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A DYNAMIC SUPERVISION APPROACH BASED ON STOCHASTIC P-TIMED PETRI NETS: APPLICATION TO A RAILWAY TRANSPORT NETWORK

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ABSTRACT

Developments presented in this paper are devoted to the monitoring of railway transport systems. Stochastic P-time Petri Nets (SP-TPN) are used for modelling. With the aim of improving the railway transport quality, we propose a new monitoring structure able to react to different situations without prior knowledge of the system's failure modes. The failure detection is based on taking into account the temporal aspect of the system to be monitored. In this context, the developed supervision approach, based on timed automaton, aims to detect, locate failures that affect system performance and reliability. Finally, to illustrate the effectiveness and accuracy of the dynamic monitoring approach, an application to realistic railway networks is outlined.

1. INTRODUCTION

Monitoring refers all implemented means (operations, steps, functions and mechanisms) to track entity state (online, in real time) in order to deal with system failures.

Over the years, railway traffic has become increasingly complex. In this transport system, journeys have temporal constraints which must be strictly adhered. The violation of these constraints can lead to traffic disruption and cumulative delays. As the railway industry evolved, maintaining operated equipment without failure became paramount. Traffic disturbances due to transport equipment breakdown were not tolerable anymore due to the increasing demand.

The objective of this study is to propose a dynamic monitoring approach to enhance the equipment availability through early failures recognition. The parameter decreasing the equipment unavailability is the detection time. Starting from a controlled transportation system, this study focuses on the supervision of the system's various activities. The developed approach consists to check that all travel and parking activities are performed within predefined deadlines in order to improve the railway system availability. This is achieved by minimizing the number of downtimes that disrupt rail traffic through monitoring the system sensors status.

The primary tenet of the supervision approach is to detect and locate faults that may affect the safety and security performance of a railway transport system. The

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developed monitoring strategy, based on timed automata, include all system's states taking into account various system functioning modes. The aim is to prevent detection lags and false alarms.

Thereby for each operating time, the implemented strategy consists in monitoring the time interval linking the command issue and the end of the operation execution. If the time between these two events is not respected, there is a failure symptom. A diagnostic operation is carried out to determine the observed problem root. In an unexpected failure, alarms are triggered

This paper is structured as following. Section II introduces the state of the art. Section III outlines the studied railway transport system and presents its SP-TPN model. Subsequently, the surveillance problematic of railway transport networks is approached. An implementation method of the dynamic monitoring approach is outlined. For each transport activity a dynamic model using timed automata and taking into account the functioning modes is developed. In section V, an application of the developed approach to the studied railway network is proposed. Lastly, a summary is presented with some prospects.

2. STATE OF ART

Rail transport systems must be supervised online to avoid potentially critical situations due to disruptions. These perturbations can affect the railway infrastructure, traffic management and can lead to a transport service declination. In this context, various research projects have been carried out on the monitoring of transportation systems to achieve time ((Lee et al., 2020) (Mhalla et al., 2020) and improve the rail service quality (Wang et al., 2021) (Tsunashima et al., 2019).

The authors in (Soilán et al., 2019) present the design of a public transportation monitoring system using Intelligent Transportation System which works in real time with an Android-based application. The traffic accident monitoring system is able to automatically detect traffic accidents and emergency events during a trip. The advantage of this system is that there is accident information that is connected to the community service when there is a suspicious activity or emergency. Experimental result shows that the traffic accident monitoring system has a high performance with four parameters, namely accuracy, robustness, integration and convenience.

The authors in (Rajes et al., 2021) propose a traffic flow detection scheme based on deep learning on the edge node. In this context, a vehicle detection algorithm based on the YOLOv3 (You Only Look Once) model trained with a great volume of traffic data is suggested. After that, the DeepSORT (Deep Simple Online and Realtime Tracking) algorithm is optimized by retraining the feature extractor for multiobject vehicle tracking. To verify the correctness and efficiency of the framework, the vehicle detection network and multiple-object tracking network are migrated and deployed on the edge device Jetson TX2 platform. The test results indicate that the proposed model can efficiently detect the traffic flow with an average processing speed of 37.9 FPS (frames per second) and an average accuracy of 92.0% on the edge device

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For railway inspection and monitoring, authors in (Handayani et al., 2019) explore the usage of the UAVs (drones) in railways and computer vision based monitoring of railway infrastructure. Employing drones for such monitoring systems enables more robust and reliable visual inspection while providing a cost effective and accurate means for tracks monitoring. By means of a camera placed on a drone the images of the rail tracks and the railway infrastructure are taken. On these images, the edge and feature extraction methods are applied to determine the rails. The preliminary obtained results are promising.

The authors in (Chen et al., 2020) presents a highly sensitive means for railway monitoring based on vibration measurement. Fiber Bragg Grating (FBG) accelerometers placed on sleeper have been employed as sensor heads, which significantly facilitated the field sensor installation work compared to the positioning on the foot of the rail. An optimized signal demodulation algorithm has been effectively used to extract from the accelerometer traces both the axle number and the average speed information. Excellent capability of the developed system to obtain both parameters has been demonstrated by the way of field trials carried out on a Belgian railway line, during its normal operation

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All previous works are different from our labor. The study purpose is to monitor rolling stock by reviewing the travel and parking times in view of increasing the Electric Multiple Unit (EMU) availability. This is accomplished by studying the travel cycle time. To the best of our knowledge, such surveillance method has been never formalized for railway transport networks. Thus paper contributes to the state-of-the-art of railway monitoring problem and address a situation where the possession time is restricted. By investigating the presented monitoring strategy, it is possible to provide an answer for infrastructure managers of complex railway networks where there's a growing demand for track use and increasing pressure to extend operating time and reduce infrastructure maintenance.

The contributions of the present study are:

(i) Development of a new monitoring approach based on the study of rolling stock travelling cycle time and the sensors states.

(ii) Implementation of a system dynamic model based on timed automaton tool to check operating time. The developed dynamic model requires the knowledge of all system forbidden situations.

3. TUNISIAN RAILWAY NETWORK

3.1 Presentation

Tunisian National Railways Company (TNRC) is a public company, which is charged to operate, maintain and manage the national railway network. The TNRC manages the Sahel railway network. This railway line connects many villages in the Sahel from Mahdia to Monastir, fig. 1. With an average frequency of 50 minutes, the Sahel Metro guarantees regular daily traffic between 5:00 am and 10:00 pm.

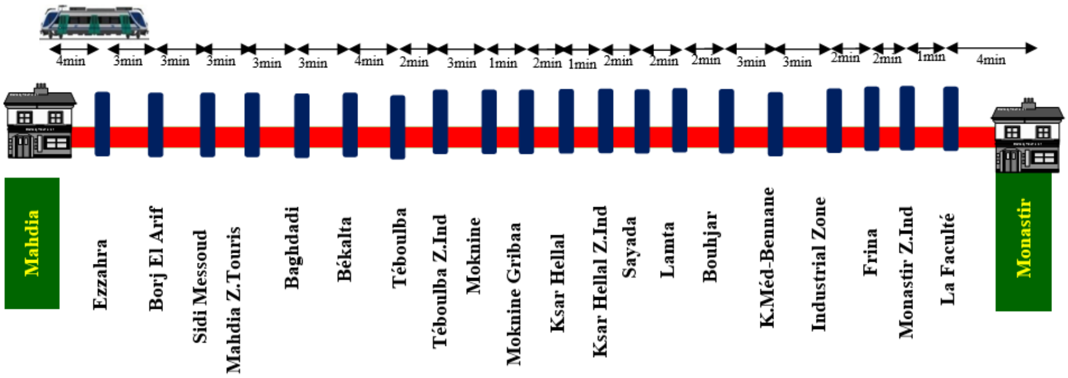


Figure 1. The Sahel Railway line

3.2 Modelling of the railway transport system

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

- R is a Petri net system,
- IS : $P \rightarrow Q^+ \times (Q^+ \cup \{+\infty\})$ such that $IS_i = [L_i, H_i]$ with $0 \leq L_i \leq H_i$ is the static interval associated to the place p_i.
- IR: $P \rightarrow Q^+ \times (Q^+ \cup \{+\infty\})$ such that $IR_i = [\alpha_i, \beta_i]$ with $L_i \leq \alpha_i \leq \beta_i \leq H_i$ is the dynamical interval associated to the place p_i.

The main impartial is to build a model able to reproduce the railway traffic behavior. From the measurements reported by the Supervisory Control And Data Acquisition (SCADA) of the TNRC company, a SP-TPN (S) model is proposed, fig. 2. The acquired S is used to the monitoring of the Tunisian Railway system.

In SP-TPN model, a specific module (VU) is introduced for bi-directional segments, fig. 2, where:

- The blue places p11 and p14 represent two resources added to avoid the train collision and the crossover of the two trains on the single tracks,
- Green places indicate the direction of train circulation (p119, p120, p121, p122, p123 and p124).

For each place of S, we denote $[L_{ij}, q_{ij}^{e}, H_{ij}]$ the lower bound of the time window, the expected sojourn time of tokens, and the upper bound of the time window, respectively.

4. THE MONITORING MODULE

The supervision approach proposed in this paper is based on a statistical analysis of the real measurements, collected by the SCADA system of the TNRC, to identify the time parameters of the SP-TPN model. The

literature reveals three approaches for supervision transport systems which are cited:

- Monitoring integrated into the control,
- Separate monitoring of the control,
- A mixed approach (combination of the two previous approaches).

In the first approach, the monitoring system is integrated with the control. It considers that abnormal operations must be known and incorporated with the control system. This supposes an absolute knowledge of all possible system evolutions. For diagnosis, the system must be able to associate to each failure probable causes.

In the second approach, the control and the monitoring system are separated. This detachment has the advantage of relieving control and the ability to implement new monitoring techniques. The main drawback is the conflicts generation between monitoring and control since they both act on the process. These conflicts arise from the segregation between normal and abnormal behavior. Indeed, what is normal for monitoring may be abnormal for control.

The mixed approach is a compromise between the two previous ones; diagnostic and decision functions are separate while detection and recovery functions are integrated into the control. In this case, the control system defines the normal behavior, consequently any change not provided by the control model will then be considered as abnormal. The advantage of this approach lies in the fact that the limit between normal and abnormal behavior is established as soon as the control model is itemized.

For the monitoring of the rail transport system, our choice is focused on the third approach because of these major advantages over the other two approaches.

White places represent the targets between two stations.

Red places represent the stands.

Brown resource places point out the metro direction .

Greeen places indicate resources to avoid the metro collision.

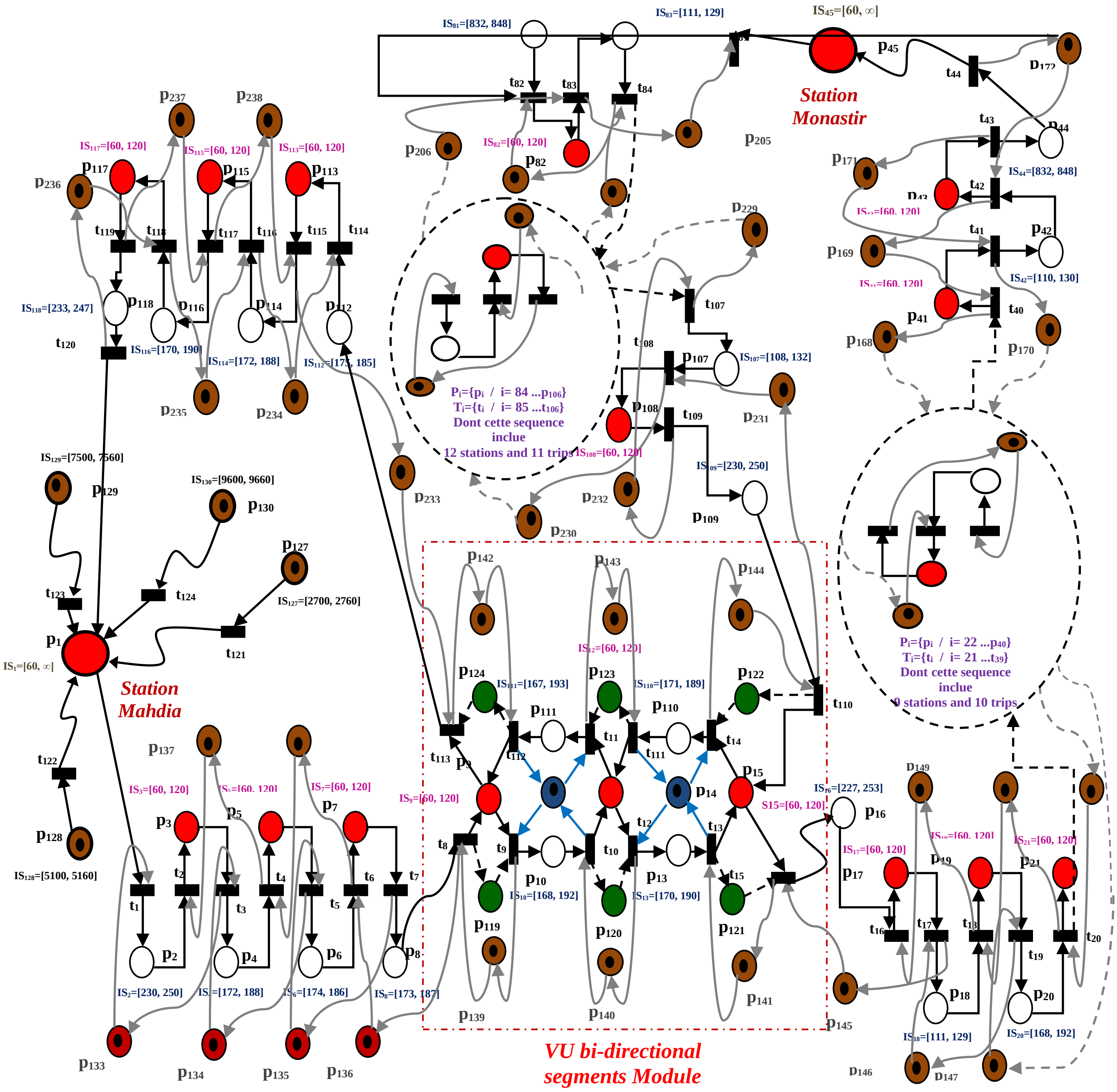


Figure 2. SP-TPN model of the Tunidsian Sahel Railway network

4.1 Monitoring structure

Some monitoring approaches found in the literature are based on the relationship between the control and the process (Banić et al., 2019), (Bianchini et al., 2020), while others are more linked to the dynamic evolution of the operational part (Priyanka et al., 2018), (Fedorko et al., 2018). In the case of rail transport networks, a failure can lead to traffic disruption and cumulative delays. Thus, the monitoring of the railway system is characterized by the monitoring of service time (travel and parking time).

The tenet of this paper is the integration of monitoring tools into a scheduled railway transport system. The proposed monitoring module receives the information from sensors which represent the basic element for the fault detection and localization, fig. 3. In the proposed approach, the recovery and emergency processing functions are included in the supervision module. While the maintenance module collects information from the monitoring module and from the supervision module (statistics of breakdowns for example) in order to establish the maintenance scheduling, fig. 4.

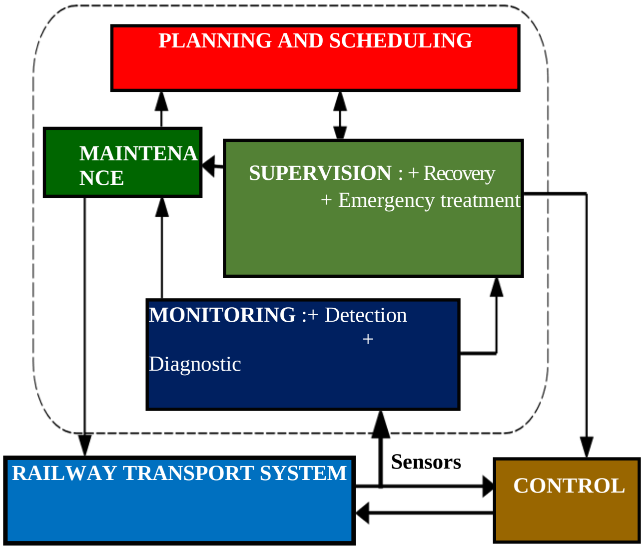


Figure 3. Proposed monitoring structure

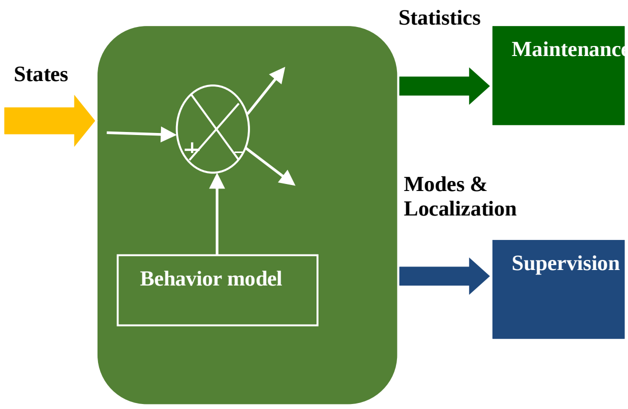


Figure 4. Monitoring Module

The only information at the input of the monitoring module is the sensor states associated to the railway transport system, fig.4. This module provides information to the maintenance and supervision modules. Information intended to the maintenance module is necessary for the recovery scheduling. The information intended for supervision module, such as faulty states and failure causes, is used to predict recovery actions.

4.2 Operating time monitoring

In transport system, the traffic duration is by hypothesis a variable which depends on the journey to be made. The idea is to associate to each railway equipment an average journey time. Monitoring is then based on supervision of these times during metro ride. A failure is detected if this duration exceeds a fixed threshold.

The tenet is to determine the threshold value noted: Ω to optimize the detection time, fig. 5. Indeed, high thresholds do not allow detecting failure on time. On the other hand low thresholds trigger to many false alarms. The purpose of the surveillance approach is to identify failures with a minimum delay equivalent to the threshold in order to oversight and diagnosis time disturbance in the Sahel railway system. The detection times will be assessed to minimize false alarms and warn catastrophic situations that adversely affect rail traffic.

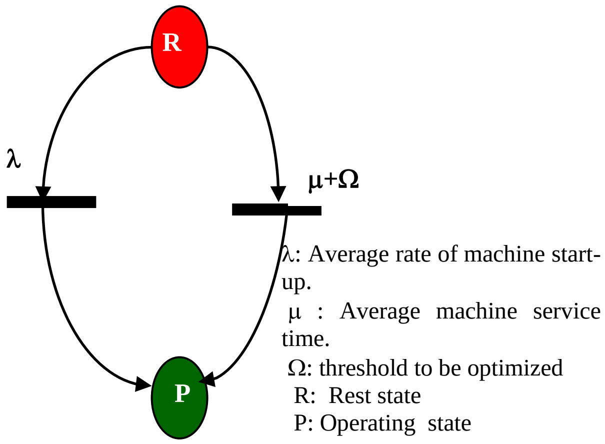


Figure 5. Monitoring approach model based on cycle time

5. MONITORING OF THE SAHEL RAILWAY NETWORKS

The developed monitoring function is a component of an overall monitoring process. Based on the information available on its operating modes, it aims to represent the sojourn time in the SP-PTN model. The tenet is to detect, locate and diagnose failures that may affect operational safety the studied transport system.

5.1 Effective sojourn time uncertainty

To each sojourn time, two intervals are defined; normal and degraded. Beyond these intervals, the system is considered as faulty, fig. 6. Therefore, tree time intervals are defined:

- Normal mode Ns = $[T^x_{min}, T^x_{max}]$,
- Degraded interval Ms= $[0\ , L^x_{min}[\cup [H^x_{max}, H^x_c]$
- and a faulty interval $]\ H^x_c, +\infty[$,

with

L^x_{min} : the minimum travelling time,

H^x_{max}: the maximum travelling time,

H^x_c: Crucial time.

As soon as an event « x» occurs beyond the permissible limit (x$\notin [T^x_{min}, T^x_{max}]$), the studied transport system switches to a degraded mode. If an event « x'» (x' is posterior to x) occurs during its degraded operating interval, the system can switches back to normal mode. From this instance, two cases can be discerned:

- x' = x+1; when the task x' is exactly executed after task x. In this case there is a false alarm.
- x''=x; when the task x that caused the transition from normal to degraded mode is also the cause of the transition to faulty mode, in this case there is a real fault detection.

In transport system, there is a normal operating mode, if an event "x" belongs to N_S interval. Otherwise there is a degraded mode. The system is faulty if the upper bound H^x_c is exceeded.

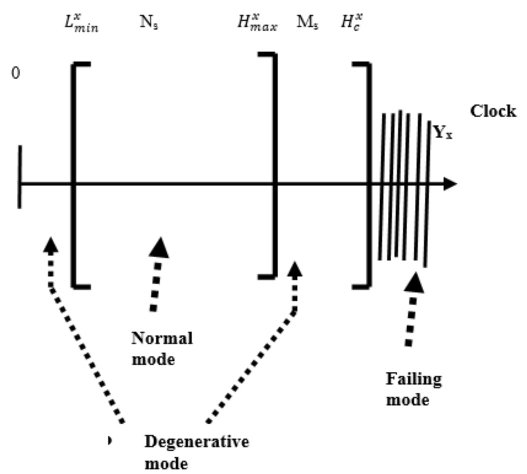


Figure 6. Operating mode

5.2 System dynamic model

The system dynamic model is created from the control model. This graph, fig. 7, represents all system possible evolutions. In fact, to each graph state is associated a clock. Each one monitors the journey travel time. In the studied transport system, these clocks are always initialized at the outset of rail traffic. Lastly, from all the states, and considering control clocks activity, a dynamic model is created on the basis of the timed automaton tool, fig. 7.

For failure detection, this monitoring approach is based on the instantaneous comparison between the process sensors states and the system behavior. Any behavioral deviation will be considered as an anomalous system situation. As long as an operation "x", belongs to the Ns interval, the monitoring module indicates system normal mode. Otherwise, it switches to the degraded/faulty mode, fig. 7. At the end of each task, the following algorithm is checked:

If x $\in [T^x_{min}, T^x_{max}]$, there is a system normal mode.

Otherwise

if x $\in [0\ , L^x_{min}[\cup [H^x_{max}, H^x_c]$, there is a degraded mode system.

Otherwise the system is in failure mode.

5.3 Timed automata modelling

Our focus is on the timed automaton as a tool for describing the transport system behavior. This section introduces a monitoring model based on timed automata. The presented model groups all system states and makes it possible to take into account the adapted operating modes.

The system states are determined on the following operating modes:

- The degraded and normal functioning modes are similar (same set of states-arcs), only delays will be stretched to the upper limit "H^x_c"of the degenerative interval Ms. Whereas the failure mode will be considered as a global failure state.
- Each operating time " x " exceeding the upper bound noted H^x_c' will generated a switching of the studied system to the failure mode
- From a degraded state, the system may revert to the normal mode, if the operational time is inside the normal functioning interval.

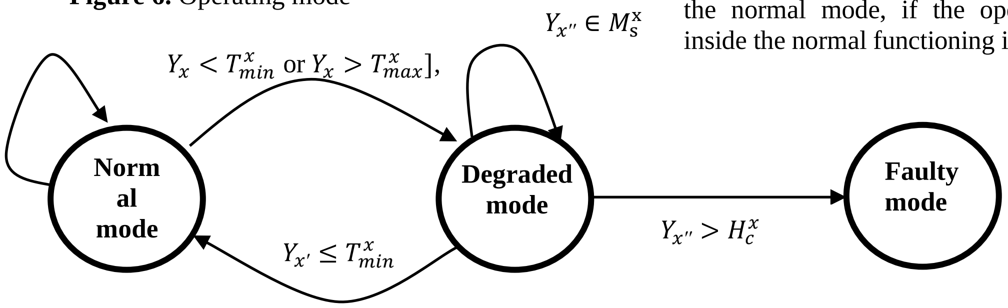
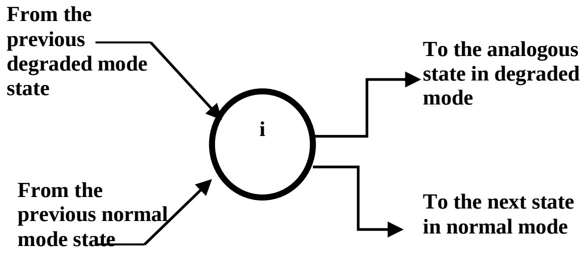


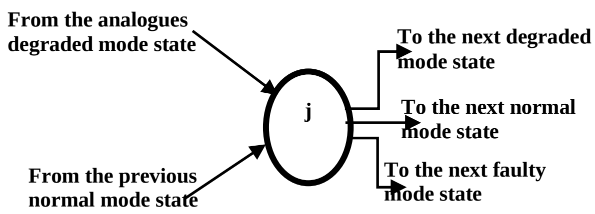
Figure 7. System dynamic model

Finally, bearing in mind these conditions, two states (i and j) can be considered, fig. 8.

- From each state "i" in normal mode, the system may transit to the next state in normal or degraded mode. The system can reach this state either from a degraded mode state, fig. 8a.
- From each state "j" in degraded mode, the system can switch either to the next state in normal (resp. degraded or faulty) mode when the travelling time exceeds a critical value, fig. 8b. This same j state can be accessed either from the analogous normal mode state if the travelling time exceeds the corresponding value T^x_{max} or from the preceding degraded mode state.



a) i represents a normal mode state



b) j represents a degraded mode state

Figure 8. Switching between the functioning modes

5.4. Implementation of the monitoring model

The recommended surveillance system is consists of a set of monitoring subsystems which operate permanently. These subsystems involve the supervision of the sensors states and the operating durations, fig. 9.

6. ILLUSTRATIVE EXAMPLE: SIMULATIONS AND VALIDATION

To assist the supervisor in recognizing traffic disruptions and alert travelers claims, an application of the dynamic monitoring approach to a railway network linking Mahdia and faculty stations is depicted, fig. 10. The tenet is the checking of a time constraint noted "A" by monitoring the travelling and staying time between metro stations. Let us take the example of the time constraint linking two events E1 (metro departure from Mahdia railway station: place p_1) and E_6 (arrival of metro to faculty stand: place p_6), fig. 10. If the time constraint is checked, the functioning mode is claimed normally. Otherwise there is a traffic disruption. In this case study, the constraint "A" is defined as $L^x_{max} \leq A \leq H^x_{max}$.

According to SP-TPN, fig.10, the minimum travel duration (L^x_{min}) between the two railway stations is 696 s whereas the maximum is (H^x_{max}) is 984s.

In the case of the metro's late departure from Mahdia station (departure at 05:26:55 see table 1), the global time constraint "A" is violated. This "D" delay disturbance (D= 105 seconds) occurring in p_6 may imply a traffic disruption and lead to a degenerative mode.

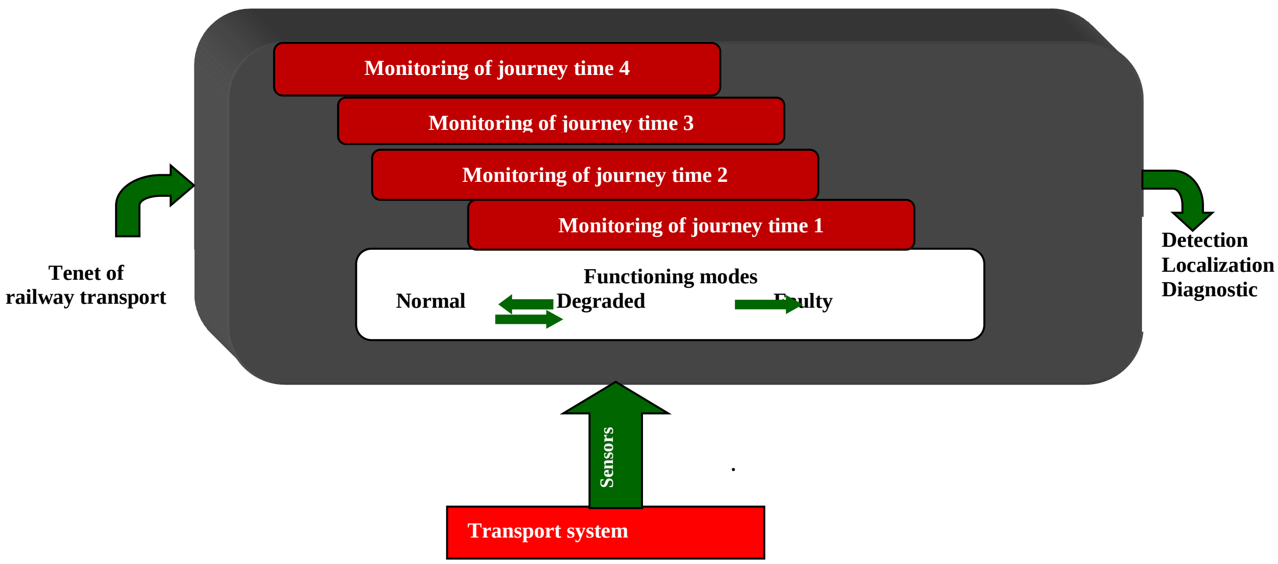


Figure 9. Global monitoring system

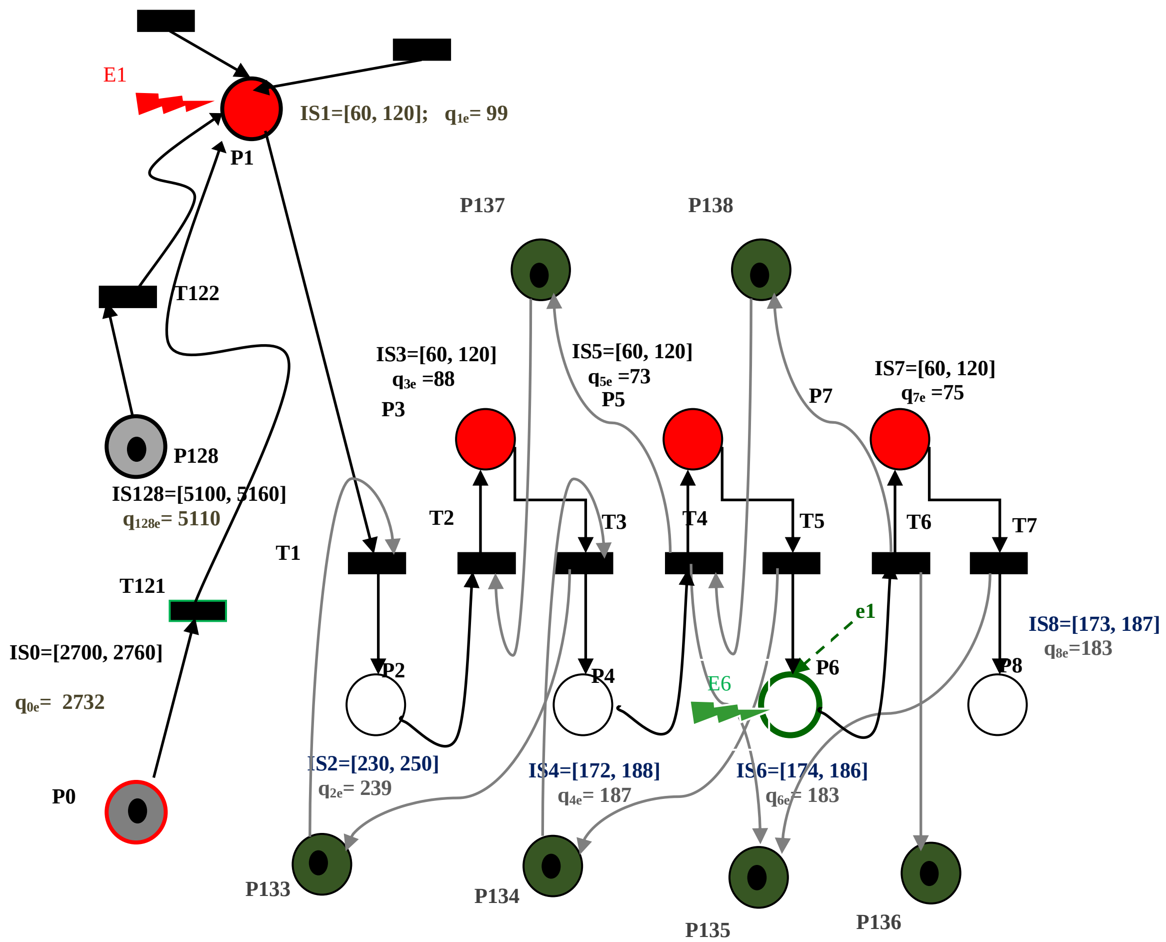


Figure 10. Monitoring of the time constraint on railway network Mahdia-faculty station

Table 1. Planned and measured times

Station	Planned time	Real time T(k)
Mahdia	05:25:00	05:26:45
Ezzahra	05:28:00	05:30:27
Borj Arif	05:31:30	05:34:15
Faculty	05:35:10	05:35:13

6.1 Simulation of the monitoring approach

In the SP-TPN model, marks represent the metro position and the transitions firing correspond to metro crossing times. The fig. 11 shows the metro position in the Sahel railway network (Y axis) over time (X-axis). The graph represents the metro positions dispersions. The dispersal rises due to the late departure of train from Mahdia station. Thus, the simulation illustrates that a metro, during its circulation, can have gaps reflected in failure and temporal disturbances in the operating times. These delays are depicted by a tokens scattering, fig. 11.

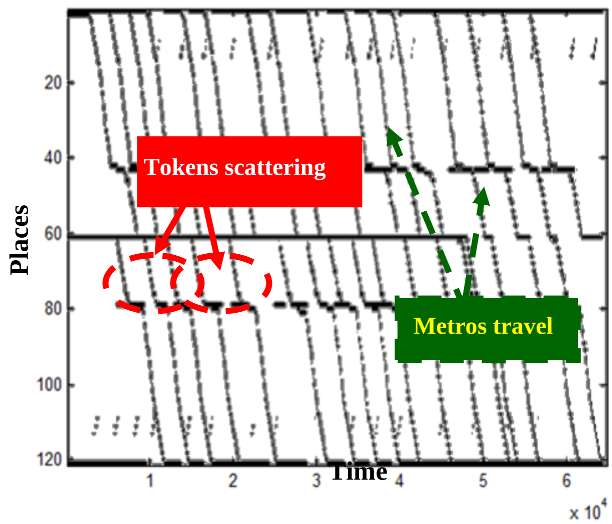


Figure 11. Mark Circulation in the places (Y-axis) with time (X-axis)

6.2 Construction of the system dynamic model

To build the system dynamic model, from the SP-TPN, fig. 10, to each graph state is assigned a clock set required to track the activities duration. In the studied railway network, to each transport and parking operation is allocated a clock.

If a transport activity has not started or finished, no associated clock is assigned. The clocks are initialized at the beginning of each supervised activity. To create the transport system dynamic model, the procedure below is followed:

In studied railway, each metro is assigned a clock "Y_M" for the tracking of the journeys and parking times.

This clock is reset at each arrival in the metro station and restarted at each subway departure, fig. 12. For example at the initial state noted (1), the clock "Y_M" is initialized to check the parking time at the Mahdia station; if Y_M falls within the normal interval N_1, fig. 12, there is a normal operating mode. This refers in the SP-TPN model to a residence time "q_1" belonging to the static interval IS_1. This procedure is performed to all dynamic model states, based on automaton timed tool, fig. 12.

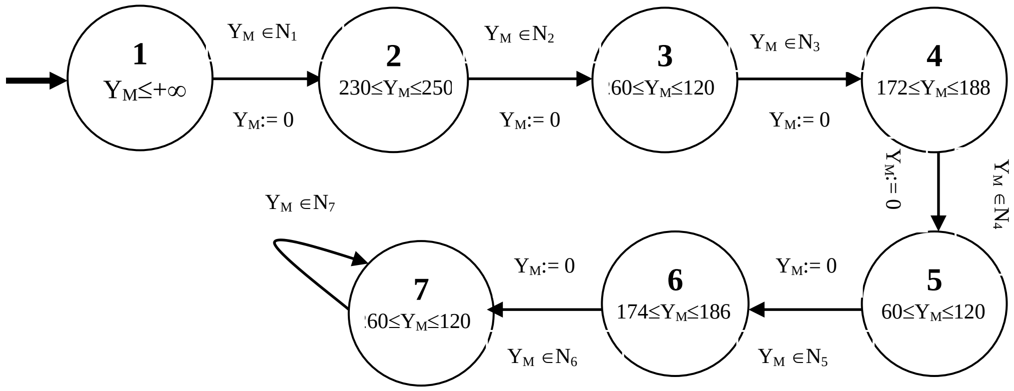


Figure 12. Timed automaton model for transport operations between Mahdia-faculty stations

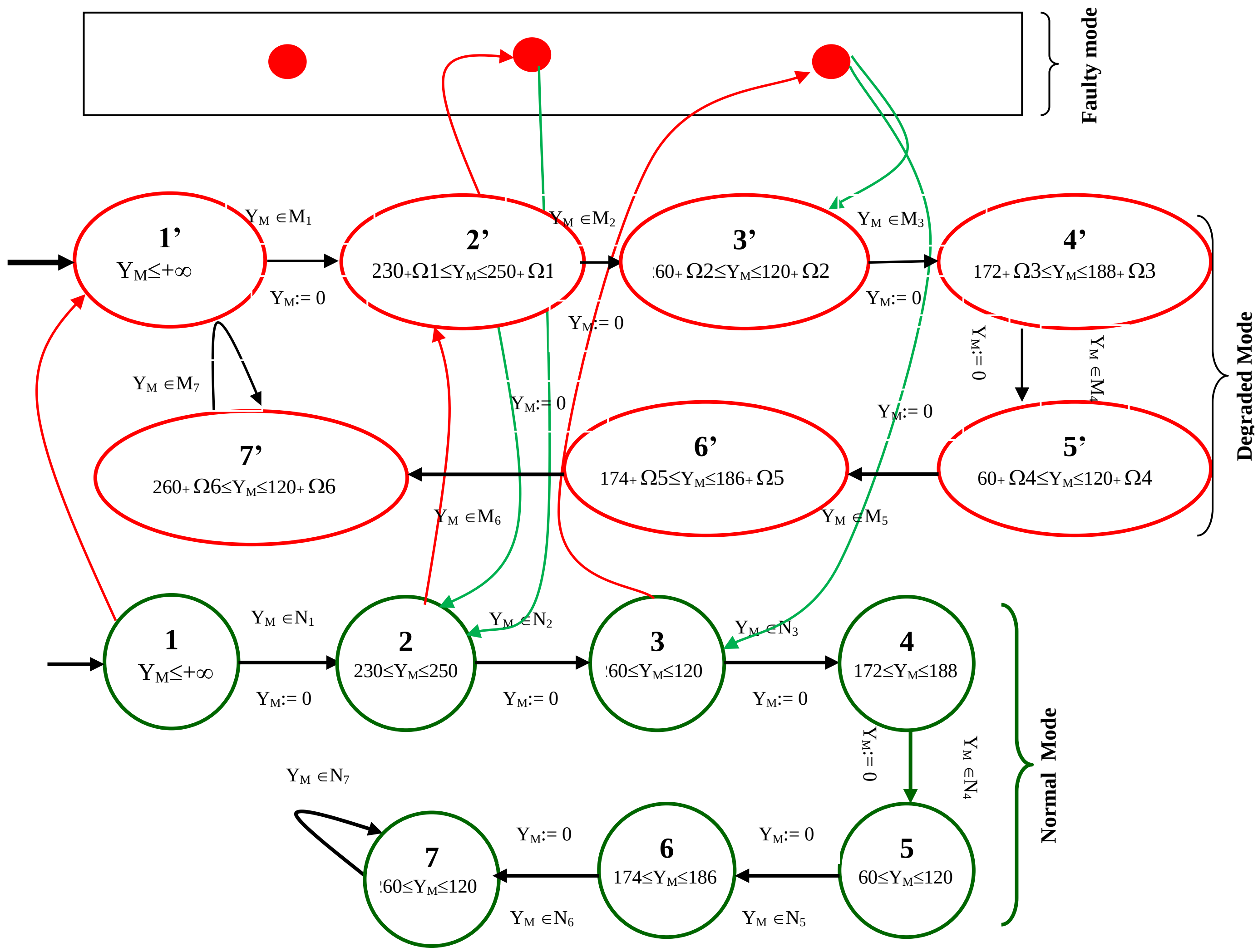


Figure 13. Monitoring model of the studied rail transport network

6.3 Monitoring model

In order to create a monitoring model from the dynamic model (corresponding to the normal functioning mode) and taking consideration of the degraded operation mode, the procedure is to extend the journey duration to the time intervals noted M previously defined. Fig. 13, presents the monitoring model of the studied railway network.

This is accomplished by applying the commutation criterion between the three system operating modes. Referring to the technical specification of the monitored transport system, a threshold tolerance margins Ω are set for each trip time.

Note:
To keep the graph as straightforward as possible, the following simplifications have been made:
- the clocks assignments corresponding to each transition are recorded in the destination state after crossing.
- the simultaneous crossing of two transitions is presumed to be not physically possible.

In this monitoring model, all initial situations are depicted, fig. 13.

These situations represent the system's state at the beginning of the railway traffic (state 1).

From this state in normal mode, if an event "x" occurs during the normal operation interval, the system switches to the state (2) in the same mode, otherwise the system shifts to the state (1') of the degraded mode. The clock "Yx" continue to count the activity duration. From this state in degraded mode noted (1'), if an event arrives before the duration end, the system proceeds in degraded mode (state (2')). Otherwise, the system switches to faulty mode and required maintenance intervention.

6.4 Monitoring approach validation

The main objective of this section is to illustrate how the SP-TPN model, after identification, simulates the Sahel Tunisian railway network in nominal and degraded modes (with and without disturbances). Thus a temporal study based on simulation is intended. In this etude, marks represent the metro position and the transitions firing correspond to metro passage times. This study is spread over a period of 30 days and the main results have been reported in fig. 14. This figure, reports the distribution of the trains departure times in various railway stations, for March month simulated period, without threshold tolerance margins. It can be noticed that the passage times dispersion reflects successive disturbances appearance.

As shown in figure 14, the dispersion rises with time: The dispersal is weak in the morning since the traffic ceases at night (see the histogram of the metro passage times at Mahdia station, transitions t1, fig. 14, up).

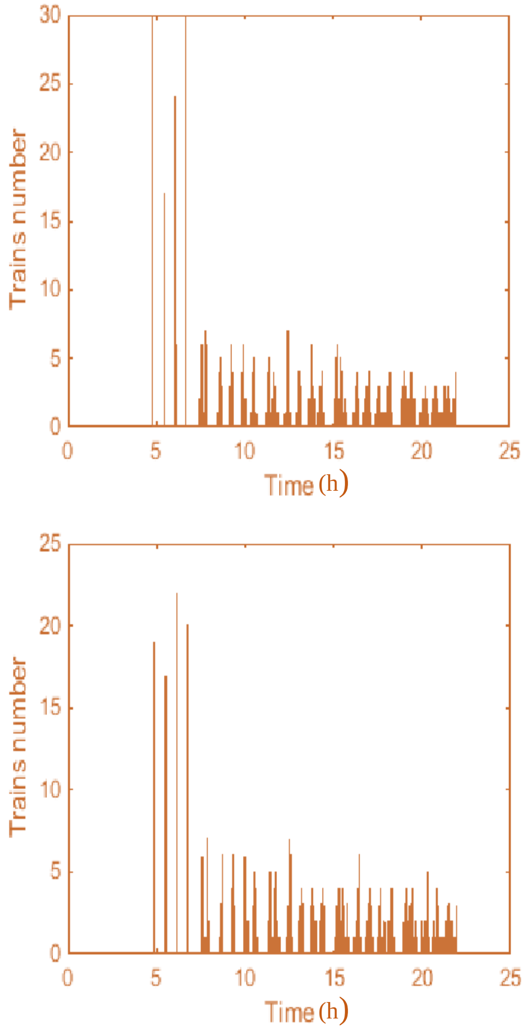


Figure 14. Passage times of metro at transitions t1 (up) and t6 (down)

In order to mitigate false alarms and prevent catastrophic situations that affect rail traffic, the dynamic monitoring approach is implemented and a set of simulations with a threshold tolerance margins Ω_i (associated to each journey time) for the month of March has been gathered. The outcomes are shown in Fig. 15. Thus, from this figure it is straightforward to check that proposed surveillance strategy leads to satisfactory results since it allows minimizing detection times and prevents false alarms arising from temporal disturbances.

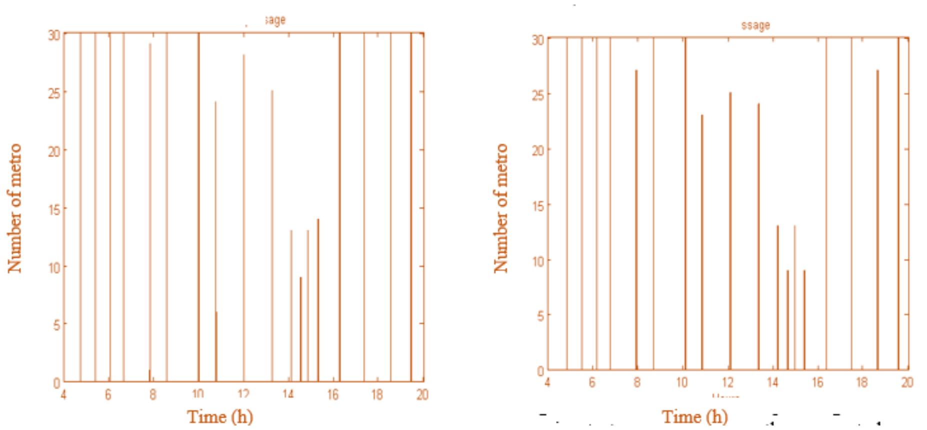


Figure 15. Passage times of metro at transitions t1 (right), t6 (left) with consdering threshold tolerance margins Ω

7. CONCLUSION

The main objective of our study is to conceive a monitoring system able to detect, pinpoint and diagnosis any failure affecting railway traffic as soon as possible. A threshold tolerance margins related to the operating time is introduced in order to contribute to the railway traffic safety.

The paper novelty is the developments of a monitoring model, supported by a set of process sensor states. The acquired approach is focused on the monitoring of travel operating time. In this framework, the system dynamic model, extracted from the control model, is used for failure detection. The application to a real transportation network highlights the significance of the surveillance procedure.

The system dynamic model is carried out using the timed automaton tool, which is well fitted for operating time monitoring. The developed dynamic model provides the focus of our monitoring strategy. The tenet is to detect and locate failures that may affect the system's performance, safety and security.

It has been shown that the detection of traffic disturbance is made by the acquaintance of the effective sojourn time which represents travel and parking time in the considered networks.

Suggested further work

As further research, we are currently developing with the engineers of the railway company a set of algorithms for computation and the optimization the tolerance thresholds. Further research with TNRC engineers is focused on incorporating maintenance and repair strategy issues into the presented supervision approach.

A second perspective that seems a priority is the diagnostic function as the monitoring model is restricted to the alarms detection and optimization.

It would be interesting to extend the presented monitoring approach to other challenges, such as the supervision of city transport networks, to mitigate disruptions in the bus operating time. As further work, we aim to develop a dynamic monitoring approach for rail transport systems, without forecasting the recovery time.

References:

Banić, M., Miltenović, A., Pavlović, M., & Ćirić, I. (2019). Intelligent machine vision based railway infrastructure inspection and monitoring using UAV. *Facta Universitatis, Series: Mechanical Engineering*, *17*(3), 357-364.

Bianchini Ciampoli, L., Gagliardi, V., Clementini, C., Latini, D., Del Frate, F., & Benedetto, A. (2020). Transport infrastructure monitoring by InSAR and GPR data fusion. *Surveys in Geophysics*, *41*(3), 371-394.

Chen, C., Liu, B., Wan, S., Qiao, P., & Pei, Q. (2020). An edge traffic flow detection scheme based on deep learning in an intelligent transportation system. *IEEE Transactions on Intelligent Transportation Systems*, *22*(3), 1840-1852.

Fedorko, G., Liptai, P., & Molnár, V. (2018). Proposal of the methodology for noise sources identification and analysis of continuous transport systems using an acoustic camera. *Engineering Failure Analysis*, *83*, 30-46.

Handayani, A. S., Putri, H. M., Soim, S., Husni, N. L., Rusmiasih, R. and Sitompul, C. R. (2019, October). Intelligent Transportation System For Traffic Accident Monitoring. In *IEEE International Conference on Electrical Engineering and Computer Science (ICECOS)* (pp. 156-161).

Khansa, W., Denat, J. P., & Collart-Dutilleul, S. (1996, August). P-Time Petri Nets for manufacturing systems. In *International Workshop on Discrete Event Systems, WODES* (Vol. 96, pp. 94-102)..

Lee, S. J., Ahn, D., You, I., Yoo, D. Y., & Kang, Y. S. (2020). Wireless cement-based sensor for self-monitoring of railway concrete infrastructures. *Automation in Construction*, Vol. 119, 103323.

M'halla, A., Lefebvre, D. and Gaied, M. (2020) . Distributed Monitoring Based on-Time Petri Nets and Chronicle Recognition of the Tunisian Railway Network". *Journal of Electrical and Computer Engineering*, Vol 2020.

Priyanka, E. B., Maheswari, C., & Thangavel, S. (2018). Online monitoring and control of flow rate in oil pipelines transportation system by using PLC based Fuzzy-PID Controller. *Flow Measurement and Instrumentation*, *62*, 144-151.

Rajes Kannan, S., & Amutha, S. (2021). Railway Wagon Health Monitoring System Using E-BMA Protocol in Wireless Sensor Networks. In *Artificial Intelligence Techniques for Advanced Computing Applications* (pp. 117-125). Springer, Singapore.

Soilán, M., Sánchez-Rodríguez, A., del Río-Barral, P., Perez-Collazo, C., Arias, P., & Riveiro, B. (2019). Review of laser scanning technologies and their applications for road and railway infrastructure monitoring. *Infrastructures*, *4*(4), 58.

Tsunashima, H. (2019). Condition monitoring of railway tracks from car-body vibration using a machine learning technique. *Applied Sciences, 9(13)*, 2734.

Wang, Y., Liu, S. Y. M., Cho, L., Lee, K., & Tam, H. (2021). A method of railway system safety analysis based on cusp catastrophe model. *Accident Analysis & Prevention*, 151, 105935.

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