A Key Performance Optimization Agent-based Approach for Public Transport Regulation

Nabil Morri[1,3][a], Sameh Hadouaj[2,3][b] and Lamjed Ben Said[3][c]
[1]IT Department, Emirates College of Technology, Abu Dhabi, U.A.E.
[2]Computer Information Systems Department, Higher Colleges of Technology, U.A.E.
[3]SMART Lab., Institut Supérieur de Gestion de Tunis, Université de Tunis, Tunisia

Keywords: Intelligent Transportation System, Multi-agent System, Optimization, Control Support System, Simulation.

Abstract: Today's, an efficient and reliable public transport system becomes essential to assist cities in their wealth creation. However, public transportation systems are highly complex because of the modes involved, the multitude of origins and destinations, and the amount and variety of traffic. They have to cope with dynamic environments where many complex and random phenomena appear and disturb the traffic network. To ensure a good quality service, perturbations caused by these phenomena must be detected and treated within an acceptable time frame via the use of a control system. The control process should rely on many criteria related to the traffic management of public transport: Key Performance Indicators. In this paper, we introduce a Regulation Support System of Public Transport (RSSPT) that detects and regulates the traffic perturbation of multimodal public transportation. The system uses optimization techniques to solve the control problem. We based our regulation support system on a multi-agent approach to cope with the distributed nature of the public transportation system. To validate our model, we conducted tests by simulating perturbation scenarios in a real traffic network. A comparison between real data and the obtained results shows an improvement in the quality service.

1 INTRODUCTION

The study of public transportation systems has changed significantly during recent years in modeling and simulation. In particular, the increasing use of vehicles, and the amplification of the public transport system with different modes (bus, metro, tram) make traffic management more complex. This complexity is due to the difficulty of respecting the scheduled timetable of vehicle departure and the potential for traffic perturbation, particularly when these perturbations are not effectively managed. Therefore, to improve the quality service for the passengers, a control support system should be built. Its main objectives consist of detecting disturbances and regulating the traffic of public transport within an acceptable time. Performance evaluation is essential in order to assess and monitor the quality service of public transport. This performance is formulated in terms of key performance indicators (KPIs). It should provide comparative information that enables the control system to identify the performance gaps and set targets and measures to fill them. In the case of perturbation, the control system has to know what quality service is expected, then proceed to optimize KPIs and regulate the traffic of public transportation towards these targets. Consequently, a good control system should take into account key performance indicators (KPIs) for public transportation traffic management to detect and identify the optimal control action. The efficient optimization method improve the traffic management of public transport in case of perturbation.

The purpose of this work is to model and implement a system that detects public traffic perturbations and provides control action based on the KPIs optimization.

This paper is organized as follows. Section 2 describes the key performance indicators for traffic

[a] https://orcid.org/0000-0002-1642-9309
[b] https://orcid.org/0000-0002-6743-4036
[c] https://orcid.org/0000-0001-9225-884X

Morri, N., Hadouaj, S. and Ben Said, L.
A Key Performance Optimization Agent-based Approach for Public Transport Regulation.
DOI: 10.5220/0009417202520259
In *Proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2020)*, pages 252-259
ISBN: 978-989-758-419-0

management of public transportation. Section 3 introduces the related works with their limits. Section 4 details the performance measurement formulas. Section 5 refers to the optimization approach. Section 6 describes the multi-agent modeling. Section 7 presents experimentations and results. In section 8 we give a conclusion and perspectives for the future works.

2 KEY PERFORMANCE INDICATORS FOR TRAFFIC MANAGEMENT (KPI)

In the absence of standard significance of performance measures, it is difficult to assess the effectiveness of the control system and the accuracy of the chosen control action. In the context of road traffic, different Key Performances Indicators (KPIs) were identified to evaluate the service quality related to traffic. The challenge in defining KPIs is to select the right keys that will give a sufficient accepting of overall performance on public transportation.

Four strategic themes of urban traffic management have been tackled in the white papers by the European Commission's strategy on the future of transport (European Commission, 2011): traffic efficiency, traffic safety, pollution reduction, and social integration and land use. It is expected that these themes would act as a long-term reference and manual for performance measurement of urban traffic management and Intelligent Transport System (ITS). In the context of this study, reference is made to traffic efficiency KPIs, as the aim is not to measure a complete set of performances, but rather focus on key ones that will provide a sufficient understanding of quality service offered to the passenger in public transportation and relative comparisons in the control process. These KPIs concern only mobility, reliability, operational efficiency, and system condition on public transportation while ignoring private transportation. Mobility is mainly concerned with the travel time on the trip of public transport networks. It is related to the ability of public transportation to provide the fastest access to workplaces, shopping, intermodal connections, etc. The reliability expresses the ease of passenger to perform their trip. This indicator concerns the variation of the line trips time in the entire journey and the number of passengers waiting at the station. The measurement of operational efficiency is related to the vehicle. It is based on the respect of the following criteria: (i) the scheduled departure time at stations for punctuality, (ii) the scheduled headways (the time interval between vehicles of the same itinerary) for regularity and (iii) the needed time of the passengers in the transfer station to change line for correspondence. Finally, system condition and performance refers to the physical condition of the transport infrastructure and equipment, which is not applicable.

3 RELATED WORKS

In the literature, several control support models have been proposed. However, most of them use control without considering properly criteria related to KPIs. In fact, (Zidi et al, 2006) offer a Support Vector Machine based technique and ant colony algorithms without taking into account the correspondence and the regularity criteria. Other approaches like (Sofiene Kachroudi and Saïd Mammar, 2010) use an optimization method for particle swarms with meta-heuristic implementation. But it ignores the correspondence and punctuality criteria. In (S.Hayat et al, 1994), the authors establish linear mathematical models characterizing the movement of vehicles ignoring the correspondence criteria. In (Radhia et al., 2013), authors perform a mesoscopic analysis using triangular Petri nets "RdPLots" by treating only the criterion of correspondence. Other approaches focus only on the control of traffic lights (Bhouri, Balbo, Pinson, Tlig, 2011). They only deal with the regulation of traffic lights in a normal state in order to deal only with the regularity criteria. In addition, other techniques in (K. Bouamrane et al., 2006) present a control model that details the cognitive activities of the process relies only on reliability and punctuality. Tan disk, (S. Carosi et al., 2015) deals only with regularity issues by rearranging crew schedules in order to cope with delays.

We conclude that the most of the existing works use control in a specific criteria with precise constraints. With this modeling gap, designing a control support system that detects perturbation and produces an optimal control action based on all KPIs is a promising solution.

4 THE PERFORMANCE MEASUREMENT FORMULAS

The performance measurement formulas are based on the description of different KPIs presented in (European Commission, 2011). The formulas described below were inspired from (Noorfakhriah Y. et al.,2011) (L. A. Bowman and M.A, 1981).

4.1 Mobility

It defines the trip travel time distribution of the line trip *i* (Kaparias, I., et al., 2008). Its formula is:

$$MOB = \frac{1}{|C|}\sum_{c\in C}^{|C|}\frac{ATT^c}{D_c} \tag{1}$$

- $|C|$: describes the number of trips in the period of the journey
- c: describes the current trip
- ATT^c: describes the estimated travel time for the trip c.

The formula for the mobility indicator I_{MOB} is:

$$I_{MOB} = \frac{S_1^2}{\overline{MOB}^2} \tag{2}$$

With

$$S_1^2 = \frac{1}{n}\sum_{i=1}^{n}(MOB_i - MOB_t)^2 \tag{3}$$

$$\overline{MOB} = \frac{1}{n}\sum_{i=1}^{n-1}(MOB_i - MOB_{i-1}) \tag{4}$$

- n: the number of vehicles on the same line arriving at a station during a period of the journey.
- $\overline{MOB}$: the mobility average for n vehicles.
- MOB_i: the real mobility of the *i-th* vehicle.
- MOB_t: the theoretical (scheduled) mobility of the *i-th* vehicle.

The unit of *MOB* is the "Travel time per km".

4.2 Reliability

It is defined as follows:

$$\mathrm{REL} = 1 - \sum_{l\in L}^{|L|} w_l \cdot \frac{CT^l}{T_{w_l}} \tag{5}$$

- L: all links to the current trip.
- CT^l: the total duration of congestion on link l.
- w_l: the relative importance of the link l.
- T_{w_l} : the period in which congestion is monitored with the importance w_l.

To compute the estimated total duration of congestion, we need to calculate the speed performance index (SPI) as an indicator to evaluate the traffic state of the link (Yan et al., 2009). The weight w_l is defined according to the length, the type (primary or secondary road), and the season or the period of the journey. The formula for the reliability indicator I_{REL} is:

$$I_{REL} = \frac{S_2^2}{\overline{REL}^2} \tag{6}$$

With

$$S_2^2 = \frac{1}{n}\sum_{i=1}^{n}(REL_i - REL_t)^2 \tag{7}$$

$$\overline{REL} = \frac{1}{n}\sum_{i=1}^{n-1}(REL_i - REL_{i-1}) \tag{8}$$

- $\overline{REL}$: the reliability average for n vehicles.
- REL_i: the real reliability of the *i-th* vehicle.
- REL_t: the theoretical (scheduled) reliability of the *i-th* vehicle.

4.3 Operational Efficiency

This KPI corresponds to the vehicle at the station. According to (Cambridge Systematics Inc., 2005), it is composed of three criteria: punctuality, regularity, and correspondence. The formula is as follows:

$$I_{OPE}(i) = W_{PUN}.I_{PUN} + W_{REG}.I_{REG} + W_{COR}.I_{COR} \tag{9}$$

Here, the W_{PUN}, W_{REG} and W_{COR} represent the importance of the criteria in the calculation of the operational efficiency and system condition KPI. E.g. the punctuality for buses of lines characterized by low-frequency services plays the most significant role; on the other hand, the regularity becomes more important for lines characterized by high frequency (Mark Trompet, 2010). It is necessary that: $W_{PUN} + W_{REG} + W_{COR} = 1$.

$\mathbf{V_{PUN}}$**:** The punctuality indicator (Noorfakhriah Y. and Madzlan N., 2011) is equal to:

$$I_{PUN} = \frac{S_3^2}{\bar{h}^2} \tag{10}$$

With

$$S_3^2 = \frac{1}{n}\sum_{i=1}^{n}(t_i - t_t)^2 \tag{11}$$

$$\bar{h} = \frac{1}{n-1}\sum_{2}^{n-1}(t_i - t_{i-1}) \tag{12}$$

- $\bar{h}$: the headway average for n vehicles.
- t_i: the real arrival time of the *i-th* vehicle.
- t_t: the theoretical (scheduled) arrival time of the *i-th* vehicle.

$\mathbf{I_{REG}}$: the regularity indicator measures the variation between the observed and the scheduled headway. It is equal to:

$$I_{REG} = \frac{S_4^2}{\bar{h}^2} \tag{13}$$

With

$$S_4^2 = \frac{1}{n-1}\sum_{i=2}^{n}(h_i - h_t)^2 \tag{14}$$

$$h_i = t_i - t_{i-1} \ (i=2,...I) \quad (15)$$

- $\bar{h}$: the headway average for n vehicles.
- h_i: the real headway of the *i-th* vehicle.
- h_t: the theoretical (scheduled) headway of the *i-th* vehicle.

I_{COR} is the value of the correspondence indicator It is equal to:

$$I_{COR} = \frac{S_5^2}{\bar{c}^2} \quad (16)$$

With

$$S_5^2 = \frac{1}{n}\sum_{i=1}^{n}(c_i - c_t)^2 \quad (17)$$

- $\bar{c}$: the correspondence average for n vehicles.
- c_i: the real correspondence of the *i-th* vehicle.
- c_t: the theoretical (scheduled) correspondence of the *i-th* vehicle.

The correspondence values c_i and c_t are the summation of the waiting time between the delayed vehicle *i* and the connecting vehicles at the transfer station. It is equal to:

$$C_i = \sum_{j=1}^{n} f_j(\Delta_{ij}) \quad (18)$$

f_j determines the importance of the factor of the connecting vehicle j. This factor is calculated according to the number of passengers waiting in the transfer station for the connector vehicle *j*. It is necessary that $\sum_{j\in n}^{|n|} f_j = 1$ and Δ_{ij} represents the waiting time between the vehicle *i* and the connecting vehicle *j*. It is equal to:

$$\Delta_{ij} = t_i - t_j \quad (19)$$

The theoretical (scheduled) correspondence value c_t is calculated in the same way by using the schedules timetables for each variable instead of the actual arrival and departure times.

5 OPTIMIZATION APPROACH

5.1 The Formula of Performance F

The perturbation detection and the control process are based on the performance 'F'. This performance is equal to:

$$F = W_{MOB}.I_{MOB} + W_{REL}.I_{REL} + W_{OPE}.I_{OPE} \quad (20)$$

Here W_{MOB}, W_{REL} and W_{OPE} represent the indicator weights. It is necessary that: $W_{MOB} + W_{REL} + W_{OPE} = 1$. Each weight indicates the importance of KPI in the control process. We suggest using the Delphi method as an expert-based technique to calculate the weights of all KPIs (Cailian Chen et al., 2017). The performance 'F' can be adjusted according to the requested KPIs by adjusting the weights. When 'F' falls on a critical area, the system should find the best control maneuver from the offered list of the feasible actions by reducing as much as possible the F value.

5.2 Optimization Resolution

Formally, an optimization problem can be described by the set *U* of potential solutions, the set *L* of feasible solutions, and the performance function *F: L → IR*. In the control problem, we are looking for control maneuver $S^* \in L$ presents KPIs that minimize the value of the performance function *F(KPI)*. We can then say that *L = {S}, with S= {KPI: ∑(Wᵢ·KPIᵢ)≤ M}* is the set of feasible solutions *S*, each solution presents a set of KPI_i with their weights W_i, and *M* defines the limit value above which the performance becomes not satisfied.

Optimizing the control problem is NP-hard. In practice, the control problem can often be solved using linear programming with *n* criteria (KPIs) as variables and *m* constraints. The linear program is the minimization of the performance function defined on vector $x=(x_1,...,x_n)$ of real-valued KPIs that represents *L*. Consequently, the performance function is the objective function *F* of *x*,

$$F: IR^n \rightarrow IR \text{ with } F(x)=c*x \quad (21)$$

Where $c = (c_1,..., c_n)$ is called cost vector. It is relative to the weights of the KPIs. The KPIs are constrained by *m* linear constraints of the form:

$$a_i*x \bowtie_i b_i, \text{ Where } \bowtie_i \in\{\leq,\geq,=\},\ a_i = (a_{i1},...,a_{in}) \in IR^n, \text{ and } b_i \in IR \text{ for } i \in 1..m. \quad (22)$$

The list of constraints depends on the properties of the course line (frequency, max speed allowed, link density, etc.). For example, in certain headways (expressed by minutes), the KPI corresponding to regularity criteria should not exceed a limit value for course lines characterized by high frequency. The set of feasible solutions is given by:

$$L=\{x\in IR^n: \forall i \in 1..m \text{ and } j\in 1..n: x_j \geq 0 \wedge a_i*x \bowtie_i b_i\} \quad (23)$$

5.3 Optimization Algorithm

After formulating the optimization problem by setting the list of the KPIs and the constraints of the control system, the system checks permanently the performance value *F*.

The decision-making starts when the performance F falls on the critical area(see Fig 3). When the

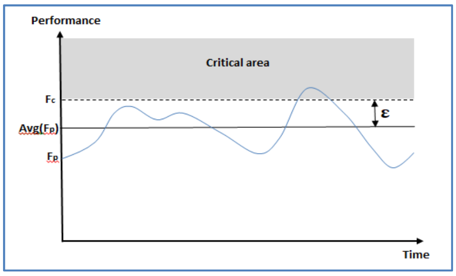

Figure 3: The critical area of the traffic management performance.

performance of the vehicle exceeds a threshold value F_c, a disturbance alert is reported. This value is calculated as follows:

$$\mathrm{F_c} = \mathrm{Avg}(\mathrm{F_p}) + \varepsilon \tag{24}$$

Here ε is the control margin, and F_p represents the performances of all trips done in the previous period. This period is fixed periodically by the expert of the traffic. In this step, the system optimizes the performance function F by applying the optimization resolution method described above. Then, based on the list of predetermined actions, it defines the list of the feasible control actions by using a classification algorithm (decision tree). The system chooses the maneuver that allows obtaining the nearest feasible performance to the optimal value. We detail these instructions on three steps in the following algorithm.

Algorithm 1.

```
//Step 1. Detection perturbation:
Loop
KPIsCurrent=Calculate the current KPIs;
Fcur=Calculate current F;
    if (Fcur in criteria area)
      EXIT;
    End if;
End Loop;
//Step 2. Computing optimal value Fopt:
KPIsOpt=Optimization(F(KPIs));
Fopt = F(KPIsOpt);
//Step 3. Find control action:
S=set of feasible actions;
S*={}; //empty control action
Min = ε; //to start the loop
   For each (control action X' in S)
    KPIx'=Calculate the KPIs of X';
   //vector of KPIs for the action X
    Freg=F(KPIx);
    if (Freg - Fopt)<Min))
       Min=Fopt - Freg;
       X=X';
    End if;
End;
S*=X;//S*: the best control action
End Algorithm
```

6 MULTI-AGENT MODELING

Multi-agent modeling can give a suitable solution to multimodal public transport network activities where autonomous entities, called agents, interact with each other in an environment which is: (i) distributed: information is geographically dispersed over the network, (ii) open: manage agents who can enter and exit freely, (iii) dynamic: there is daily change of information, (iii) heterogeneous: There are varied actors and (iv) complex: entities require cooperation to resolve conflicts. We present our MAS architecture in figure 4. The architecture contains 5 type of agent populations: link, vehicle, station, KPI and Regulator.

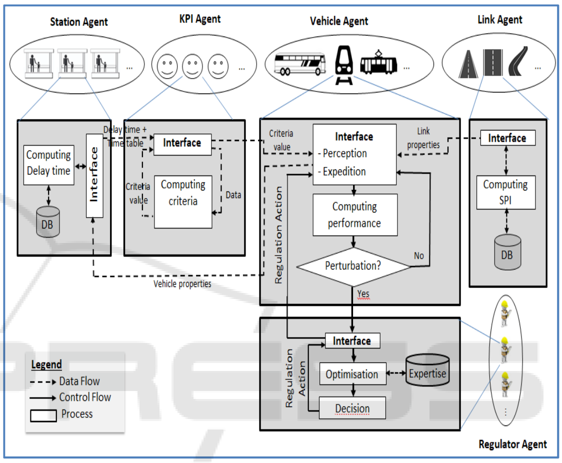

Figure 4: Multi-agent architecture of RSSPT.

Permanently, the vehicle agents apply the disturbance process detection. They use the information that is received by GPS. This information represents all properties of the vehicle (type, mode, driver, position, charge, working time, line…) and traffic state of the link. The station agent receives the necessary information from vehicle agent, creates the necessaries KPIs agent according to the KPIs used in performance formula, then calculates and sends to each KPI agent the delay time in reference to the scheduled timetable. Each KPI agent of the concerned vehicle calculates its KPI value and sends it to the corresponding vehicle agent. The vehicle agent uses these values to calculate the performance F and detect a disturbance. When there is a disturbance (F exceeds the critical value F_c), the corresponding regulator agent agent calculates the optimal vector *KPIsOpt* and finds the adequate control action from the list.

7 EXPERIMENTATION AND RESULTS

To validate the control strategy of our system, we tested our model on a real traffic network of Portland city in Oregon State using the simulator AnyLogic (see figure 5).

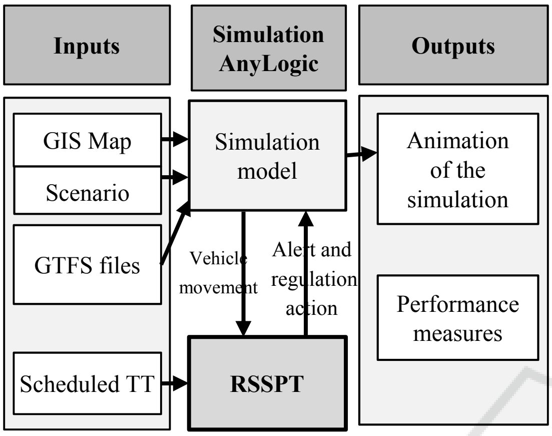

Figure 5: Simulation components.

The data were collected from the General Transit Feed of The Tri-County Metropolitan Transportation District of Oregon (TriMet) network. TriMet is responsible for the management of all ground transportation in the city of Portland. These data were imported to the AnyLogic as a GTFS files to model the public transportation map data like course lines, links, stations, vehicles. AnyLogic is a simulation software toolkit that provides a graphical interface for modeling complex environments as transportation traffic. In addition, it provides models, which allow visualizing both the animation and the logical analysis.

The scenario presents traffic congestion observed in 2-Division Line for the course line to Gresham Transit Center due to the inclement weather conditions (see figure 6).

Before testing our RSSPT, We provide the scheduled and the simulated travel time of all trips in figure 7 with no perturbation. We want to show that the developed simulation model behaves in a realistic way in regular situations. The results allow concluding that the simulation model reasonably represents the behavior of the road traffic system.

In the context of this scenario, we assume, that the distribution of weights WREG, WPUN, and WCOR gives more importance to the regularity criteria because the itinerary 2-Division Line is characterized by high frequency. In fact, there are 83 trips during the journey. We adjust the weight values according to the studied itinerary (see table 1).

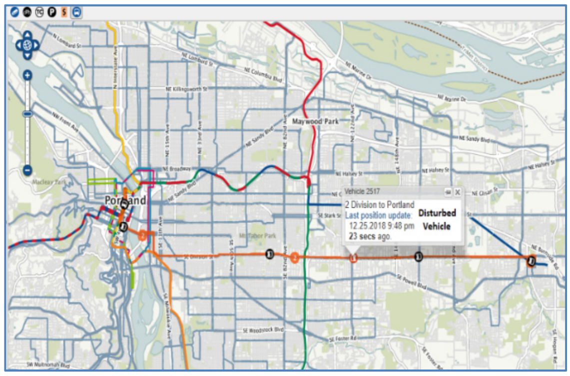

Figure 6: Traffic network congestion in 2-Division line of TriMet.

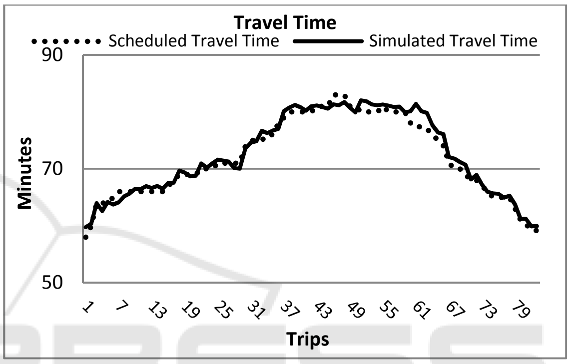

Figure 7: Scheduled trip travel time for 2-Division Line in the journey.

Table 1: Weight KPIs distribution of the itinerary "2-Division".

W_{mob}	W_{REL}	W_{OPE}	W_{REG}	W_{PUN}	W_{COR}
0.25	0.25	0.5	0.5	0.25	0.25

In order to formulate our optimization model, we define the objective function as well as the set of constraints. The objective function is the minimization of the performance F(KPIs). The first constraint ensures that the KPIs are non-negative and don't exceed the value 1 ($KPIs \in [0,1]$). The second constraint requires that $(W_{OPE}.I_{OPE} > W_{MOB}.I_{MOB} + W_{REL}.I_{REL})$ to guarantee that the operational efficiency of the vehicle stays more important than the mobility and reliability key performances of the line course. In addition, we have to ensure that for each vehicle the sum of its regularity time and its punctuality indicators does not exceed its scheduled headway.

To detect perturbation, each vehicle checks its performance F. When it exceeds the critic value (we suppose that this value is fixed to 0.15 by the experts of the traffic) the vehicle agent identifies the SPI to classify the link state and send the necessary data to the corresponding regulator. The regulator starts the optimization phase. Then, it extracts the list of the feasible control actions and chooses the one offering the more close lowest value of F.

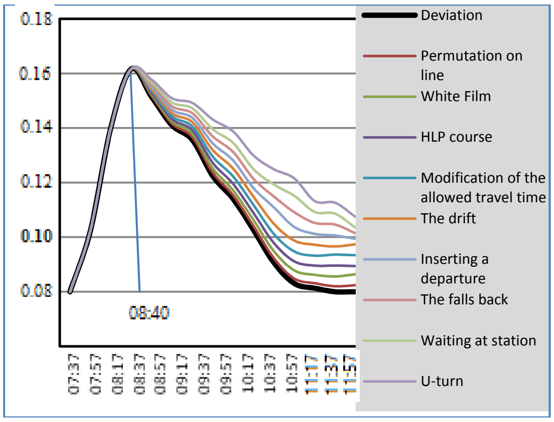

Figure 8: Evolution of the performance F for each control action of the itinerary “2-Division.

After the simulation, some vehicles detect perturbation at 8:40 am on the trip 10 at the stop id 1375 (SE Division & 12^{th}) when the performance of F becomes greater than the critic value 0.15 (See figure 8). After optimization, the regulator chooses “the deviation maneuver” for all vehicles in the disturbed zone with the lowest average F equal to 0.105 (This same average was estimated to 0.068 before perturbation). We remark that the performance of the traffic evolution is improved by the considerable decrease in the F value for each feasible control action but the best one is the deviation decision.

Figure 9 shows the three curves of the trip travel time during the perturbation period from trip 10 to trip: scheduled, observed without control model and after optimization with control model during the perturbation period.

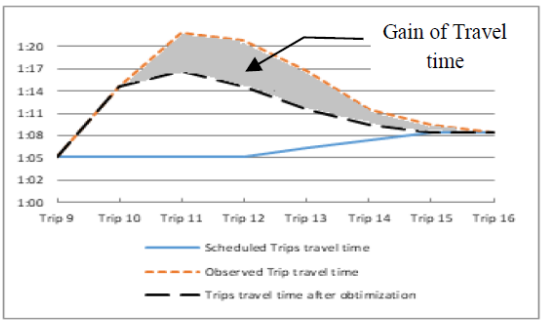

Figure 9: Scheduled, observed and optimized trips travel time.

The obtained results show an improvement on the travel time. We observe that the time lost by perturbation is reduced when applying our control model.

8 CONCLUSIONS AND PERSPECTIVE

The primary contribution of this paper has been to provide a framework of multi-agent modeling for Control Support System of Public Transport (RSSPT) based on key performance optimization. Our system ensures the two phases of control: detection of perturbation and decision-making. We have detailed the multi-agent modeling approach to describe the system. This new model is based on the principle of coordination between autonomous different agents to solve the traffic perturbation of public transportation. We have discussed the optimization problem that is based on KPIs. Finally, we have tested our multi-agent model by simulating perturbation scenarios in real traffic networks. The obtained results show an improvement in the quality of service when we apply our RSSPT.

A future work direction consists of providing the regulator agent with an evolutional approach for the optimization problem in order to remember the results for future situations. Therefore, when there is a new situation (unknown disturbance, new traffic parameter, etc.), our model should suggest a new solution as a future action with new experiments using the learning process. Thus, in this situation, the control system should improve its behavior by updating its knowledge base. This new solution must take into account the most appropriate value of the performance F. It will be injected as a new rule into the knowledge base of the vehicle agent to be used in the next generation of candidate maneuvers in the step 3 of the algorithm.

REFERENCES

European Commission, 2011. “White paper - Roadmap to a single European Transport Area”- Towards a competitive and resource efficient transport system. 2011.

Zidi et al, 2006, S. Zidi ; S. Maouche ; S. Hammadi, “Real-Time Route Planning of the Public Transportation System”. 2006 IEEE Intelligent Transportation Systems Conference, Toronto, Ont., Canada, DOI: 10.1109/ITSC.2006.1706718

Sofiene Kachroudi and Saïd Mammar, 2010, "The effects of the control and prediction horizons on the urban traffic regulation", 13th International IEEE Conference on Intelligent Transportation Systems, Funchal, Portugal, DOI: 10.1109/ITSC.2010.5625056

S. Hayat, R.Hartani, S.Sellam, R.Hartani, B.Bouchon-Meunier, P.Gallinari, 1094, "Modelling of an Automatic Subway Traffic Control by Fuzzy Logic and Neural Networks Theory", IFAC Proceedings Volumes,DOI: 10.1016/S1474-6670(17)47467-2.

Radhia Gaddouri, Leonardo Brenner and Isabel Demongodin, 2013. "Mesoscopic event model of highway traffic by Batches Petri nets", 6th IFAC proceeding. DOI:10.3182/20130911-3-BR3021.00051

Neïla Bhouri, Flavien Balbo, Suzanne Pinson, Mohamed Tlig, 2011. "Collaborative Agents for Modeling Traffic Regulation Systems",IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology, wi-iat, vol. 2, pp.

Bouamrane K., A. Liazid, F. Amrani, D. Hamdadou, 2006. "Modelling and Cognitive Simulation in Dynamic Situation: Decision-Making for Regulation of an Urban Transportation System", Amman Jordanie. (ISBN 9957-8592-0-X).

S. Carosi , S. Gualandi, F. Malucelli, E. Tresoldi, 2015. "Delay management in public transportation: service regularity issues and crew re-scheduling", 18th Euro Working Group on transportation, Delft, The Netherlands.

Noorfakhriah Yaakub and Madzlan Napiah, 2011. "Public Transport: Punctuality Index for Bus Operation", International Journal of Civil and Environmental Engineering, Vol:5, No:12.

L. A. Bowman and M.A, 1981. "Turnquist. Service frequency, Schedeule, Reliability and Passenger wait Times At transit Stops". Transportation research, Vol, 15A, No. 06, pp. 465-471

Kaparias, I., Bell, M. G. H., and Belzner, 2008. "H. A new measure of travel time reliability for in-vehicle navigation systems", Journal of Intelligent Transportation System, pages 202-211.

Yan, XY and Crookes, RJ, 2009. "Reduction potentials of energy demand and GHG emissions in China's road transport sector". Energy Policy, Vol. 37, pp. 658-668.

Mark Trompet, 2010. "The Development of a Performance Indicator to Compare Regularity of Service between Urban Bus Operators", Imperial College London.

Cailian Chen, Tom Hao Luan, Xinping Guan, Ning Lu and Yunshu Liu, 2011. "Connected Vehicular Transportation: Data Analytics and Traffic-dependent Networking", arXiv:1704.08125v1 [cs.NI].