DOTSIM
A Simulation-based Optimization Methodology for the Optimal Duplication Sequence on Freight Transportation Systems

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Abstract: The definition of the best sequence on route duplication of freight systems consists on a complex NP-hard problem. There exists a huge variety of meta-heuristics (MH) capable of generating satisfactory solutions. However, it is fastidious to know which MH will produce the best solution for a Duplication Sequencing Problem (DSP). There not exists a methodology to structure, plan and control algorithms and processes in modeling the various MH applied to find the best solution in this type of problems. This paper proposes a process development methodology which guides to evaluate the best duplication sequence comparing the MH's performance with existing approaches such as linear analytical method (LAM). The potential of this methodology is demonstrated by a case study in railway systems.

1 INTRODUCTION

Rail transportation is one of the most efficient transportation ways due to its capacities to freight and passengers at low costs comparing with road transportation. The growth of its support infrastructure is complex as much as its importance.

The duplication sequence problem (DSP) is described as a set of single segments or routes in a transportation system, the link between these routes (usually duplicated where vehicles can park) called crossing loops, and the travel cost between the connected crossing loops. The best solution for a DSP is the sequence which has lower cost, besides that all routes should be duplicated one at a time. For most of DSP problems the search for the best solution is relevantly hard. A problem with 10 single routes has about 3.5 x 10^6 feasible solutions. An exhaustive search runned by a computer with capacity to process 1 billion solutions per second would find the best solution in about four years.

For this kind of problem, a satisfactory solution, close to an optimal one, may be obtained by meta-heuristics (MHs). MHs are optimization methods based in robust strategies to avoid optimal local solutions (Gendreau and Potvin, 2010). Different MHs provide satisfactory solutions for different instances from PSD, however, how to select the most promising for an specific DSP? It involves a typical selection problem algorithm (Rice, 1976). According to the theorem *"No free Lunch"* (Wolpert and Macready, 1997) always selecting the same algorithm does not produce satisfactory results. On the other hand, by processing all available algorithms for the desired instance and after select the best solution would be relevantly expensive. A computational methodology could provide a comprehensive framework for MHs management including to plan, run, schedule, control and analyse different algorithms and results on the duplication sequence problems. To the best of our knowledge, there is no methodology available which describes how to conduct a feasibility way to find the best solution in DSP problems. This paper proposes a methodology based on simulation and optimization techniques to identify satisfactory solutions for a determined DSP problem, comparing the performance between different MHs in order to find which is the more promising over different instances. The remaining of this paper is organized as follows: section 2 describes the DSP problem. Section 3, presents a brief literature review of Railway Capacity Concepts, Simulation and Optimization approaches in transportation systems. Three varieties of algorithms are discussed based on the searching space model. Section 4 presents and explains the methodology; in section 5, a mathematical modeling is depicted; a case study based in railway systems is reported in section 6. Section 7 gives conclusions and final remarks.

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2 DUPLICATION SEQUENCE PROBLEM IN TRANSPORTATION SYSTEMS - DSP

For most of the DSP problems the exhaustive search for the best solution requires complex modeling and hard computational efforts. A problem with 10 single routes has about 3.5 x 10^6 viable solutions. An exhaustive search processed by a computer with capacity to process 1 billion solutions per second would find the best one in about four years. Certainly, an analyst will not spend all this time to define the best duplication sequence for a transportation system which needs investments in its infrastructure.

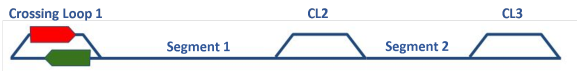


Figure 1: A Rail Transportation System with two single segments and three crossing loops.

DSP basically consists on defining the best priority duplication sequence in transportation systems that still have single routes or segments (as depicted in figure 1) and that is experiencing a need to increase its transportation capacity to support an increase in demand. Moreover, in DSP all single routes should be duplicated and the priority of each route must be defined. The complexity of a DSP increases exponentially according to the amount of singles segments as showed in figure 2.

We can also observe in figure 2 an example of priority for a system with N=5 single segments. The priority defined is shown by the arrow, in other words, the *"S1"* is going to be the first segment duplicated, and the last will be the *"S5"*. In additional, for each route selected to duplicate, there are *N-1* more possibilities. That is the reason for DSP become a permutation problem. For system with 5 segments, we would have a search space with 5! or 120 viable solutions.

Segments	S1	S2	S3	S4	S5
Priority	1º	2º	3º	4º	5º
Possibilities	N	N-1	N-2	N-3	N-4

Figure 2: Feasible Solutions for a railway with 5 singles segments/routes.

Each segment has a cost which can be represented by a variety of variables which depend on the objective of the transport route analyst, *e.g*, investment costs, capacity costs, or the average between them, etc.

There are a variety of applications in the real world that are modeled through the DSP, such as freight and passenger in onshore transportation systems, *e.g.* railways, LRVs (Light Rail Vehicles), highways, roads, subway etc.

3 RAILWAY CAPACITY CONCEPTS

3.1 Simulation

(Pegden et al., 1995) presents a more complete definition, covering the entire simulation process. He mentions that "simulation is the process of designing a computer model of a real system and conducting experiments with this model in order to understand their behavior and/or evaluate strategies for their operation." As noted, the mentioned author considers that simulation as a larger process, including not only the construction of the template, but also all the following experimental method, searching excessively: (i) To describe the system behaviour, (ii) To build theories and hypotheses considering the observations made, (iii) To provide a base model for future behaviour predictions, that means, the effects produced by changes in the system or employed in methods over its operation.

There are a variety of simulation software which can measure the cost for feasible solutions to DSP problems such as GPSS, JSL, Arena, ProModel, Simul8 and FlexSim among more than sixty commercial simulators.

In this research, a framework and open source software called the Java Simulation Library (JSL) is used as a simulation environment. The JSL has been used in a number of researches and educational settings; however, its implementation has not been fully described in the literature except through its many applications (Rossetti, 2008).

This paper uses a simulation model as an objective function in the search for optimal solutions. The key indicator defined by the analyst is collected in the simulation model which should be maximized or minimized. Detailed information about the infrastructure (*e.g.* rail segments capacities, disturbances, preventive maintenance, number of trains, headway, etc) are necessaries to specify the input data for the simulation model.

3.2 Optimization Approach

Simulation-Optimization and its applications in railways: Simulation-based optimization stands for a programming problem (usually a stochastic one) whose objective function is evaluated by means of an experimental simulation. Due to the complexity and the stochasticity considered within the simulation, the objective function is (i) usually subject to several levels of random noise, (ii) not necessarily differentiable, and (iii) expensive to evaluate from the computational standpoint. It is intuitive that simulation optimization problems can be intractable if the optimization problem has a large number of variables and/or the simulation involves many parameters and many interactions to be described. The mathematical formalization and the computational complexity of optimizing via simulation is clearly described in (Fu, 1994; Fu, 2002).

In the field of railway systems, simulation-based optimization has been used to face different problems regarding the design of both train operations and infrastructure. A method for robust timetabling is introduced by (Kroon et al., 2008) which adopts a stochastic optimization model to allocate time supplements and buffer times in a timetable in order to make it robust against stochastic disturbances during real operations.

It is important to emphasize that this work treats the duplication railway sequence as a classic problem of permutation considering as an NP-hard problem in combinatorial optimization. (Kang et al., 2014) mentions that the MHs more used to similar permutation problems, such as the Travelling Salesman Problem (TSP) are: Tabu-Search (TS), Greedy Randomized Adaptive Search Procedure (GRASP), Simulated Annealing (SA), genetic Algorithm (GA), and Colony Optimization Algorithm (COA).

3.3 Optimization Approach for DSP in Railways

In this paper, three approaches were explored:

Genetic Algorithm: Genetic techniques were chosen because of their suitability in optimizing non-polynomial (NP) complete problems. GAs have already been used for symbolic layout, (Fourman, 1985), and work scheduling (Davis, 1985).

Chromosomes were constructed in which each gene represents the segment to be duplicated in chronological order. Connected with each chromosome is a fitness represented by the amount of discharged trains which is collected from the simulation model. The method use a population of chromosomes, each chromosome is tested and a fitness is evaluated. A new population of chromosomes is bred from the current population, with the parents chosen on a fitness basis.

Each generation was evaluated in the following manner: it is created an initial population which is randomly generated with one hundred duplication rail sequences. Then each member of the population is then evaluated and a fitness for that individual is simulated.

In the selection stage the current population is improved discarding the bad designs and only keep the best individuals in the population. The basic idea was fitter individuals were selected for next generations. During crossover new individuals or duplication sequences were created by combining aspects of our selected individuals. This 'combining aspects' is to cross two individuals and create two new sons who combine part of the chromosome from their parents. The goal is that this aspect combination between individuals create an even 'fitter' offspring which will inherit the best traits from each of their parents. To add a little bit randomness into our population's genetics it was implemented a mutation state which typically random swaps were done to individuals genome. Now we provide our next generation and we can start again until a termination condition.

Tabu-Search: The tabu search (TS) is a deterministic metaheuristic based on local search (Glover, 1986), which makes extensive use of memory for guiding the search. Basic elements of a tabu search are the concepts of move and tabu list, which restrict the set of solutions to explore. From the incumbent solution, non-tabu moves define a set of solutions, called the neighborhood of the incumbent solution. At each step, the best solution in this set is chosen as the new incumbent solution. Then, some attributes of the former incumbent are stored in a tabu list (TL), used by the algorithm to avoid being trapped in local optima and to avoid re-visiting the same solution. The moves in the tabu list are forbidden as long as these are in the list, unless an aspiration criterion is satisfied. The tabu list length can remain constant or be dynamically modified during the search.

Simulated Annealing: SA has been adopted widely to solve engineering problems,*e.g.*, trains platform problem (Kang et al., 2014), transit network optimization problem (Zhao and Zeng, 2006), and bottleneck routing problem at railway stations (Wu et al., 2012), etc. The SA starts from an initial solution at a high temperature, and makes a number of changes according to annealing schedules. For any two iterations, there are two objective values marked as few and fold, and the difference between the objective values (Δf - fnew - fold) is calculated.If Δf¡= 0, then the new solution is accepted with probability ρ-1. Otherwise, it is accepted with a small probability ρm, ρ-exp(-Δf/T), where T is the current annealing temperature (Kang et al., 2014). As the cooling proceeds to the set frozen point, the algorithm terminates.

4 DOTSIM METHODOLOGY

In this paper, we propose the DOTSIM methodology to aid finding solutions with high quality in duplication sequencing problem in complex transportation systems. Our methodology has the following characteristics:

(i) We assume that the methodology can be applied for any onshore freight and passengers transportation system such as: railways, LRVs (Light Rail Vehicles), highways, roads, public transportation (e.g. subway), etc, that is experiencing a need to increase its capacity of transport so as to support an increase in demand.

(ii) The objective function is strictly a simulation model inside a optimization loop.

(iii) Our methodology is meant for both researchers and practitioners and those users having a basic knowledge of simulation and optimization techniques.

We distinguish the relationships among simulation model, definition of the problem, optimization techniques and linear analytical method (LAM) in figure 3.

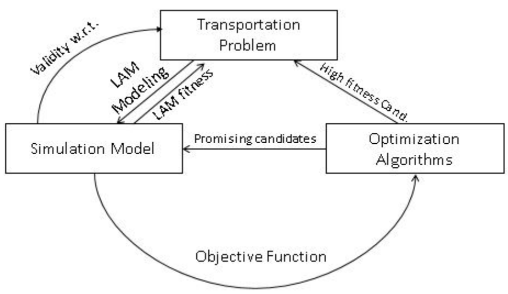


Figure 3: Simulation model, definition of the problem, optimization techniques and LAM.

A transportation problem is a transportation system (real or proposed) that can be modeled. *A simulation model* is a casual model of infrastructure of the transportation system; this model may have deterministic or stochastic variables as inputs. It tests duplication sequence candidates coming from the optimization algorithms and the own transportation system through the LAM and works as an *objective function*. *The optimization algorithms* are the MHs which will choose promising candidates to the simulation model and receive feedbacks with the candidate's fitness. Candidates with high quality fitness are ranked by the MHs and compared with a LAM with is measured by the Simulation Model. *Validation* is a key part of the methodology because it confirms that the model works in accordance with the analyst's objective. Figure 3 shows that validation of a simulation model relates to the transportation system, where w.r.t. stands for 'with respect to' (for validation of simulation models see (de Freitas Filho, 2001)).

5 MATHEMATICAL MODELING

A railroad train analyses the capacity of the railway line by measuring the practical and theoretical capacity of the rail network. The theoretical capacity is considered as the maximum limit to the number of trains that can simultaneously navigate a particular stretch, also known as a theoretical maximum capacity.

The theoretical maximum capacity is characterized by the temporal spacing between trains, which depends on the commercial speed of each train, travel times and resources offered by signaling and existing licensing systems.

In the case of simple line, the interval between trains is proportional to the distance between consecutive intersection of deviations away from the one that can be counted among axes of stations, or between a starting signal consecutive patios (when there is appropriate signaling system, or when you can compute the blocking times of simple line).

The maximum theoretical capacity can be equated by the following mathematical expression:

$$C = \frac{24}{T} \tag{1}$$

The C means capacity in number of trains/day and the T means Travel time between shifts , round trip ("headway").

The value of the capacity is inversely proportional to the travel times between shifts (equation 1). The lower capacity snippets generate critical sections or bottlenecks that determine the flow capacity of the entire line.

Traffic or flow capacity of a rail section is defined by the number of trains which may move within a given time interval (BRINA, 1982). The author indicates two possibilities of calculation , one through the actual graphic movement of trains and analytically by Colson method , according to equation 2.

For this method, (BRINA, 1982) indicates the need to use a factor that differentiates the rail according to its efficiency, ranging from 60% to 80%, termed ”K” factor. Addition of (BRINA, 1982), (Kraft, 1982) mentions that this K factor can vary between 60% and 75%. (Krueger et al., 2000) quoted in (Barros, 2013), cites that this parameter, the value of the factor K, is the capacity that can be permanently provided under normal operating conditions and is approximately 2/3 of the theoretical capacity.

However , (Krueger et al., 2000) quoted in (Barros, 2013), uses three different definitions to classify the types of capacity in evaluating the performance of a railway system, unlike Brina, as follows: theoretical capacity, practical and used.

The theoretical capacity is defined by (Krueger et al., 2000) cited (Barros, 2013) as the number of trains that travel on a route in a given set period of time, under ideal conditions, characterized by a virtual scenario in which the trains have movement constant with minimum headway between them. This parameter expresses the maximum traffic capacity, whereas the movement of the trains is homogeneous throughout the day, they are spaced evenly and no interruptions in the system. To be a value obtained by empirical formula and does not consider the effects of traffic variation and operations is impossible to be practiced in real conditions.

The practical capacity is the number of boundary units that can move on the railway line with a certain level of reliability. A factor reflecting the conditions of circulation of different types of trains with distinct priorities, according to the accumulated traffic and other system conditions, it is a more realistic measure of capacity. How is the specific combination of infrastructure, traffic and operations to move the maximum amount of products with a level of service and predetermined reliability is the most significant media capacity of the rail system. (Krueger et al., 2000)

The following mathematical formula that expresses the above definition:

$$C = k * \frac{24 - Tm}{Ts + Td} \tag{2}$$

In this case the Tm means time allowed for the maintenance of permanent way, Ts rise time or loading transit, Td fall time or unloading transit and K a operational efficiency factor.

Table 1: SUBSCRIPTS AND PARAMETERS.

Symbol	Definition
C	Traffic of flow capacity of a rail section
Tm	Time allowed for the maintenance of permanent way
Ts	Rise time or loading transit
Td	Fall time or unloading transit
K	Operational efficiency factor

6 CASE STUDY: DEFINING BEST DUPLICATION SEQUENCE OF SINGLE-TRACK RAILWAYS IN ORDER TO INCREASE CAPACITY OF TRANSPORTATION

Companies have used LAMs to obtain optimal solutions for railways duplication strategy. In this method, the single-track segments that are prioritized in an ’optimal’ sequencing. That sequence is the one which has the lowest ratio between practical capacity (trains/day) and demand (also trains/day). In the case shown in table 2 there is a clear imbalance in the capacities of segments (column 2), which in practice is very common to happen because different altimetry profiles pathway, communities near the railway, bridges, viaducts etc.

Table 2: Practical Capacity versus Segment’s Demand (trains/day).

Segment	Practical Capacity	Demand	Balance
0-1	10.0	3.0	7
1-2	12.0	8.5	3.5
2-3	5.0	2.0	3
3-4	20.0	5.0	15
4-5	8.0	4.0	4

Given the results of table 3, the best strategy for doubling this railway would be:

For the above example with 5 single-track segments, it is possible to evaluate a combination of 5! different layouts or 120 possibilities. This complexity tends to increase in railways with large distances. For example, for a railway with 10 segments is possible to evaluate a combination of almost four million different duplication sequences.

It is common practice in companies find difficulty to duplicate a lot of single-track segments in a short

Table 3: Optimal Duplication Sequence by analytical method.

Segment	Priority
0-1	4
1-2	2
2-3	1
3-4	5
4-5	3

space of time, as this often conflicts with hand limitations of skilled labor, large equipment etc. Also the investments are very aggressive with values that fluctuate between 1.5 and 3.5 million dollars per kilometer of railway line built.

In an attempt to avoid processing a problem with this level of complexity with linear analytical methods, the *DOTSIM* is applied in order to identify the optimal solution to increase the capacity of a single-track railway.

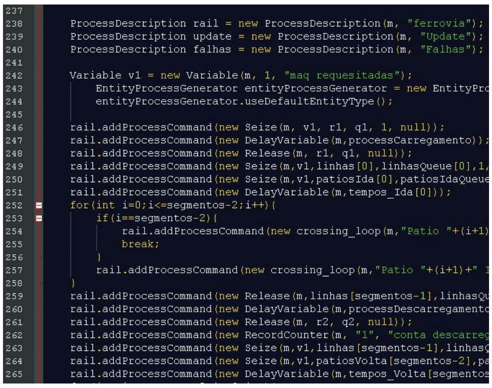
6.1 Modeling the Problem in JSL

In this paper an "own-built" model has been used to have a flexible simulation environment that can be effectively interfaced with mathematical tool-boxes for white-box optimization, this means to be flexible enough to implement optimization algorithms and to be adapted to the own needs of the user.

The framework used to model the railway is the JSL. For introduction of modeling a passing loop of JSL, was adopted a generic, hypothetical example. Entities (trains) coming into the system and make the discharge point of control or join a queue if it is busy. In this problem we have to study a system which transports a product from the loading point to the unloading point, with N passing loops or rail-houses (RH) following the premises of times and movements of the logistic system. The values of headway involved in the computational process were obtained randomly according to specific route and operating characteristics as well as happens in dynamics complicated systems or heavy-haul railways.

For all instances was adopted a saturation condition or heavy traffic in the system. For each duplication was adopted a period of 7 days. In order to ensure statistical confidence level was defined an amount of 10 replications, based on a tolerance of at least 90% through of the observation of the moving average fitness, a simulation model output.

The model was developed in JSL generically representing railways with up to N segments. In other simulation languages, this is a similar concept to opening a model building window (creating a model) and dragging and dropping simulation constructs into the model (Rossetti, 2008). Figure 4 presents the model for the railway system proposed. The class 'ferrovia' represents the entire system and can hold instances of segments.


```
ProcessDescription rail = new ProcessDescription(m, "ferrovia");
ProcessDescription update = new ProcessDescription(m, "Update");
ProcessDescription falhas = new ProcessDescription(m, "Falhas");

Variable v1 = new Variable(m, 1, "maq requesitadas");
    EntityProcessGenerator entityProcessGenerator = new EntityPro
    entityProcessGenerator.useDefaultEntityType();

rail.addProcessCommand(new Seize(m, v1, r1, q1, 1, null));
rail.addProcessCommand(new DelayVariable(m,processCarregamento));
rail.addProcessCommand(new Release(m, r1, q1, null));
rail.addProcessCommand(new Seize(m,v1,linhas[0],linhasQueue[0],1,
rail.addProcessCommand(new Seize(m,v1,patiosIda[0],patiosIdaQueue
rail.addProcessCommand(new DelayVariable(m,tempos_Ida[0]));
for(int i=0;i<=segmentos-2;i++){
    if(i==segmentos-2){
        rail.addProcessCommand(new crossing_loop(m,"Patio "+(i+1)
        break;
    }
    rail.addProcessCommand(new crossing_loop(m,"Patio "+(i+1)+" I
}
rail.addProcessCommand(new Release(m,linhas[segmentos-1],linhasQu
rail.addProcessCommand(new DelayVariable(m,processDescarregamento
rail.addProcessCommand(new Release(m, r2, q2, null));
rail.addProcessCommand(new RecordCounter(m, "1", "conta descarreg
rail.addProcessCommand(new Seize(m,v1,linhas[segmentos-1],linhasQ
rail.addProcessCommand(new Seize(m,v1,patiosVolta[segmentos-2],pa
rail.addProcessCommand(new DelayVariable(m,tempos_Volta[segmentos
```

Figure 4: Java code based on JSL for a railway model.

Stochastic disturbances were implemented in the JSL model by using a random routine creating events that make the segments unavailable or failed (also randomly). We defined to the railway system studied in this work, random distributions to represent the time between failures and deterministic time for the duration of the failure.

The JSL administer inputs data in the three following different interacting modules:

- *Infrastructure module:* Input data required by this module concern to tracks capacity (single or duplicated) as well as the railway duplication strategy setting up the order of each segment.

- *Rolling stock module:* Rail vehicles have been represented in this model by defining the amount of trains which are in the closed rail system.

- *Timetable module:* Import and export times between stations or passing loops with or without train stop, stay times inside the load and unload points, are all input data of this module.

The conception of the JSL rail model is based on (Araújo, 2013) which uses licensing rules, a set of rules and procedures to ensure the safe movement of trains.

6.2 Results

Results obtained for each instance are considered as the average of simulation results over the 10 different disturbed scenarios, or replications. The duplication sequence problem has been solved for all the scenarios, considering a comparison with the LAM for this problem.

In figures 5 and 6 are shown the evolution curves of the three MHs for 1000 iterations or generations in the case of GA. It is possible to achieve a gain of 10% in the first instance. Furthermore, it is possible to observe a decrease of this gain according to the increase of the amount of segments. This probably happens because the search space increases exponentially with more single-tracks in the problem as said in the section 5.

Figure 5 reports the results for each MH in the 3 instances. The genetic algorithm achieves the best results unanimously for all the scenarios. We can also analyze that the best result for the GA is achieved with almost 400 iterations and after that we see just a constant behavior (Fig. 7); in the figure 7 the blue line refers to the GA, orange line to SA and gray line to Tabu-Search.The tabu-search algorithm waits a little more to achieve its best result as well as the simulated annealing algorithm. This behavior is also observed in the other instances, with another conclusion which it indicates that the SA moves more away of the best candidates.

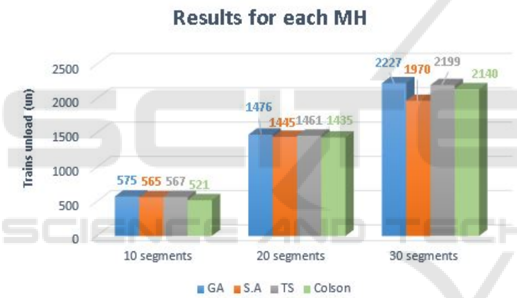


Figure 5: Ranking of Meta Heuristics for the railway duplication sequencing problem.

Another advantage for the GA is the computing time as shown in the table 4. The SA spent less time than the GA and Tabu-search but do not achieve the best candidate comparing with the LAM. The tabu-search spent a huge computing time to explore the search space specially in the 30-segments railway scenario.

Table 4: Computing times to solve the optimization problem (hours).

MH	10 segments	20 segments	30 segments
G.A.	3.7	16.5	40
S.A.	0.2	0.5	1.5
Tabu Search	10.3	45.4	140

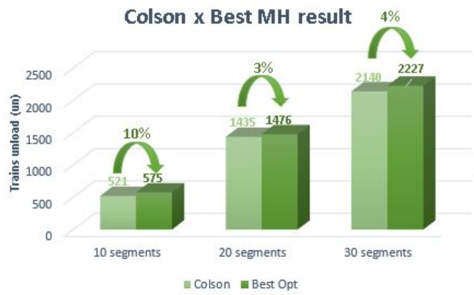


Figure 6: Comparison between best MH result and the LAM (Colson).

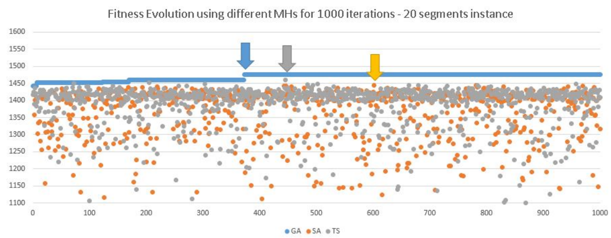


Figure 7: Fitness Evolution using different MHs for 1000 iterations - 20 instance segments.

7 CONCLUSIONS

Practitioners strongly need to increase the capacity level of freight transportation systems in order to meet growing levels in passengers and freight demand. To achieve this objective, to duplicate the routes of the system is sometimes necessary. Duplication sequencing problems are NP-hard optimization problems. Up to now both in practice and in scientific literature, companies and existing approaches have used analytical linear methods for a problem which is naturally complex and non-linear.

To solve this problem a simulation-based optimization methodology is presented which guides searching the optimal duplication sequence on routes of freight transportation systems.

A case study with different instances for railways is presented with the application of three MHs. The objective of this study is finding satisfactory solutions compared with analytical linear methods, which is relevant because it can help railway companies to minimize costs and to increase railway productivities. Furthermore, the duplication strategy in a whole railway can be defined by considering only a single optimization problem.

Results of models in different instances with N single segments and stochastic factors which maximize the number of unloaded trains during the construction period and which are also robust with respect to random operation disturbances show the ability of DOTSIM to search global optimal solutions for supporting duplication strategies in railways.

A comparison with analytical method underlined that the proposed method strongly increases the railway capacity and consequently decreases investment costs.

Further research will be addressed to evaluate more instances, more complex disturbances that can influence the integrated system, such as several load and unload points, exchange points etc.

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