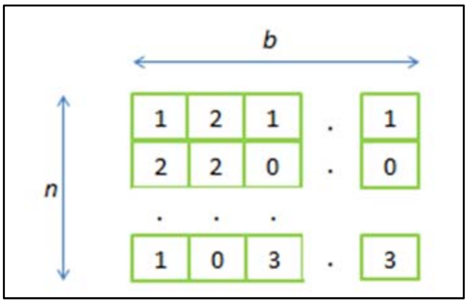

Fig.8 Molecular Structure for Ship un-loader allocation

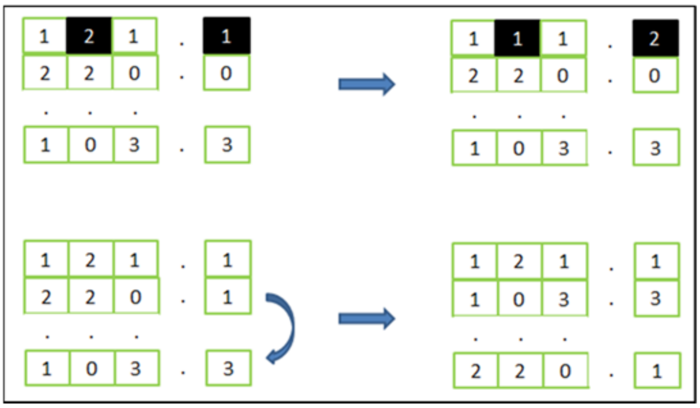

Fig.9. On wall Ineffective collision

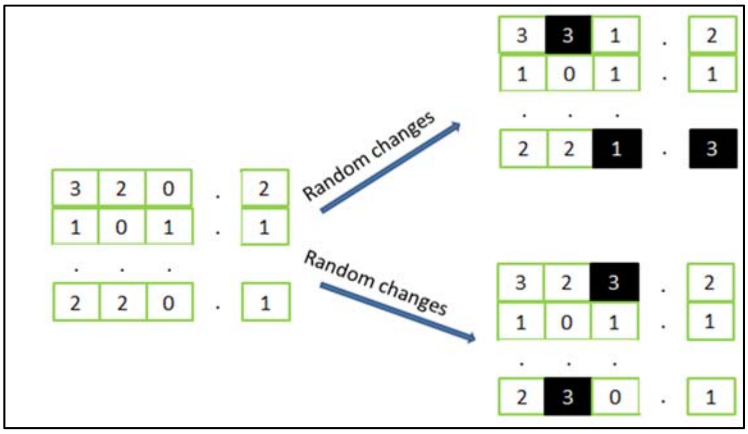

Fig.10. Decomposition

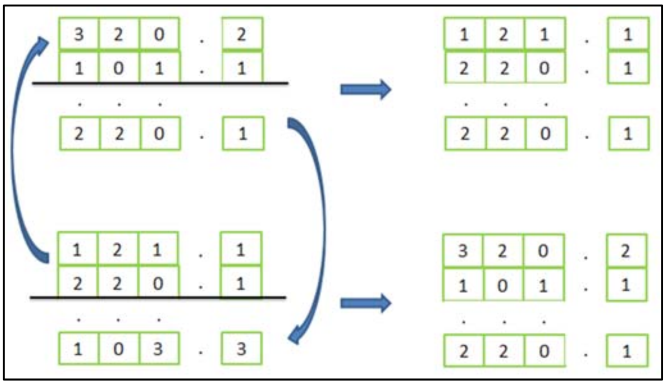

Fig.11. Inter –molecular Ineffective collision

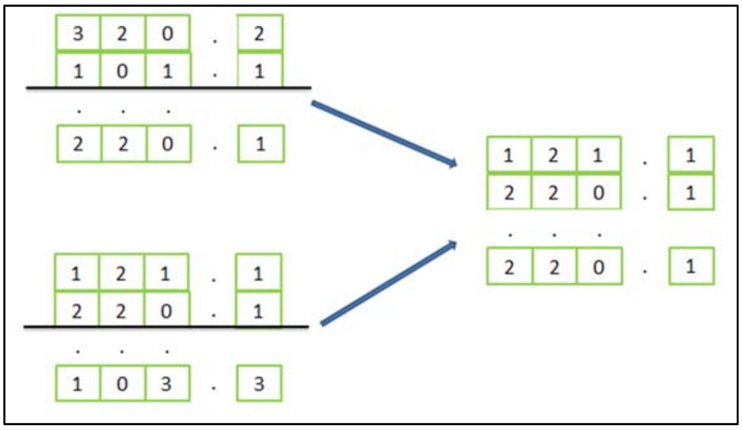

Fig.12. Synthesis

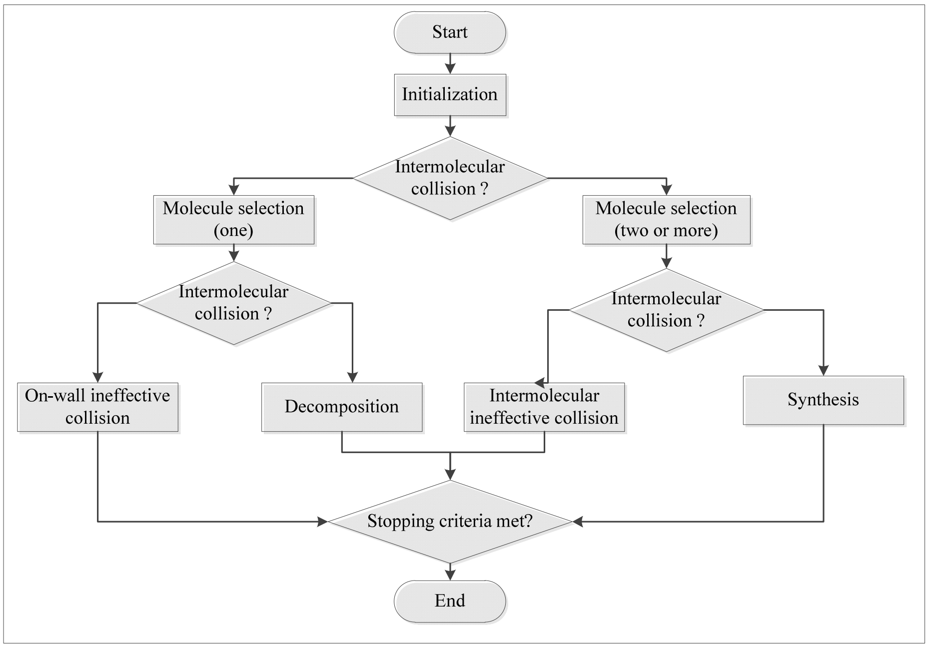

Fig.13: Framework for Chemical Reaction Optimization

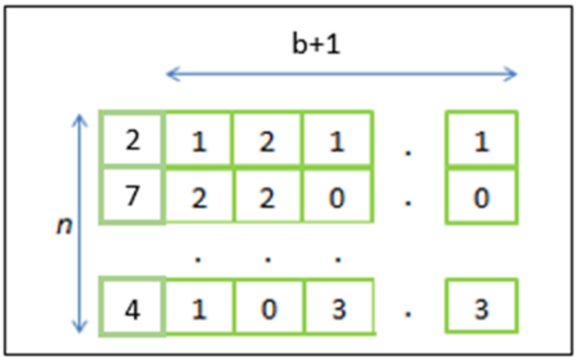

Figure 14. Chromosome for the Integrated Approach

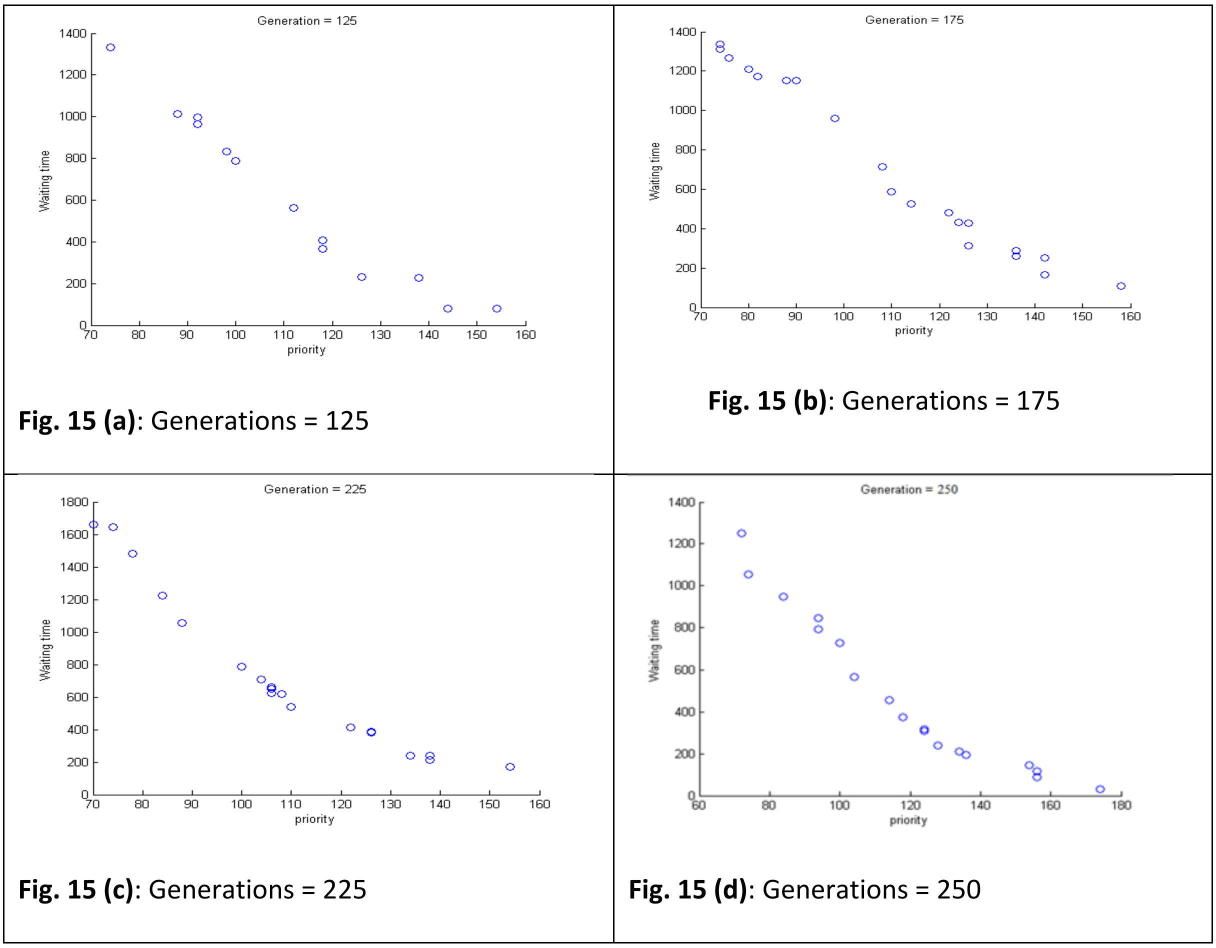

Fig. 15 (a): Generations = 125

Fig. 15 (b): Generations = 175

Fig. 15 (c): Generations = 225

Fig. 15 (d): Generations = 250

Fig. 15 (a) to Fig.15 (d): The Pareto front for CENSGA-II, shows the solution quality with respect to the generations (Model 1)

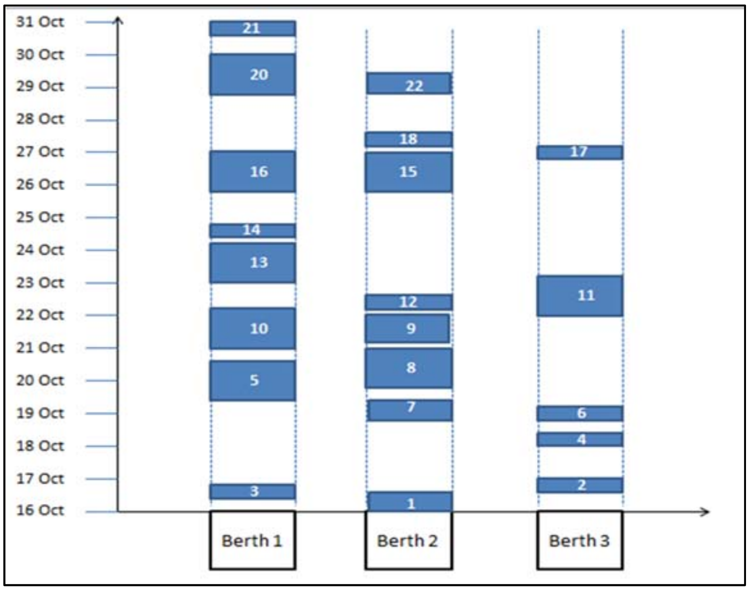

Fig. 16. Ship berth allocation

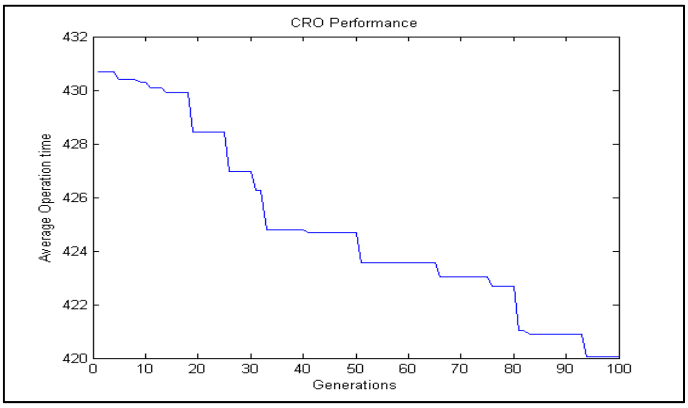

Fig.18. Average Objective values of MinPE (CRO)

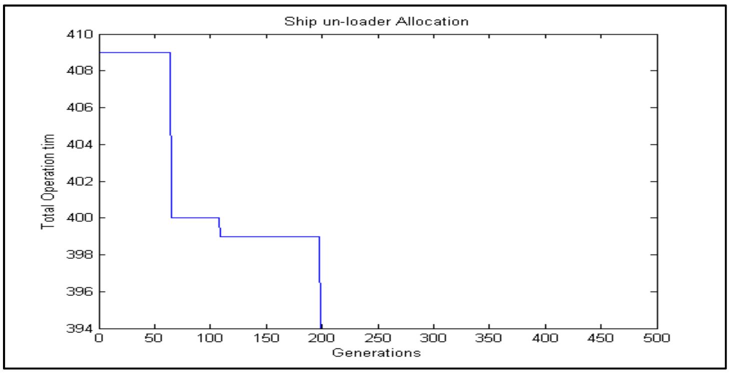

Fig.19. Objective value using GA

Berth1	Berth2	Berth3
2	1	2
3	1	1
2	2	1
2	1	2
2	1	2
3	1	1
3	1	1
2	2	1
3	1	1
2	2	1
2	2	1
3	1	1
3	1	1
2	2	1
3	1	1
2	1	2
2	1	2
2	2	1
2	2	1
2	1	2
3	1	1
2	2	1

Fig.20: Optimal Allocation of ship un-loaders

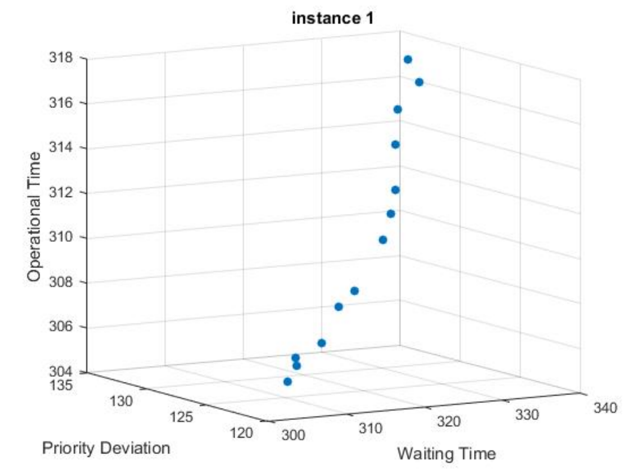

Fig.20 (a): Pareto front for instance 1 (Model 2)

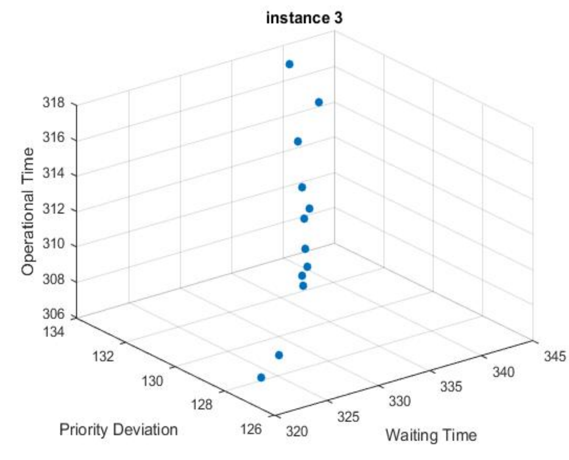

Fig.20 (b): Pareto front for instance 3 (Model 2)

Table 1. Computational experiments

Instan-ces	Number of berths	Number of ship un-loaders	Average objective value (efficient frontier)		Average objective value (100 random solutions)		Operating time (CRO) in hrs.	Operating time (GA) in hrs.
			Waiting time (in hrs.)	Priority deviation	Waiting time (in hrs.)	Priority deviation		
1	3	6	329	129	2684	159	308 (71)	316(182)
2	3	7	528	109	2661	157	265(53)	283(137)
3	3	8	251	131	2609	150	235(92)	240(169)
4	4	6	156	127	1988	162	374(98)	386(204)
5	4	7	302	116	1951	153	327(101)	353(223)
6	4	8	308	109	1988	151	287(99)	300(259)
7	5	7	168	104	1600	156	285(112)	317(110)
8	5	8	76	151	1470	162	267(95)	269(170)
9	5	9	116	140	1504	160	245(100)	264(220)
10	5	10	111	157	1547	161	237(58)	257(192)

Table 2. Computational experiments

Instan-ces	Number of berths	Number of ship un-loaders	Average objective value (efficient frontier) Sequential Approach		Operating time (CRO) in hrs.	Average objective value (efficient frontier) Integrated Approach		
			Waiting time (in hrs.)	Priority deviation		Waiting time (in hrs.)	Priority deviation	Operating time in hrs.
1	3	6	329	129	308	332	130	312
2	3	7	528	109	265	531	113	276
3	3	8	251	131	235	269	132	238
4	4	6	156	127	374	172	129	383
5	4	7	302	116	327	321	119	339
6	4	8	308	109	287	336	121	301
7	5	7	168	104	285	176	116	296
8	5	8	76	151	267	87	159	271
9	5	9	116	140	245	121	153	249
10	5	10	111	157	237	119	163	241