A Multi-objective Optimization of Sino-Kazakh Container Flow through Dostyk-Alashankou Node of the New Eurasian Land Bridge

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Abstract

Cross-border container delivery time is determined by container flow rate between and through border-point nodes. For businesses to gain competitive advantagethere is need to shorten delivery time by increasing flow of containers through supply chain nodes. Container flow should be optimal to ensure proper resource utilization and profitability to players. This paper presents a multi-objective optimization of container flow through Dostyk and Alashankou, both of which form a critical node in China-Kazakhstan New Eurasian Land Bridge supply chains. The research used evolutionary multi-objective optimization approach to analyze data. Results show that there are cost savings and low demand dissatisfaction using IMEA optimization. Dostyk station showed higher demand dissatisfaction than Alashankou. The findings are important to policymakers and management in developing approaches that can optimize flow of containers at border points.

Keywords: Optimization, Container flow, New Eurasian Land Bridge

I. Introduction

Effective utilization of the New Eurasian Land Bridge has potential to open new developmental horizons in Europe and Asian regions (Schiller Institute, 2001; Ilie, 2010). The nature and the level of use of railway infrastructure are correlated to its economic contributions to the countries it passes through (Tennenbaum, 2001). Moreover, carrying capacity utilization and container traffic flow is vital in railway transportation (Zhu, 2001).

Since commodity delivery time is a critical factor in business, it is important to develop strategies to reduce it by improving inter-nodal and intra-nodal flow of containers (Emerson & Vinokurov, 2009). Supply chain nodes,like railway border-point stations of Kazakhstan's Dostyk and China's Alashankou, are found to be great contributors to longer delivery times (Sanhey, 2005) and therefore important in research addressing container flows. Supply chains depending on New Eurasian Land Bridge as a multi-nodal infrastructure are influenced by operational efficiencies and capacities of Dostyk-Alashankou border-point stations from which there is a dendrite of railway lines connecting the stations to Europe, Central Asia, South Asia and Russia (Junussova, 2006). Operational efficiencies and inefficiencies in addition to capacity of the stations have effects on intra-nodal container flow (Ye, et al., 2007) hence influence commodity delivery time.

Some research has previously been done in the area of container flow (Development Research Centre, 2002; Pittman, 2002; Liu, 2003; Kie & Akhmet, 2009; Wu & Nash, 2000; Wan & Liu, 2009; Xiao, et al., 2003). Most of the research work dwelt on nodal and inter-nodal infrastructural development, cost factors, schedulingand efficiencies. Various optimization approaches have been applied to container transport problems but with limited success. Algorithmic methodshave been used but with difficulties (European Commission, 2006).

Computer simulation approaches have also been applied to optimize railway container transport with a focus on carrying capacity (Zhu, 2001). Some researchers used game theory to analyze railway track capacity allocation and container transport cost problems (Fragnelli, 2005; Gonzalez & Herrero, 2004; Norde et al., 2002). However, few researchers have focused on intra-nodal flow of containers especially with reference to border point railway stations or dry ports.

The question of what causes delay of containers at border-points has not been adequately addressed. Optimal level of container flow through the two critical border-points of Dostyk and Alashankou is not clear since previous research has not objectively tackled the matter. Optimality and rationality of railway transport is considered an area of paramount importance for success of rail transport project like the New Eurasian Land Bridge (Altshuler, et al., 2012).

This research addresses the gaps by using an evolutionary multi-objective optimization of container flow to analyze Dostyk-Alashankou node with an objective of establishing determinants of flow and obtaining time-variant optimal levels using data between 2004 and 2012. Multi-objective approach is applied due to multi-attribute nature of container flow ranging from flow volumes to time and cost factors; all of which need to be optimized.

Section I of the paper presents introduction while Section II outlines literature review relevant to the research.Section III details the stepsin evolutionary multi-objective algorithm. Data and analysis are presented in Section IV followed by Section V which presents research findings andDiscussions. Implications of research findings are in Section VIwhile limitations and recommendations for further research are presented in Section VII. Summary and Conclusions are given in Section VIII.

II. Literature Review

A great deal of research has been done in the area of railway optimization. Survey approaches of optimization have been used by various researchers (Bussieck et al, 1997; Caprara, et al., 2005; Cordeau, et al., 1998; Desrosiers, et al., 1995). The research focused on major areas of optimization which include timetabling, platforming, unit shunting, line planning, rolling stock circulation and crew planning (Cacchiani, 2006) but was not specific to containers.

Different timetabling approaches have been used to optimize railway container transport. Mistry and Kwan (2003) used algorithmic approach to study train timetables. Kroon, et al. (2005) studied periodic event scheduling problems using stochastic optimization. Evolutionary algorithm for timetabling was applied by Semet and Schoenauer (2005) to minimize delay.

Platforming is concerned with decision of routes followed by scheduled trains on entering, stopping and exiting a station (Cacchiani, 2006). Billionnet (2003) applied integer programming to solve train platforming problems. Moreover, algorithms for solving platforming problems were developed (Caprara et al., 2006). Kroon et, al (2001) studied complexity issues in train routing through railway stations. De Luca and Mione (1998) used graph coloring approach to address platforming issues.

Alfieri, et al (2006) used transition graph concept to study multiple roll stocks on single railway line. Focusing on Dutch trains, Fioole, et al (2006) obtained a description of convex hull of integer solutions to combining and splitting of trains. Maroti (2006) identified rolling stock planning problems and proposed models to describe them while Peeters and Kroon (2008) applied branch-and-price algorithm for determination of rolling stock circulation on train lines.

Train unit shunting is the process of sorting items of rolling stock into complete train sets. Tomii et al (1999) used a probabilistic searches algorithm to study off-line shunting scheduling to solve train unit shunting problems but their research did not include disturbances. Sato, et al (2007) took account of the disturbances but left out train faults. Sugi, et al (2010) conducted an in-depth study of train shunting in the event of troubles with resources.

A number of studies in line planning lines have considered lines to be of similar type (Bussieck, 1998; Claessens, et al, 1998; Goossens, et al, 2001). Oltrogge (1994) applied system split procedure to solve multiple line type problems involving different trains. Goossens, et al (2004) further developed the approach by using cost-optimization line planning.

Many researchers have studied crew planning using various approaches (Balas & Carrera, 1990; Barnhart, et al, 1994; Beasley, 1990; Bolc & Cytowski, 1992; Caprara, et al, 1999; Fisher & Kedia, 1990; Wedelin, 1995). Ernst, et al (2001) developed an integrated optimization model for crew scheduling and cyclic and non-cyclic crew rostering.

Various multi-objective evolutionary algorithms have been developed to efficiently solve optimization problems especially in railway networks (Vrugt and Robinson 2007; Chen and Mahfouf 2006; Tan et al. 2001; Zitzler and Thiele 1999; Fonseca and Fleming 1995). Biologically inspired immunity-based is one of the algorithms (Timmis & Niel, 2000; Luh, et al., 2004). Keko, et al (2003) used vaccinated genetic algorithm with improved solution speeds and less susceptibility to parameter changes.

This research applies immunized multi-objective evolutionary algorithm (IMEA) using clonal selection, somatic mutation and immune suppression approaches to optimize container flow through Dostyk-Alashankou border point.

III. Immunized Multi-objective Evolutionary Algorithm

Immunized multi-objective evolutionary algorithm is characterized by "distributed immune memory, reinforcement learning, self-regulation and diversity" (Wong, et al, 2010, p.741). Immune response becomes effective to antigen encounters due to memory linked to previous infection. Local memory stores cloned high affinity antibodies. Immunized evolutionary algorithm uses suppression, recruitment and crossover to regulate number of antibodies and diversify them (Wong, et al, 2010).

Exploitation of optimal solutions is done using clonal selection (Deb, 2001). For two solutions x_1 and x_2, x_1 dominates $x_2$if:

1. Solution x_1 is no worse than x_2 in all objectives, and;
2. Solution x_1 is strictly better than $x_2$in at least one objective.

For constrained non-dominance of two antibodies a_1 and a_2, a_1 dominates a_2 if:

a. Antibody a_1 is feasible while a_2 is infeasible;
b. Both solutions are infeasible, a_1 having less constraint violations;
c. Both solutions are infeasible and with equal number of constraints;
d. Both solutions feasible, a_1 dominates a_2 as per basic definition.

Diversification of optimal solution is done through the adoption of suppression characteristics. This research applies harmonic average distance to calculate diversity affinity (Huang, et al, 2006).
Steps in immunized evolutionary algorithm are as follows:

1. *Initialization*
   Random sets of solutions are generated initial population, IP;
2. *Activation*
   The affinity values of the solutions are calculated. Non-dominated index of zero is assigned to every solution. The index remains unchanged if the solution dominates another and increases by 1 if it is dominated by others. The non-dominated index is the non-dominated affinity of the solution.
3. *Selection*
   The whole population is sorted based on non-dominated affinity then on diversity affinity. Ranking is done using non-dominated affinity. After sorting, the initial population is divided into three groups: best 30% termed optimal affinity subset (OA); next 40% known as medium affinity subset (MA) and the rest as worst affinity subset (WA).
4. *Cloning*
   Solution sets in OA are cloned for crossover and stored for subsequent iteration for searching global optimal. The cloned solutions are called (CL).
5. *Mutation*
   Solutions in MA are taken through mutation at a rate of 1/n, where n is the number of variables in the solutions. Selected variable is multiplied by random numbers ranging from 0.8 to 1.2.The mutated subset is termed MU.

6. *Population Suppression*
   Solutions in worst affinity subset undergo suppression, while 10% of in the initial population with worst affinity values are discarded. The rest of the solution form suppression subset, SU.
7. *Recruitment*
   Recruitment is done after population suppression to increase diversity in the population. The solutions are grouped as immune network subset, IN.
8. *Crossover*
   Solutions in IN crossover with those in CL at a rate of 0.9; each IN solution is assigned with parent solution in CL.
   Given A as a set of the solutions in IN, B as that of the parents, and C as child set, with $A(a_1, a_2, \ldots\ldots\ldots a_n)$, $B(b_1, b_2, \ldots\ldots b_n)$ and $C(c_1, c_2 \ldots\ldots\ldots c_n)$:
   $c_i = a_i$ for $0 \leq j_i < 0.9$; (1)
   $c_i = b_i$ for $0 \leq j_i < 1$. (2)
   where j_i is any random number from 0 to 1.
   The solutions obtained after having crossover are termed diversified subset, DI.
9. *Iteration*
   The three resulting sets CL, MU and DI become the new population for next simulation. Steps 2 to 8 are repeated until termination conditions are satisfied. Termination conditions are set based on number of iterations, best affinity value or the standard deviation of affinity values in the best subset. When termination conditions are met, global optimal solution, GO, is obtained,
   MATLAB R2013a Version 8 will be used in this research for analysis because of its flexibility, dynamic functionality and efficiency (Hoffmeyr& Forrest, 2000).

IV. Data and Analysis

Container throughput as one of the measures of container flow is defined as average quantity of containers that can pass through a station or port on daily basis or that handled over a period of time (Military Dictionary, 2008). Figures 1 and 2 show container traffic data at Dostyk and Alashankou, between 2004 and 2012.

Flow of containers is based on demand and supply constraints; the two determine container flow through each of the stations. Objective functions that represent container flow are given by:

Cost function

$$\text{Minimize } f_1: C_{total} = \sum_{i=1}^{|S|} \sum_{j=1}^{|D|} \sum_{k=1}^{|V|} (C_{ijk} Q_{ijk}) \quad (1)$$

Dissatisfied demand function

$$\text{Minimize } f_2: D_{total} = \sum_{j=1}^{|D|} D_j \quad (2)$$

Where, C_{ijk} is the cost of transporting container through the border station from origin $i \in S$ to destination $j \in D$ with station train service $k \in V$. Q_{ijk} is the quantity of containers supply location i to destination j through station train service k. D_j is the unit of dissatisfied demand at destination. Costs used in the analysis are that of 20 feet containers because data on other container sizes were limited.
Objective functions are subject to both supply and train container capacity constraints as follows:

Supply constraints

The total quantity of containers through the border stations from i^{th} location must not exceed maximum supply units Q_i that the station can handle.

$$\sum_{j=1}^{|D|} \sum_{k=1}^{|V|} Q_{ijk} \leq Q_i \quad (3)$$

Train capacity/space constraints

The total quantity of containers by k^{th} train service must be less or equal to the maximum available space/capacity the k^{th} train service, Q_k.

$$\sum_{i=1}^{|S|} \sum_{j=1}^{|D|} Q_{ijk} \leq Q_k \quad (4)$$

Non-negativity constraints

$$Q_{ijk} \geq 0 \text{ and } Q_{ijk} \in I \quad (5)$$

MATLAB codes for the genetic algorithm are presented in Figures3 – 7 (see Appendices).

V. Findingsand Discussions

Table 2 shows simulated results of 5 cases for Dostyk and Alashankou using Immunity-based Multi-objective evolutionary algorithm (IMEA) and that of current practice using AIS-based hybrid algorithm (HAIS). Figures 8 and 9 show percentage unsatisfied demand with respect to total cost of container flow through the two border stations. Simulations were done with population size of 50 and 1500 iterations.

Results in Table 2 show that more optimal solutions can be obtained by IMEA compared to current practice using HAIS. The differences in costs between the two approaches also indicate that there is cost-saving when IMEA is used for optimization though unsatisfied demand is approximately a fifth of total demand (in the range of 20 – 22%) for both. Dostyk station showed higher levels of demand dissatisfaction than Alashankou. Higher optimal total costs were obtained for Alashankou than Dostyk, that is, for example, US$ 782,208,000 and US$ 434,560,000 respectively in case 1(refer to Table 2, Figures 8 and 9). This higher total cost for Alashankou is possibly due to more containers handled at the station than at Dostyk (Figures 1 and 2).

VI. Implications of Findings

Findings of this research show that optimization using immunized multi-objective evolutionary algorithm is a viable approach that can help border station management and railway container transport companies to make decision and plan for more cost-effective container flow through them.

VII. Limitations and Further Research

This research considered flow of 20 feet containers due to inadequate data on other container sizes. The analysis did not explore different approaches to the processes of suppression and crossover that could result in improvement of convergence. Further research should be conducted to include containers of different sizes and to apply more efficient ways of improving convergence.

VIII. Summary and Conclusion

This paper aims to contribute to body of research in application of multi-objective evolutionary algorithms in the area of transport and logistics. It reviewed various optimization approaches applicable to railway border stations focusing on aspects like time-tabling, platforming, rolling stock circulation, train shunting, line planning and crew planning. Throughput and cost data for Dostyk and Alashankou were analyzed using IMEA using Matlab software. Results show that optimal container flow can be achieved using IMEA compared to current practice that is using HAIS approach. Further research is recommended in this area to explore ways of improving convergence and incorporate variety of container sizes in optimization.

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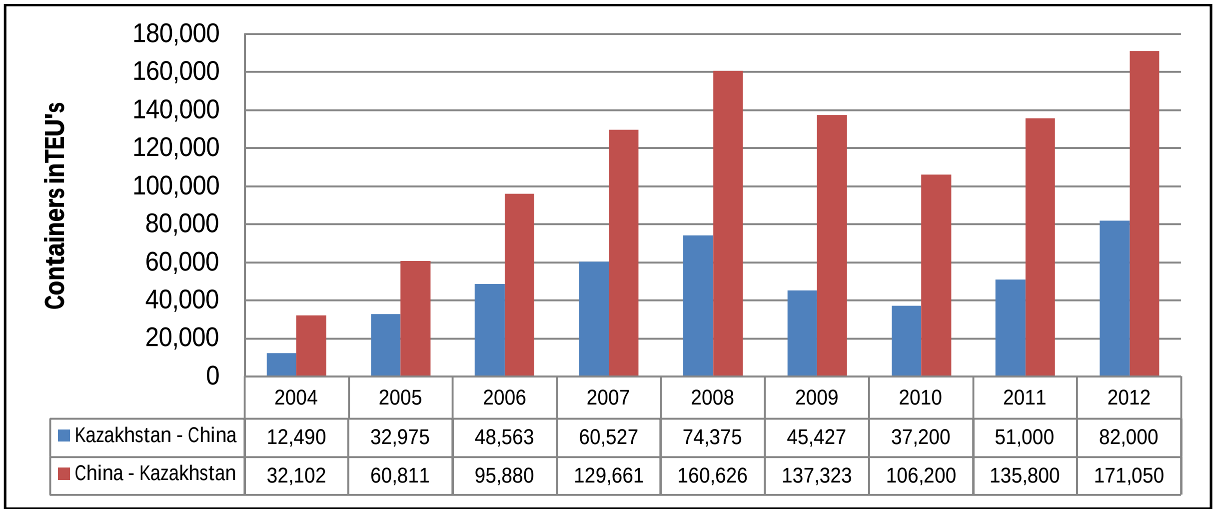
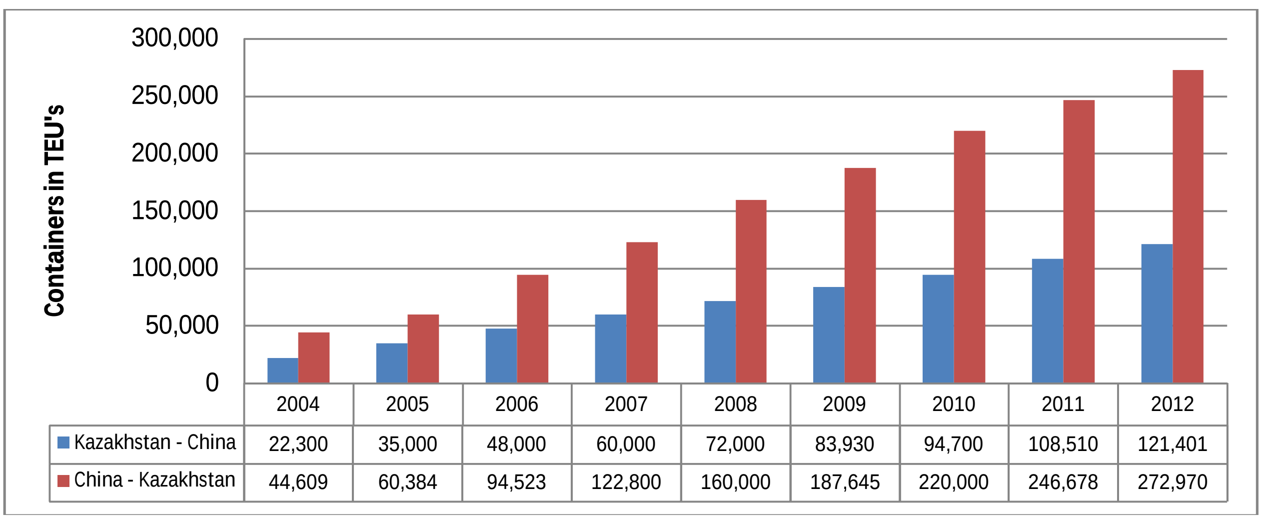
Appendices



	2004	2005	2006	2007	2008	2009	2010	2011	2012
Kazakhstan - China	12,490	32,975	48,563	60,527	74,375	45,427	37,200	51,000	82,000
China - Kazakhstan	32,102	60,811	95,880	129,661	160,626	137,323	106,200	135,800	171,050

Figure 1 Container traffic through Dostyk*Data Sources*: Kaztranservice (KTS) and www.transbaltic.eu



	2004	2005	2006	2007	2008	2009	2010	2011	2012
Kazakhstan - China	22,300	35,000	48,000	60,000	72,000	83,930	94,700	108,510	121,401
China - Kazakhstan	44,609	60,384	94,523	122,800	160,000	187,645	220,000	246,678	272,970

Figure 2 Container traffic through Alashankou*Data Source*: www.transbaltic.eu

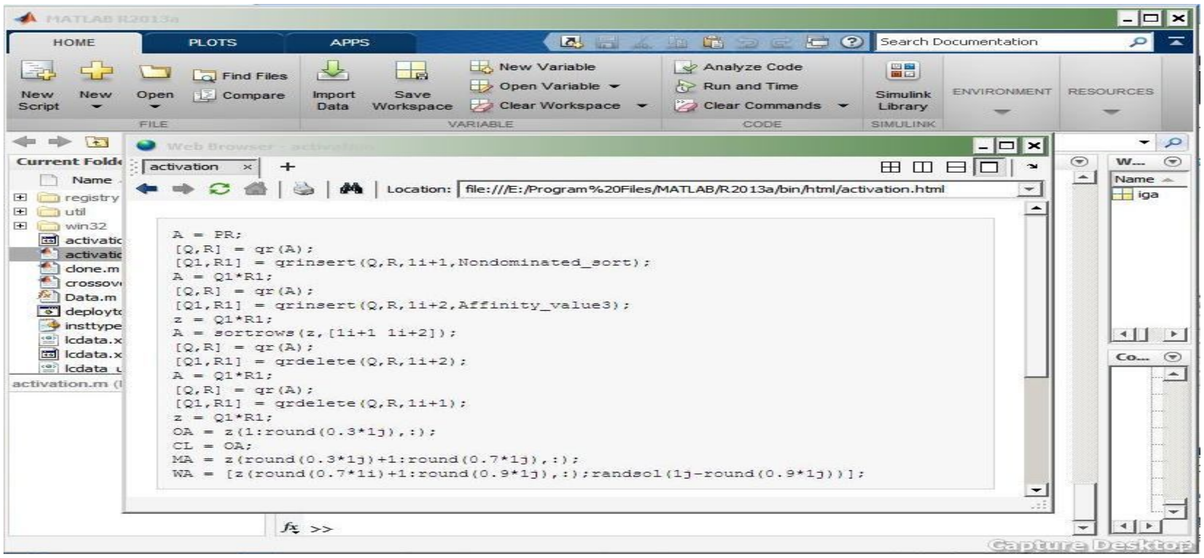


Figure 3 Matlab code for Activation

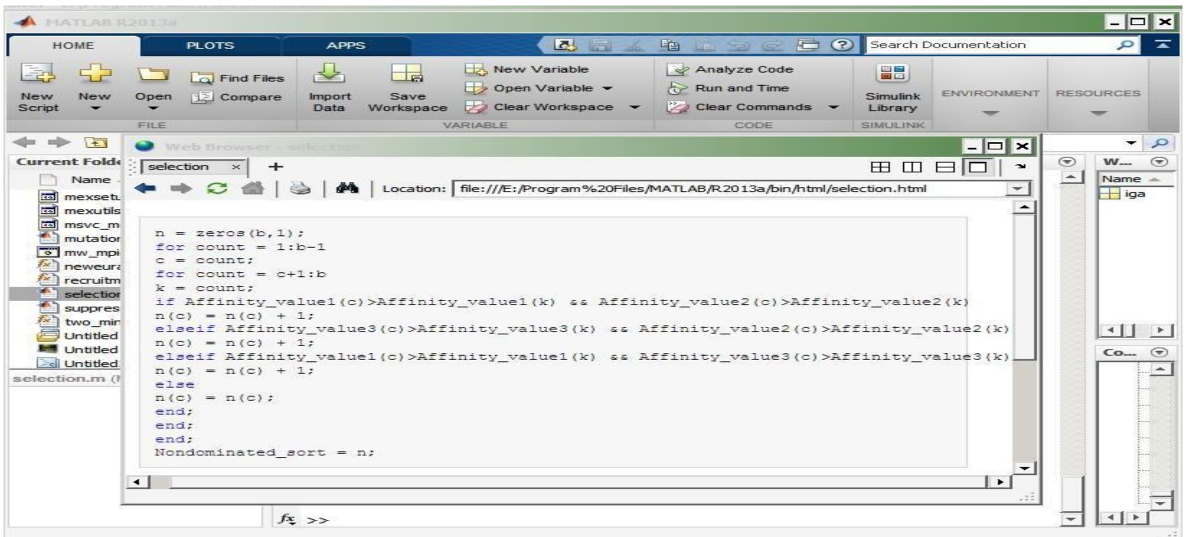


Figure 4 Matlab code for selection

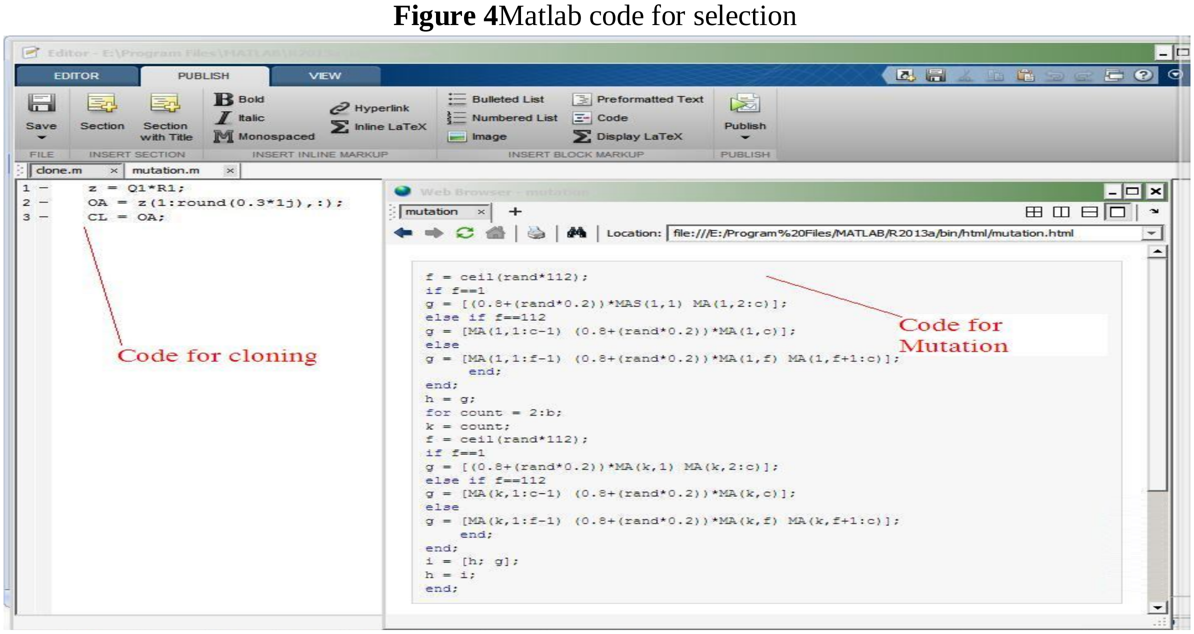


Figure 5 Matlab codes for cloning and mutation

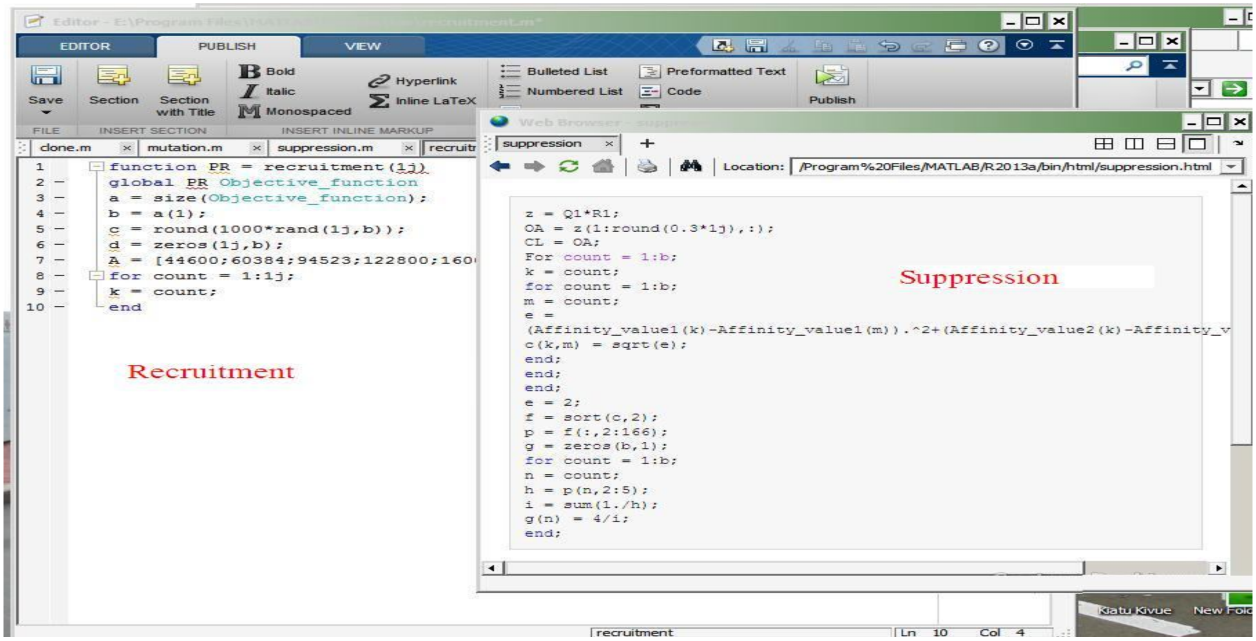


Figure 6 Matlab codes for recruitment and suppression

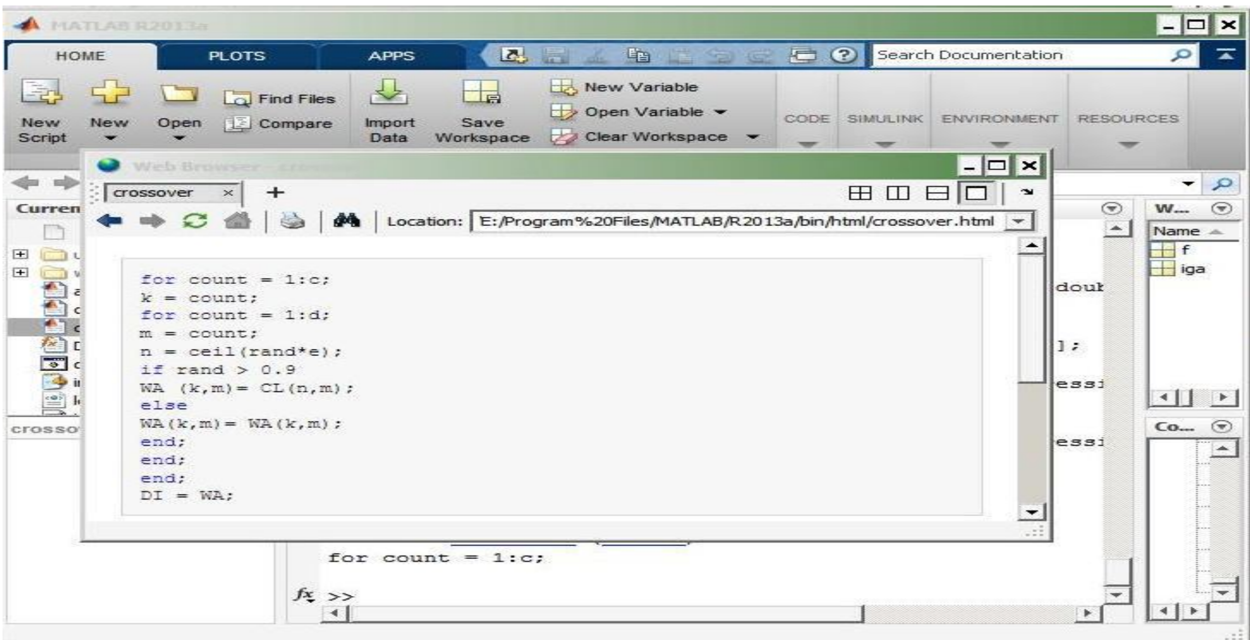


Figure 7 Matlab code for crossover

Table 1 Dostyk-Alashankou-Klaipeda rates for the year 2012

Containers	Rates (US $ per container)
20 Feet Containers	3,200
40 Feet Containers	4,800
45 Feet Containers	5,760

Source: www.suntrain.eu

Table 2 Simulated results of optimization using IMEA and current practice

CASE	DOSTYK			ALASHANKOU		
	IMEA		Total Cost (USD) Current Practice HAIS	IMEA		Total Cost (USD) Current Practice HAIS
	Total Cost (USD)	% Dissatisfaction		Total Cost (USD)	% Dissatisfaction	
1	434,560,000.00	20.8	456,288,000	782,208,000.00	20.3	784,189,728
2	414,915,200.00	21.1	435,660,960	925,205,760.00	20.9	971,466,048
3	439,433,600.00	21	461,405,280	790,980,480.00	20.6	830,529,504
4	350,271,360.00	21	367,784,928	746,847,360.00	20.2	821,318,400
5	547,360,000.00	22.5	574,728,000	985,248,000.00	20.5	1034,510,400

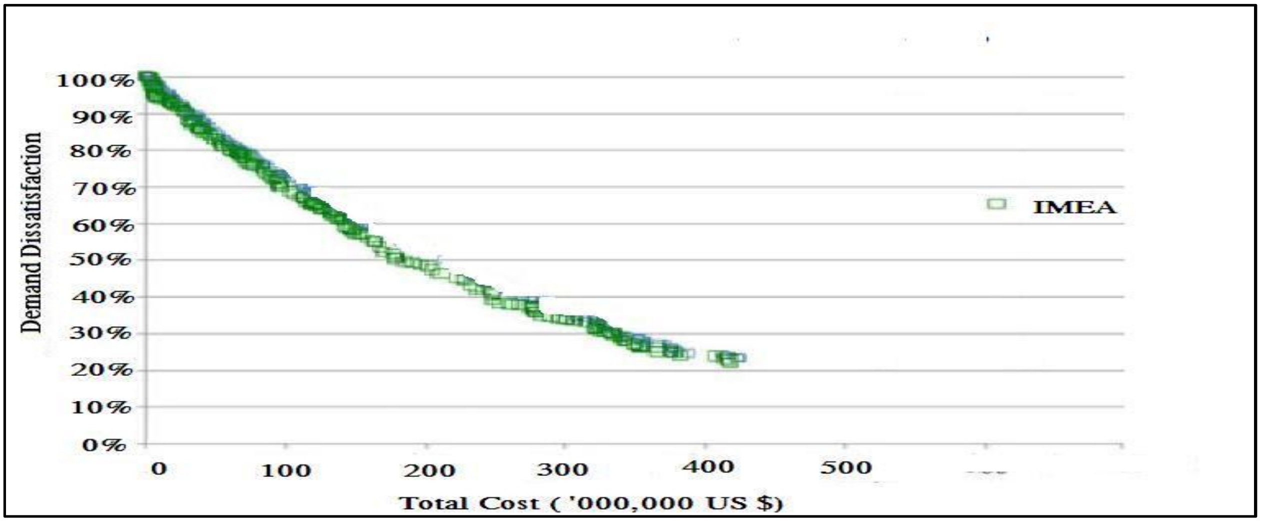


Figure 8 Simulation results for multi-objective container flow for Dostyk Case 1

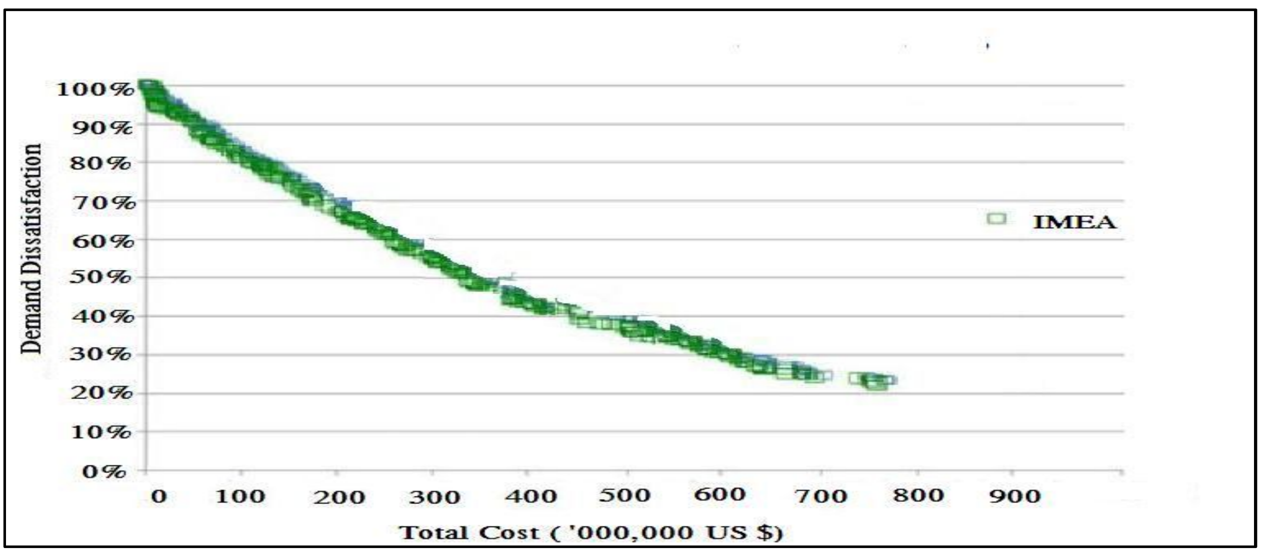


Figure 9 Simulation results for multi-objective container flow for Alashankou Case 1