# SCHEDULING OPTIMIZATION OF THE TUNISIAN RAILWAY NETWORKS TAKING INTO ACCOUNT PREDICTIVE TASKS 

Anis M'halla ${ }^{1}$<br>Mohammed Jawad Abed

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#### Abstract

Developments presented in this paper are devoted to the dynalic scheduling of railway transport systems. In this context, our study deals with the implementation of cooperative methodologies to solve railway scheduling problems with predictive or unpredictable demands. Stochastic P-time Petri Nets (SP-TPN) are used for modelling. A new scheduling method based on genetic algorithms and allowing the insertion of predicted jobs is presented, in order to improve a number of traffic criteria such as travel time, total cost and maintenance activities. The aim of the proposed insertion method is to integrate the forecasted demand operations in the availabilities of the rolling stock, in order to minimize the inactivity periods and to increase the traffic rate. Finally, to illustrate the effectiveness and accuracy of the insertion approach, an application to a Sahel Railway networks is outlined.


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## 1. INTRODUCTION

Scheduling consists in planning the execution of a series of tasks (or operations) on a set of physical resources (human and technical), seeking to optimize specific criteria (financial or technological) and respecting the manufacturing and organizational constraints.

In railway networks, a distinction can be made between the transport and management systems. The management system's duty is to "control and supervise" the transportation network by respecting a set of temporal and logistical constraints, in order to achieve specific objectives. While the transport system gathers all the resources needed to provide a service in order to satisfy the customers' needs.

The transport networks scheduling problem constitutes the main challenges of management and control system. Indeed, multiple and complex traffic characteristics must be taken into account as the internal (breakdowns of transport equipment, etc.) and external (climatic disturbances, accidents, strikes, etc.) disturbances.

The train scheduling is divided into two steps. The first is tactical planning, in which planners define the most appropriate service frequency for railway line, so that all travel requirements are met and specific targets are reached, e.g. maximizing passenger service quality and mitigating the rail operating costs. The second is timetable development, in which schedulers set planned train operations across the day, subject to network considerations and other constraints. The outcome of timetable development is a series of train journeys,

[^0]determined by the departure and arrival times from/to depot stations. Then, in the Rolling Stock (RS) allocation problem, the appropriate metro and fleet compositions are allocated to these trips, ensuring that the train capacity matches closely the request and that the fleet cost is kept to a minimum.

This article deals with the next step, where the rail network is redesigned following the established rolling stock allocation. Each train journey has a particular type and composition assigned to it. The aim of this step is to dedicate individual units of rolling stock (trains) to these journeys. This is done taking into account capacity, cost and maintenance requirements.

The aim of this paper is to contribute to the state of the art of the management and scheduling of railway transport system. In the category of the transport system concerned by this paper, the travelling operations have temporal constraints which must be strictly respected. The violation of these constraints can lead to traffic disruption and cumulative delays. To remedy this problem, a genetic algorithm allowing the insertion of predictive demands in the availability of machines, in order to reduce inactivity periods and to raise the traffic rate.

This paper is organized as follows. Section II presents the state of the art. In the subsequent section, the problem of the scheduling of the railway transport network is considered. An original management approach based on genetic algorithms is presented. Section IV presents the investigated rail transport system and the SP-TPN model of the Tunisian Sahel railway network. An application of the implemented scheduling approach to the investigated railway is featured. Lastly, a conclusion with some perspectives is provided.

## 2. STATE OF ART

Rail transport systems should be scheduled online to prevent emergency situations due to disturbances. These perturbations can affect the railway infrastructure or traffic management and they can lead to a the transport service declination. The problem consists in suggesting a scheduling system that optimizes traffic criteria and respect temporal and logistical constraints.

In this framework, diverse researches have been released on the scheduling of transportation systems to save time and enhance the railways service quality (Antov, 2020), (Younes et al., 2018), (Lv et al., 2020), (Moreno et al., 2019), (Mhalla et al., 2020) (Nemavhola \& Ramdass, 2017).

The authors in (Lima et al. 2015) propose a procedure which allows an intelligent planning and control of transport flows in seaport terminal. The transport scheduling performed by an agent at the intermodal
terminal was taken into consideration. The decisionmaking agent considers data acquired at distant points in the system. The results indicate the relevance of continuously considering, for transport scheduling and monitoring, the expected transit time and subsequent waiting times in port logistics systems.

The authors in (Moghimi \& Beheshtinia, 2021) study the optimization of the scheduling transport systems by simultaneously considering Delay Time (DT) and environmental pollution (EP). A bi-objective model is proposed to optimize the production and transportation process with the objectives of minimizing DT and EP using a Social Dynamic Genetic Algorithm (SDGA). Results clearly depict the efficiency of the proposed algorithm and model in the production scheduling and transportation systems with the objectives of minimizing DT and EP concurrently.

For railway planning, authors in (Zhao et al., 2021) propose an approach to optimize Line Planning Problem (LPP) for the High-Speed Railway (HSR) network to provide higher service level for time-varying demand. A bi-level programming model based on Stackelberg game theory is constructed, incorporating passenger flow assignment into line planning. The model is solved under the framework of Simulated Annealing Algorithm (SAA) by a decomposition searching strategy combining the efficiency evaluation of in-line sub plans and the whole network line plan to improve the stability of solutions. The preliminary obtained results are promising.

In (Khadilkar, 2018) the author describe an algorithm for scheduling bidirectional railway lines using a Rinforcement Learning (RL) approach. The tenet is to determine the track allocations and arrival/departure times for all trains on the line, given their initial positions, priority and traversal times, by reducing the total priority-weighted delay. The advantage of the algorithm compared to exact approaches is its scalability, and compared to heuristic approaches is its solution quality. To illustrate the efficiency of the proposed approach an application to Indian rail network is done.

Other scheduling approach based on the Multimodal Alternative Services for Possessions (MASP) problem is presented in (Borecka \& Bešinović, 2021). The concept is to provide the planning of alternative services, from the passenger and transport operator points of view, including adjustable train timetable, bus bridging services and extra train services. The MASP issue is developed based on the service network design and the vehicle routing issues.

All previous studies are quite different from our work. The aim of this paper is to try to optimize scheduling taking into consideration forecasted demand operations in order to increase the availability of the Electrical

Multiple Unit (EMU). This is done by inserting genetic algorithms. This work is a contribution to the current state of art of the railway scheduling challenge and discusses a situation where the journey time is bounded. By analyzing the presented scheduling approach, this article can offer an insight to infrastructure planners of complicated railway networks where there is an escalating demand for track use and there is increased pressure to extend the operating time, thus reducing the available maintenance infrastructure.

## 3. DYNAMIC SCHEDULING OF A RAILWAY TRANSPORT NETWORK

Given a set of unexpected events/ tasks, it is interesting to investigate appropriate scheduling to reduce traffic disruptions. Hence, the impartial aims of scheduling are: mitigating disruptions in the equipment operation/service program and avoiding disastrous scenarios by preserving the stability and safety of the investigated railway networks.

A scheduling is defined as a procedural method elaboration which enables provisional jobs insertion into previous planned solutions, while optimizing a certain parameters number. Two insertion methods can be distinguished: static and dynamic.
Static insertion methods permit:

- the forecasted demands integration in the machine availability to diminish downtime and improve productivity, specific operations rescheduling, if the machine availability is insufficient, to reduce the total production time of all jobs.

The dynamic methods enable:

- rescheduling of incoming requests when job specifications change. This is the case when it
is required to generate machine availability by postponing elective operations in order to accommodate urgent work or requests with tight delivery times.


### 3.1 Dynamic scheduling principle

A dynamic scheduling operation insertion problem can be described by the following fundamentals:

- a firm task scheduling problem defined by a set of resources, jobs and constraints,
- a sequence of operations $S$ for this scheduling problem,
- an operation $\mathrm{O}_{\mathrm{ij}}$ not involved in the initial scheduling problem.

The operation $\mathrm{O}_{\mathrm{ij}}$ insertion problem is equivalent to proposing a new operations sequence for a problem which is defined by the firm task scheduling to which an operation $\mathrm{O}_{\mathrm{ij}}$ is inserted.

To deal with this issue, an alternative approach in the railway transport systems consists in solving the new scheduling problem by minimising the insertion impact of firm task on the total travelling time and transport cost. The target is to insert $\mathrm{O}_{\mathrm{ij}}$ into the scheduling system respecting the following constraints:

- No change in the allocation of scheduled operations,
- Minimal violation of the end dates of the previously scheduled operations.

In the studied transport network, the insertion problem can be decomposed into two sub-problems: the assignment problem (metro selection) and the scheduling problem (position selection) of this operation, figure 1.


Figure 1. Dynamic insertion principle

This section suggests a dynamic scheduling concept for studying the rolling stock travelling cycle time by implementing unexpected jobs in a railway network. The planning method enables the inclusion of preventive/emergency requests when the EMU is available in order to raise the railway traffic rate. In this regard, a genetic algorithm enabling the insertion of projected jobs in the availability of transport equipment periods, by modifying the initial planning solution will
be discussed in the following section. An implantation of the scheduling method to a Tunisian railway network will be carried out.

### 3.2 Dynamic scheduling problem components

The dynamic scheduling problem is founded on the following concepts:

- the human-machine resources availliblity,
- the endogenic and exogenous constraints,
- optimisation criteria choice.

Endogenous constraints represent requirements directly associated with the transport system and its efficiency. These include transport equipements availability and excuted travel sequences. While exogenous constraints include externally imposed constraintes, independently of transport system, such as journeys due dates usually imposed by scheduling supervisor, priority jobs and trips delays.

For the dynamic planning, there are two main optimization criteria: time and cost. The first criterion concerns the supervision of tasks completion date imposed by the scheduling layer and the optimizing of trips delays. The second includes the rolling stock operating costs, the maintenance and unforeseen accidents charges.
The most used criteria to judge the schedule quality are:

- The total duration " $C_{m a x}$ ", is equivalent tothe last task's completion date: $C_{\max }=\max _{j \in J}\left(C_{j}\right)$, with $C_{j}$ represent the date of the journey $j$.
- Latest end date: In the investigated transport system, it is necessary to respect latest end dates, this is accomplished by minimizing delays $D_{\max }=\max _{j \in J}\left(D_{j}\right)$ with $D j$ the delay related to the journey $j$.
- Cost minimization: this criterion can be applied in several forms by minimizing cumulated delays, maintenance and travel cost reducing, etc.

Rail companies must provide traffic quality in response to increasingly uncertain requirements. For these
companies, management issues are vital. Few works has been carried out on predictive planning of rail traffic, leading to approaches allowing the traffic schedule definition and balances planned workloads with available transport resources. Therefore, it is imperative to keep time, deadlines and costs to a minimum, even if this involves a risk by integrating precarious assignments.

In rail transport networks, two classical combinatorial optimization problems arise:

The first is the linear assignment problem, since an itinerary can be performed by one or more metros with different running times. The second consists in finding an appropriate execution order for these trips though respecting all time constraints and unpredictable orders/requests.

### 3.3 Genetic algorithm and scheduling

This section is devoted to the presentation of genetic algorithms used to solving firm scheduling problems in rail transport networks

## A/ Principle

Genetic algorithms (GAs), more generally referred to evolutionary algorithms (EAs), include various stochastic optimization methods. They involve developing individual population with stochastic operations (crossover, mutation, selection), figure 2. Such algorithms can be applied to monitor system evolving over time, such as a production line, transport system or nuclear production line, as the population can accommodate changing conditions.


Figure 2. Genetic algorithm principle

The GAs aim is to identify the most appropriate elements in view of optimizing some system parameters (cost, time, delays...). At each iteration, a new population is created, using the best elements parts of the previous generation, as well as innovative parts, figure 2. Genetic algorithms efficiently exploit the information obtained previously to predict the new point
position to be explored, with the expectation that the new individuals will gravitate towards the evaluation function optimization.

These algorithms are particularly advantageous for complex problems, such as scheduling issues (Abbasi et al., 2020), (Zhang \& Huang, 2018), (Kaffash et al.,
2021), (Mfenjou et al., 2018), for which mainly deterministic techniques frequently fail owing to time constraints (Köksal et al. 2022), (Gola \& Kłosowski, 2019), (Hina et al. 2022), (Zhang et al., 2018), (Fazayel et al., 2018), (Fazayeli et al., 2018), (.

## B/ Insertion method with machine availability extended windows

The proposed genetic algorithm empowers to insert the forecasted jobs into the machine availability periods with modifying the initial scheduling solution. There are several priority rules for inserting jobs into a production schedule. These include the PST rule (Priority to the operation with the Shortest execution Time) the PLT rule (Priority to the operation with the Longest execution Time), the PDD rule (Priority to the operation with the smallest Delivery Date).

In our problem, the ECT (Earliest Completion Time) heuristic was employed in the proposed algorithm, which considers as a priority the EMU availability period with a shortest completion time operation. This intuitively aims to reduce the process end date ( $C_{\max }$ ).

## Notations

The following notations are used throughout the paper to describe the studied problem,
K : Metro index , $\mathrm{k}=1, \ldots, \mathrm{~K}$, where Kis the number of metro (EMU),
j : Index for travelling time, $\mathrm{j}=1, \ldots, \mathrm{~J}$, where J is the number of travelling time
i: Index for predictive/ unpredictable Jobs (PJ), $\mathrm{i}=1, \ldots, \mathrm{I}$, where I is the jobs number.
STj :Starting travelling time j of a metro k
ETj: Ending travelling time j of a metro k
STpI : Starting time of predictive job i
ETpJ: Ending time of predictive job i
Ak : Availability interval of EMU k
$\mathrm{C}_{\text {max }}$ the last task's completion date
$P_{P \mathrm{Pk}}=1$ Insertion ability of PJ for EMU k
Ootherwise


Algorithm
For ( $\mathbf{i = 1 ;} \mathbf{i}<\mathbf{I}$ ); $\mathbf{P}_{\text {PJk }}=\mathbf{0} ; \mathbf{A}_{\mathrm{k}}=\varnothing$
For ( $k=1 ; k<K$ )
If
\{
$\mathrm{C}_{\text {max }}=\operatorname{Inf}_{\mathrm{k}}\left(\sum_{\mathrm{j}=1}^{\mathrm{J}}(\mathrm{ETj}-\mathrm{STj})\right)$
$\mathrm{PJ}_{k} \subset \mathrm{~A}_{\mathrm{k}}$ (The operation's insertion period corresponds to the EMU availability) Checked Time constraints
then
$\mathrm{P}_{\mathrm{PJ}}=1 ; \mathrm{ECT}_{\mathrm{k}}=\sum_{\mathrm{i}=1}^{\mathrm{I}}\left(\mathrm{ET}_{\mathrm{PJ}}-\mathrm{ST}_{\mathrm{PJ}}\right)$
(Earliest Completion Time for a EMU k)
\}

## End

Insert a predictive job on the EMU $\mathrm{k}\left(\mathrm{PJ}_{\mathrm{k}}\right)$
Shifting the next scheduled operations to the right if necessary
End
Redo the same procedure for all Metros.

## 4. CASE STUDY: DESCRIPTION AND INTERPRETATIONS

### 4.1 Sahel Railway Network A/ Overview

Tunisian National Railways Company (TNRC) is a state owned company, which operates the Sahel railway line, linking the main cities of the Tunisian Sahel region. It begins from the Sousse station crosses Sahline until Monastir station, figure 3. The Sahel Metro has an average frequency of 40 minutes and a daily traffic of 16 hours.


Figure 3. The Sahel Railway Network

## B/ Modelling of the railway transport system

In the reviewed transport system, travelling times should be respected. Stochastic P-time Petri Nets (SPTPNs) are convenient tools for modelling the investigated railway system where the journey times are inaccurately.

Definition 1 (Khansa et al.,1996): A SP-TPN system is a triplet<R, IS, IR>where:

- R is a Petri net system,
- IS : $\mathrm{P} \rightarrow \mathrm{Q}^{+} \times\left(\mathrm{Q}^{+} \cup\{+\infty\}\right)$ such that $\mathrm{IS}_{\mathrm{i}}=\left[\mathrm{a}_{\mathrm{i}}\right.$, $b_{i}$ ] with $0 \leq a_{i} \leq b_{i}$ is the static interval associated to the place $p_{i}$.
- IR: $\mathrm{P} \rightarrow \mathrm{Q}^{+} \times\left(\mathrm{Q}^{+} \cup\{+\infty\}\right)$ such that $\mathrm{IR}_{\mathrm{i}}=\left[\alpha_{\mathrm{i}}\right.$, $\beta_{\mathrm{i}}$ ] with $\mathrm{a}_{\mathrm{i}} \leq \alpha_{\mathrm{i}} \leq \beta_{\mathrm{i}} \leq \mathrm{b}_{\mathrm{i}}$ is the dynamical interval associated to the place $p_{i}$.

The main purpose is to develop a model able to replicate the railway traffic behavior. According to the measurements extracted from the TNRC Supervision Control And Data Acquisition (SCADA) system, a SPTPN model (M) is builded, Figure 4 (see Appendix 1). In this model, the token denotes the rail traffic on the considered network and for each place; we respectively designate $\left[a_{i j}, q_{i j}{ }^{e}, b_{i j}\right]$ the lower time window boundary, the expected token residence time and the upper time window boundary. All static intervals and sojourn time are summarized in Table 1 (see Appendix $2)$.

As the sojourn times in the places have not the same functional meanings, a split of the SP-TPN model into three sets is done, figure 4:

- $\mathrm{J}_{\mathrm{T}}$ : the set of places representing the journey between two successive stands. Time associated to these places represent travel durations.
- $\quad \mathrm{R}_{\mathrm{s}}$ : the set of places depicting railway stations. Each place has an assigned parking time.
- $\mathrm{T}_{\mathrm{p}}$ : ensemble of places indicating the metro's traffic pattern

This functional decomposition is carried out in order to study the scheduling problems in railway transport network. It is not a valid proof for all transport topologies. We only claim that it corresponds to a good decomposition for many railway systems.

### 4.2 Dynamic integration of a predictive job in railway networks

## A/ Cyclic scheduling of a journey between Sousse and Monastir stations

The figure 5, shows the metro itinerary and the precedence constraints in the studied Sahel railway networks, and can easily check the time windows associated to each travel and standing operation. For 1cyclic scheduling, the travel operations are repetitive throughout the day. Thus it suffices to study the processing activities in one cycle time rather than considering the whole traffic period activities.

Taking the example of travel itinerary associated to the "metro 1" with the sojourn operation $\left(\mathrm{P}_{45}\right)$ as its first transaction. According to the effective sojourn time " $\mathrm{q}_{\mathrm{i}}{ }^{\text {e" }}$ " (table 1), the travel cycle time associated to this path (from Monastir to Sousse) is 1851 unit time (u.t), figure 5. The time windows associated to each travel and sojourn operation limits on what proportion time and/or distance the metro will operate before the next compulsory Inspection/control.


Figure 5. Journey and staying time Scheduling

## B/ Dynamic integration of a predicted operation

The proposed scheduling, figure 5, displays inactive metro periods (parking time at main stations; represented by $\mathrm{P}_{45}$ and $\mathrm{P}_{63}$ ). The main aim is to take benefit from these inactivity periods to start predictive tasks (inspection, control,...). Thus, this approach is used to embed predictive or unpredictable demands in subway availability period, taking account of the existing scheduling solution.

Considering the following example of the itinerary 1 , connecting Monastir to Sousse station. The figure 6, represent an integration of two additional jobs (Job1 and Job 2) representing a sequence, of Daily Inspection (DI). Indeed a metro must undergo a DI after operating for one or two days or for ten thousand kilometers before it can circulate again. The inspection duties insertion must inevitably respect the transport scheduling and the time constraints. Theses inspections have a mean duration of 20 to 30 minutes and they are performed by an expert.


Figure 6. Maintenance scheduling of EMU

Based on the proposed dynamic railway scheduling approach, the mission of a railway manager is to identify the subway itinerary that spans all scheduled journeys and mitigates the operating costs, while respecting the maximum travel time and distance before inspections. Assuming that each train journey has been allocated, a trade-off for satisfying the demand and maintenance allocation problem attempts to identify each metro journey whereby the inspection constraints mentioned above are satisfied.

## Remarks

- The genetic algorithms development has enable to enhance the scheduling quality by embedding predictive tasks in the transport equipment
availabilities as well as to enhance the human/machine interaction, via a scheduling support system by assigning criteria preferences in the context of amulticriteria system. This cooperation must be narrow and cover certain scheduling aspects.
- After scheduling the firm jobs (for example Job 1, figure 6), a shift can be generated if the availability does not correspond to the operation's execution time. Thus, the dynamic insertion method based on genetic algorithms may lead to the initial scheduling solution change.
- The dynamic scheduling approach can be surely applied to other transportation systems, although it fails to cover the defect progression: Daily/weekly inspections may not enable the determination of
fault triggering or damage quantification, however they may be valuable in prompting preventive and corrective maintenance tasks.


### 4.3 Simulation and validation of the dynamic scheduling method

Referring to the SP-TPN model, figure 4 (see appendix), where the marks represent the subway location and the transitions firing correspond to metro passage times, two figures $7 \mathrm{a} \& \mathrm{~b}$ is built, for an itinerary linking the Monastir and Sousse stations, with the CPLEX 12.5 on a computer with Intel (R) at 2.6 GHz and 2 GB RAM. This temporal study based on simulation is carried out during the July month, 2022.

Both figures depict the metro positions in the Sahel rail network ( Y axis) over time ( X axis). As shown in figure 7 a , according to the measurements extracted from the TNRC SCADA system (taken the $1^{\text {st }}$ july), the dispersion rises with time due to the integration of a set of predictive or unpredictable jobs in the railway transport equipment availability. Thus the tokens scattering reflect delays caused by the inclusion of daily inspection tasks since the scheduling of firm jobs can generate occasionally a shift if the availability does not correspond to the operation's execution time.

The application of the dynamic insertion method throughout the July month enabled to reduce this dispersion. As a result, figure 7 b , a simulation performed on 31 July, reveals that these discrepancies and temporal disturbances have been reduced in the operating time.


Figure 7. Metro itenerary from Monastir to Sousse Station without and with dynamic scheduling

In our research, we considered the fact that the Sahel railway line has more than twenty five metro daily trips between the depots. Thus, the inspection periods are reduced and only short duration are considered.

## 5. CONCLUSION

The main paper's contribution is the dynamic insertion of a set of predictive or unpredictable jobs in the railway transport equipment availability. In this regard, a genetic algorithm enables the insertion of a range of urgent actions is developed. The purpose is to keep operating costs and penalties associated with waiting times and maintenance by keeping the trains' scheduling.

In order to take into account, at the scheduling level the command uncertainty, the proposed algorithm allows integrating these jobs into the machine availabilities. To this end, the scheduling must be done chronologically and accept slight modifications in the obtained solutions. The objective is to minimize the insertion impact on the total journey time and the travel cost in the transport system. This embedding method demonstrates the optimal scheduling of unexpected and urgent tasks allowing optimizing transport criteria. The highlight of the newly insertion method is the incorporation of daily inspections actions and the achievement of a real-time scheduling of these acts in compliance with the transport constraints.

The GA algorithms, as a combinatorial search method, provide a set of efficient search heuristics in complex
spaces, requiring no in-depth knowledge of the field under consideration. The proven integration approach enabled the inclusion of supplementary forecasted jobs in the rolling stock availability with the flexibility to amend the original scheduling solution. This strategy allows, in the poorest case scenario, to proceed with the traffic in degraded mode.

When time disturbance occurs in railway networks, it is crucial to intervene in real time to sustain traffic stability and prevent overlaps, delays and train collisions. It has been shown that genetic algoritm has a meaningful contribution to this problem, by making the real scheduling more efficient. This is very relevant for the maintenance task.

The results obtained in this manuscript are very promising. It would be interesting to develop further aspects, which are envisaged in our future research work:

- Systematic experimentation of this insertion method to study its efficiency according to the predicted job features
- Application of the newly proposed approach to other optimization problems, such as organization problems in port and aeronautical terminals, telecommunication networks.
- Application of genetic algorithms to the insertion of forecasting demands into equipment availabilities, as well as the case study of demand withdrawals before the optimization is completed.


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## Anis Mhalla

National Engineering School of Monastir
(ENIM),
Monastir
Tunisia
anis.mhalla@enim.rnu.tn
ORCID: 0000-0002-7703-8205

## Mohamed Jawad Abed

National Engineering School of Monastir
(ENIM),
Monastir
Tunisia
mohammedjwad54@gmail.com
ORCID: 0000-0002-6498-4315

## APPENDIX:

## Appendix 1:



Figure 4. Railway network modeled by Stochastic P-time Petri Net

## Appendix 2:

Table 1. Staying and travelling times

| Place | $a_{i}$ | $b_{i}$ | $q e_{i}$ |
| :---: | :---: | :---: | :---: |
| 45 | 48 | 63 | 58 |
| 46 | 128 | 222 | 161 |
| 47 | 36 | 44 | 38 |
| 48 | 131 | 439 | 322 |
| 49 | 28 | 32 | 30 |
| 50 | 29 | 344 | 74 |
| 51 | 28 | 32 | 30 |
| 52 | 79 | 213 | 146 |
| 53 | 38 | 42 | 40 |
| 54 | 30 | 140 | 91 |
| 55 | 28 | 32 | 30 |
| 56 | 148 | 238 | 184 |
| 57 | 28 | 32 | 30 |
| 58 | 167 | 386 | 247 |
| 59 | 28 | 32 | 30 |
| 60 | 150 | 312 | 216 |
| 61 | 28 | 32 | 30 |
| 62 | 9 | 131 | 44 |
| 63 | 48 | 52 | 50 |
| 64 | 89 | 242 | 119 |
| 65 | 28 | 32 | 30 |
| 66 | 149 | 285 | 217 |
| 67 | 28 | 32 | 30 |
| 68 | 149 | 280 | 222 |
| 69 | 28 | 32 | 30 |
| 70 | 148 | 227 | 175 |
| 71 | 28 | 32 | 30 |
| 72 | 19 | 103 | 79 |
| 73 | 38 | 42 | 40 |
| 74 | 89 | 178 | 132 |
| 75 | 28 | 32 | 30 |
| 76 | 29 | 118 | 74 |
| 77 | 28 | 32 | 30 |
| 78 | 319 | 406 | 344 |
| 79 | 38 | 42 | 40 |
| 80 | 471 | 889 | 668 |


[^0]:    ${ }^{1}$ Corresponding author: Anis Mhalla
    Email: anis.mhalla@enim.rnu.tn

