An Application of Data-Driven Analysis in Road Tunnels Monitoring

Rossana Coccia, Alessandro Corsini, Fabrizio Bonacina, Mara Lombardi
Department of Mechanical and Aerospace Engineering
Sapienza University of Rome
Via Eudossiana, 18 - 00184 Roma, Italy
rossana.coccia@uniroma1.it, alessandro.corsini@uniroma1.it, fabrizio.bonacina@uniroma1.it, mara.lombardi@uniroma1.it

Lorenzo Ricciardi Celsi
Elis innovation Hub
Via Sandro Sandri, 81 - 00159 – Roma
l.ricciardicelsi@elis.org

Natale Marco Pellicanò, Novella Zangheri, Nicola Savini
Autostrade per l'Italia Spa, Via Alberto Bergamini, 50 - 00159 Roma, Italy
natalemarco.pellicano@autostrade.it, novella.zangheri@autostrade.it, nicola.savini@autostrade.it

Fabio Santucci, Samuel Salini, Marzia Malavisi
Movyon (Autostrade Tech), Via A. Bergamini, 50- 00159 Roma RM, Italy
fabio.santucci@autostrade.it, samuel.salini@autostrade.it, marzia.malavisi@autostrade.it

Abstract

In order to comply with the minimum safety requirements imposed by the Directive 2004/54/EC it is of paramount importance to correctly manage the operation and maintenance of road tunnels. This research describes how Artificial Intelligence techniques can play a supportive role both for maintenance operators in monitoring tunnels and for safety managers in operation. It is possible to extract relevant information from large volumes of data from sensor equipment in an efficient, fast, dynamic and adaptive way and make it immediately usable by those who manage machinery and services to aid quick decisions. Carrying out an analysis based on sensors in motorway tunnels, represents an important technological innovation, which would simplify tunnels management activities and therefore the detection of any possible deterioration, while keeping the risk within tolerance limits. The idea involves the creation of an algorithm for the detection of faults by acquiring data in real time from the sensors of tunnel sub-systems and using them to help identify the service state of the tunnel. The AI models are trained on a period of 6 months with one hour time series granularity measured on a road tunnel part of the Italian motorway systems. The verification has been done with reference to a number of recorded sensor faults.

Keywords
Artificial Intelligence, Sensor, Road Tunnel, Safety and Maintenance.

1. Introduction
Road tunnels are key infrastructures to facilitate inter-regional transportation with a significant direct economic impact. Minimum safety requirements have been recently updated to be applied to existing as well as new tunnels, including a series of measures inherent to design, safety installations, traffic management, emergency response, accident management and to the communication of information. Among the diverse factors, risk mitigation measures

have been often proposed to be linked to the empowerment of tunnel monitoring systems to keep an adequate maintenance of the safety installations.

Advances in data intensive technologies are enabling the valuation of historical data while, at the same time, broadening the potential outcomes of data analysis in the perspective of forecasting. The continuous development of sensors and measurement techniques allows to collect a large volume of data relative to each individual equipment in any complex engineering systems, in the attempt of unveiling real-time correlations of data and operating status of the systems. The data-driven causal analysis is most of the time motivated by fault-detection and diagnosis goals, or it can be used in a more sophisticated way for control purposes. With the rapid development of sensor technology, wireless transmission technology, network communication technology, cloud computing, and smart mobile devices, large amounts of data have been accumulated in almost every aspects of our lives. Moreover, the volume of data is growing rapidly with increasingly complex structures and forms. However, this huge amount of data, therefore the potential content of information, is often underutilized because data are analyzed with classical statistical tools. The scientific and industrial communities agreed that the data explosion in companies' businesses will be a source of competitive advantage able to lead the improvement of efficiency and sustainability of production cycles. Technology infrastructure can be monitored and operated even over huge physical distances. Networking enables simultaneous control and optimal coordination of a wide variety of complex technological processes. Digitalization is facing various challenges in the world of infrastructure, such as challenges in operational efficiency and cost control, system stability and reliability, renewable energy management, energy efficiency and environmental issues, as well as consumer engagement and service improvement. Data driven and artificial intelligence methods can be developed to help detecting and even anticipating anomalies and failures during the operations. Specifically, nowcasting systems can be equipped with learning mechanisms based on monitored time series evolution from the tunnel sensor network. The idea presented in the paper advocates the detection of faults by acquiring data in real time from the sensors of tunnel sub-systems and using them to help identifying the service state of the tunnel. Tunnel sensors have their own specific models based on multivariate regression to model the reciprocal influence among sensor signals. The proposed innovative application handles the use of Artificial Intelligence as an important tool that can be helpful for improving and optimizing the managing of road tunnels.

1.1 Objectives

The present paper focuses specifically on the use of data from sensor network equipping tunnel auxiliary plants in a view to define service state, contribute to tunnel safety management and data-driven maintenance. The large volume of data, derived from sensors, give us relevant information and make it usable to those who are managing the machinery and services, enabling them to make effective and quick decisions. In motorway tunnels, carrying out a data analysis, simplifies the management activities of the tunnels and therefore the restoration of any degradation, managing road tunnels. The proposed idea envisages the creation of a regression algorithm capable of acquiring data from the tunnel sensors and made detection of faults. The regressor model is built starting form data exploration, in an attempt to understand which the recurring dynamics are, to discover patterns in data trying to find subgroups, and to identify the subsystems of variables that exhibit the same dynamics.

2. Literature Review

The maintenance operations on the equipment could be preventive or corrective (Figure 1).
Preventive maintenance is carried out at fixed intervals with the objective of maintaining the equipment in a good operating condition. Preventive maintenance leads to high costs if the interventions are too frequent. Corrective actions instead are carried out when a system or a part of a system has failed or has been damaged, offers the advantage of using a system to the maximum extent of its service life. Its disadvantage however, is that it cannot be planned and therefore emergency repairs are normally carried out with a significant surplus cost and consequences for the traffic flow. It may be noted, nonetheless, that even when preventive maintenance is carried out the operator cannot avoid corrective interventions. They therefore need to be suitably optimized with predictive maintenance. Many publications focus on data-based maintenance, and others describe the general inspection of the equipment and service of the tunnels by inspectors. To this end predictive failure detection has not yet been explored, especially in tunnels. Several papers describe how to use predictive maintenance for specific systems in mechanical engineering, manufacturing processes, and other fields, for example. Even though tunnel systems are the subject of analysis for maintenance purposes, this analysis usually focuses on the structural part instead of on the technological part. Currently, the technological part of tunnel system consists of many different devices and technologies, some of them critical to the tunnel safety. Tomáš Tichý et al. very recently presented the results of the research on predictive maintenance of

technological devices in tunnel systems. This investigation has shown that predictive maintenance for technological devices in tunnel systems might bring benefits. In view of this survey, the main goal of our paper is to assess the approaches and possibilities that could be applied for tunnel systems in the future, in particular on the basis of data captured in tunnels.

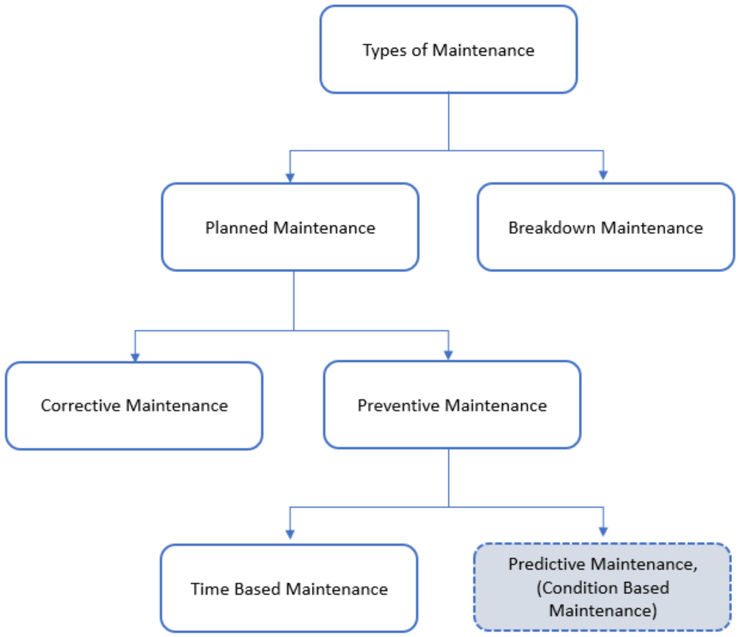

Figure 1.Types of Maintenance

3. Methods

The methodology consists of a first step entailing the labeling of available time series (from sensors) and traffic data. The labeling makes use of the information from the system status data (bi-hourly) and from the historical levels of service of galleries. The outputs of this last step are processed time series and traffic data, as shown in Figure 2.

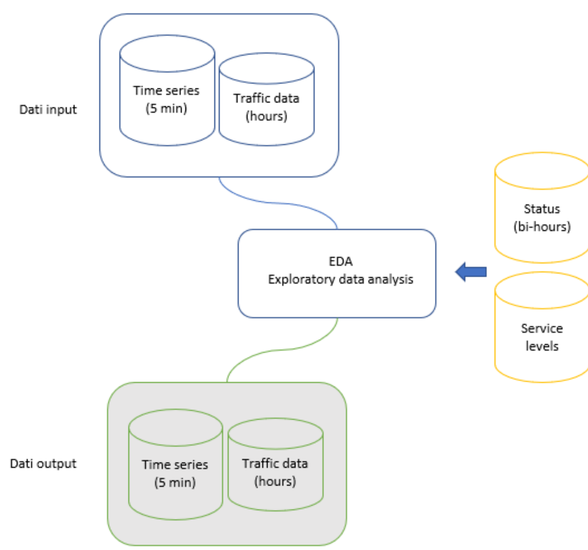

Figure 2. Data labeling and pre-processing

The processed input data collections are then divided to obtain training and test datasets. In so doing, the learner model is developed following the rationale illustrated in Figure 3.

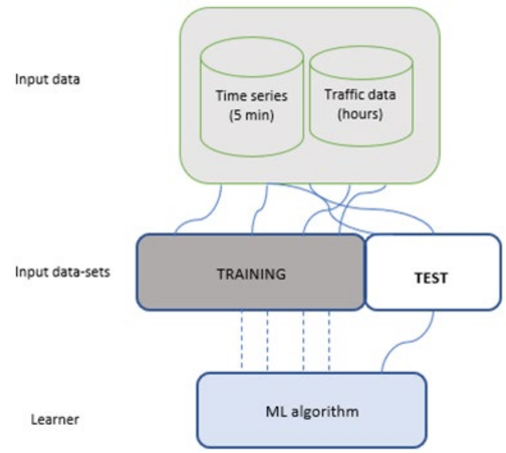

Figure 3. Data flow

Concerning the regressor, it is based on a Multivariate regression scheme used to predict the value of a variable *y* (dependent) based on the value of *n* variables x_i (independent), with $i = 1, n$.
The mathematical formulation of the multivariate regressor reads as:

$$y = \beta_0 + \beta_1 \cdot x_1 + \cdots + \beta_n \cdot x_n,$$

being the purpose of multiple regression equation the estimation of the coefficients β_j with $j = 0, n$. Specifically the regressor coefficients are computed by means of a least square estimation by minimizing, during the training phase, a function that assigns a cost to instances where the model *y* deviates from the observed data h. The cost function is in the form of a MSE:

$$J(\theta_0, \theta_1, \dots, \theta_n) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\theta(x^i) - y^i\right)^2$$

as the summation of square of difference between our predicted value and the actual value divided by twice of length of data set. Here the cost function is used along with the Gradient Descent algorithm to find the best parameters.

$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta_0, \dots, \theta_n)$$

4. Data collection and processing

This article is based on the data measured in a specific tunnel part of the Italian motorway network. Specifically, the sample tunnel for the present study is a twin-tube tunnel over 1.000 m long. The analysis refers to a 6 month period, from November 2019 to April 2020.

The initial investigations consist of patterns recognition, individuation of spot anomalies, test hypothesis and check assumptions with the help of summary statistics and graphical representations. The analysis has been carried out with reference to the sensor network which monitors the tunnel ventilation sub-system (including smoke management function and ventilation parameters detection). Figure 3 illustrates the flow chart of the ventilation sub-system monitoring.

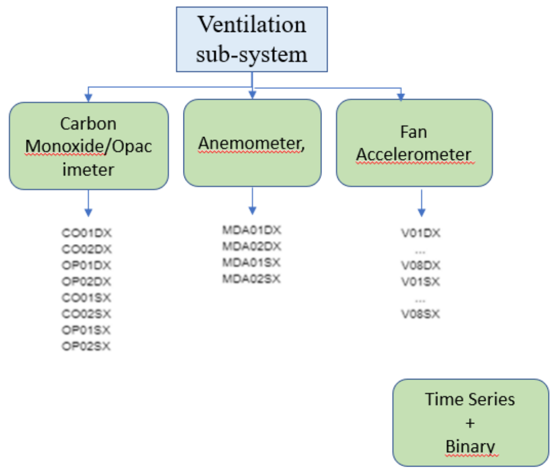

Figure 3. Ventilation sub-system sensor network nomenclature (SX and DX suffices indicate respectively left and right tube; CO: carbon monoxide, OP: opacimeter, MDA: anemometer, V: fan accelerometer)

Concerning the traffic data, characteristic patterns were recognized on a global scale as indicate in Figure 4. Notably, traffic data, either on light or heavy vehicles, did show a discontinuity during the lockdown period e.g. March – April 2020.
The time series from the sensor network were made available through the motorway concessionary with 1 hour sampling interval. By analyzing the time series from the sensors, the trends reveal particular dynamics in the period under scrutiny. Figure 5, as an example shows the anemometer Carbon monoxide sensors and opacimeters data series as recorded by the tunnel monitoring system.

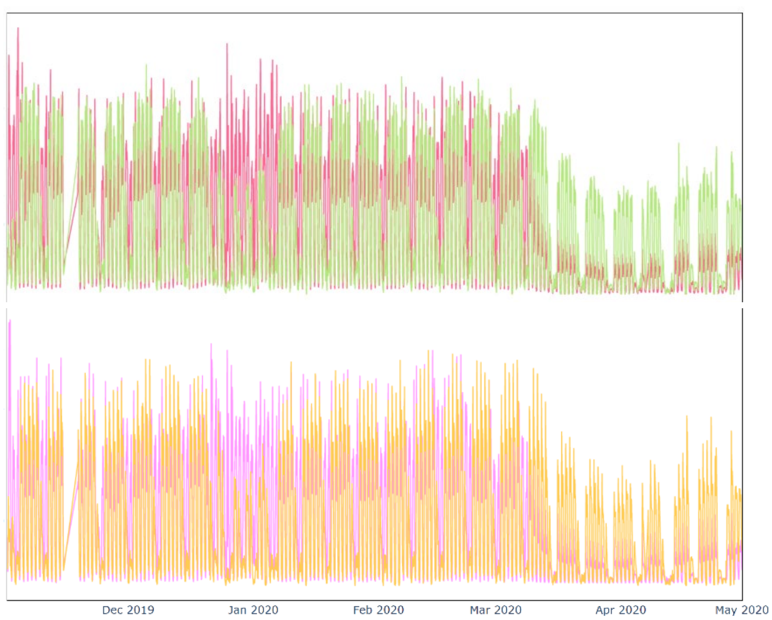

Figure 4. Normalized traffic trend of the sample tunnel, a) SX tube (heavy: pink, green: light), b) DX tube (heavy: purple, yellow: light)

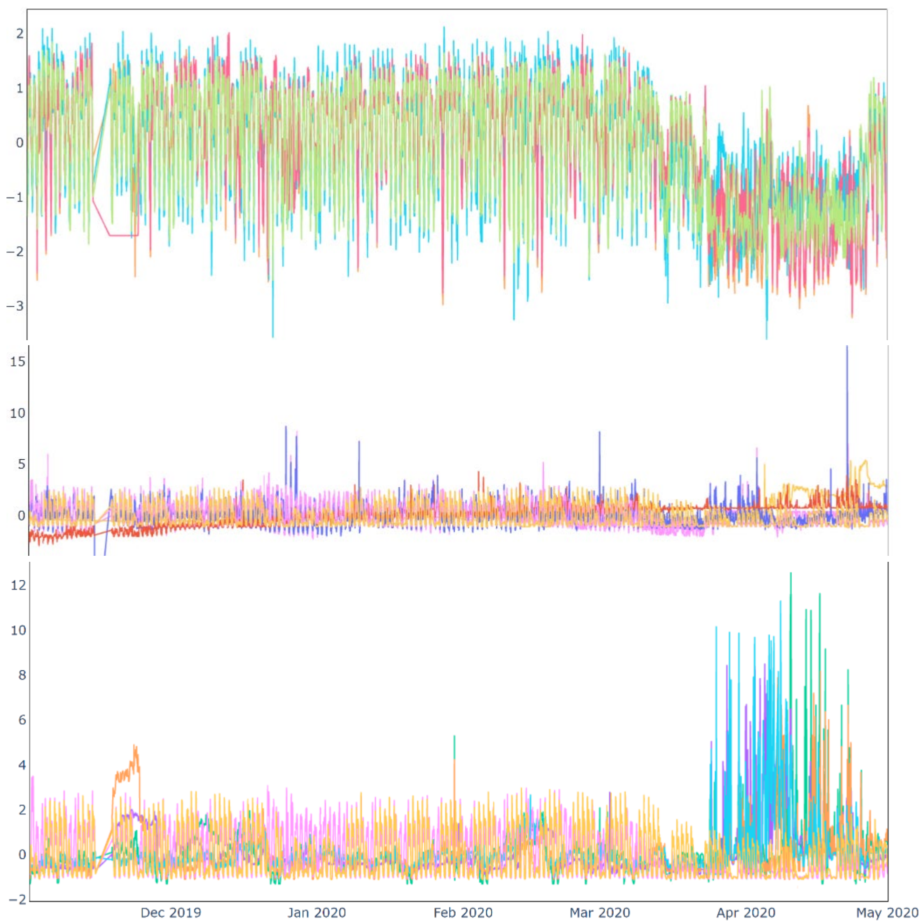

Figure 5. Normalized sensor time series trends: a) anemometer, b) Carbon monoxide sensors and c) opacimeters.

Concerning data preprocessing, the available sensor time series have been corrected with missing values substitution using data interpolation technique; moreover, outlier detection using sigma-rule and z-score (also called standard score) for data normalization.

5. Results and discussion

On the basis of pre-processed datasets, we developed a learner for each sensor in the ventilation sub-system of the sample tunnel. Sensor nowcasting models aimed at the determination of dis-ambiguous information on the level of degradation corresponding to sensor failure events, in order to guarantee a reduction in response times and accuracy of the intervention. As for the training data sub-set we did consider the period from November 2019 to April 2020 by eliminating all time interval corresponding to sensor failure events. On such data sets, specific models have been trained for each sensor to predict the sensor signal based on all other sensor behaviors in the short term (i.e. 1 hour). The quality of the training of sensor-specific learners is shown in Table 1, by introducing the principal metrics of the multi-variate regression. In particular, Table 1 collects the R-score and the error per type of sensor.

Concerning the testing phase, the data set is extended to include the failures recorded during the monitoring interval. To this end, Table 2 collects the statistical information that characterize the corrective maintenance carried out during the period under scrutiny. While, Table 2 confirms a high level of availability of the tunnel monitoring system, it also demonstrate the occurrence of a sufficient number of failure events to motivate the present study.

Table 1. Training results

Sensor	*R*	*Error*	*Samples*
Anemometer DX	0.96	0.01	4065
Anemometer SX	0.93	0.02	2716
CO meter DX	0.75	0.03	4065
CO meter SX	0.70	0.04	2716
Opacimeter DX	0.77	0.03	4065
Opacimeter SX	0.75	0.03	2716

Table 2. Summary of the ventilation sub-system maintenance data

MTBF	*Average Downtime*	*Availability*
(hours)	(hours)	-
312	36	0.9

To this end, Table 3 lists the failure events used to populate the testing datasets.

Table 3. Fault events

Sensor category	*Sensor code*	*Event date*	*Type of event*
Anemometers	MDA01DX	24/03-25/03	Loss of Communication
	MDA02DX	14/11-24/11	Fault: Alarm Switch
	MDA02SX	14/11-18/11	Fault: Alarm Switch
		24/03-25/03	Loss of Communication
Carbon monoxide sensors	CO01SX	1/11-21/11	Generic fault
		13/02-14/02	Generic fault
		17/02-19/02	Generic fault
		9/03	Generic fault
		24/03-25/03	Loss of Communication
	CO02SX	24/03-25/03	Loss of Communication
	CO01DX	24/03-25/03	Loss of Communication
Opacimeters	OP01DX	24/03-25/03	Loss of Communication
	OP01SX	14/11-18/11	Generic fault
		21/11	Generic fault
		24/03-25/03	Loss of Communication
	OP02DX	14/11-18/11	Generic fault
	OP02SX	24/03-25/03	Loss of Communication

The nowcasting performance of the developed models have been tested introducing into the data sets the actual series of fault occurred to the sensors in the period under scrutiny. To give more hints on the results of the sensor-specific nowcasters the following figures show details of the behavior of predicted against actual sensor time series in the vicinity of the ensuing period: sensor CO01SX in December 2019 (Figure 6), sensor OP02DX on November 14th 2019 (Figure 7), and sensor MA02DX on November 14th 2019 (Figure 8).

Figure 6, first, illustrates the behavior of the Carbon monoxide sensor CO01SX during a period of stable operation coinciding with December 1st to December 31st 2019. It is worth noting that the quality of the multi-variate learner is confirmed by the capability of reproduce the short-time signal dynamics as well as the long-term ones driven by the weekly cycles or to the traffic increment around the December vacation time.

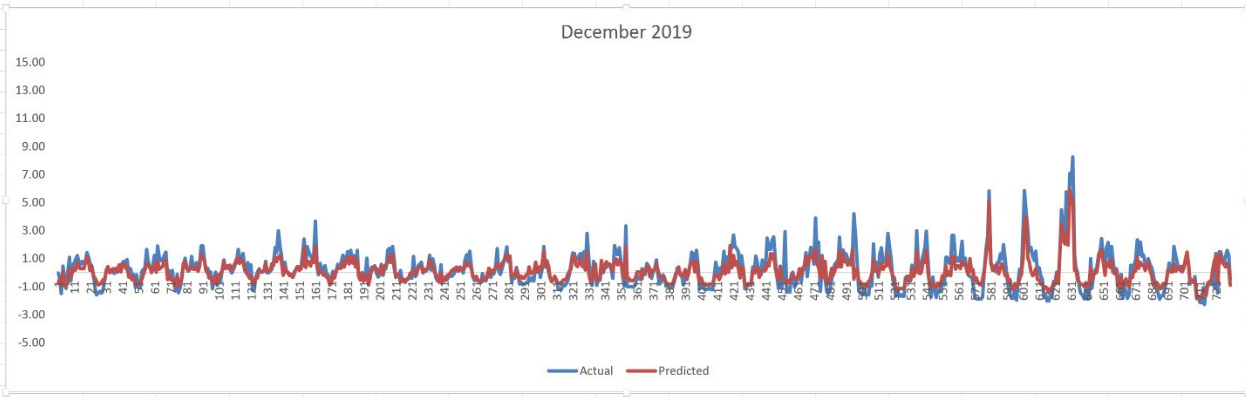

Figure 6. Normalized CO01 SX signal during December 2019: actual (blue) and predicted (red).

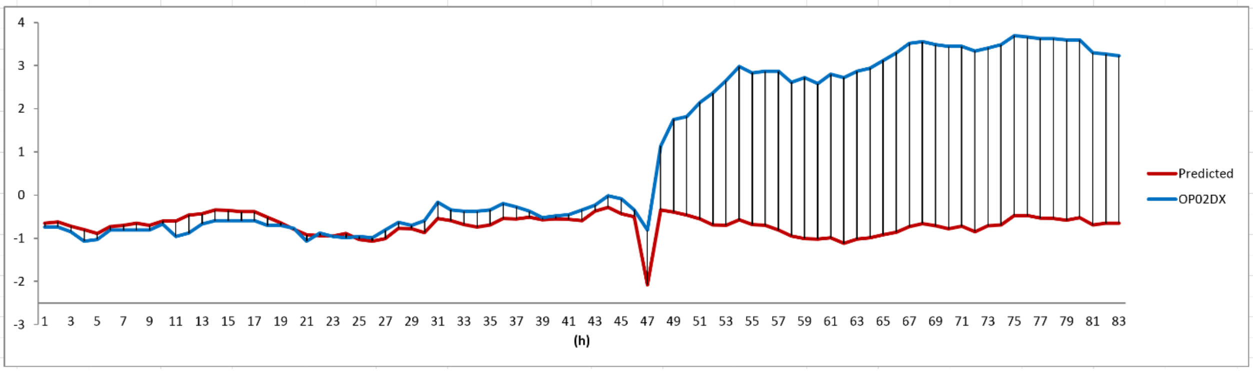

Figure 7. Normalized OP02 DX signal on November 14th 2019: actual (blue) and predicted (red).

Figure 7, on the other hand, shows the OP02DX signals around November 14th 2019. Specifically, the plot demonstrates the intervention of the nowcaster for sensor OP02DX at the occurrence of the fault on November 14th 2019. The evidence of the failure is proven by the departure of the actual signal from the predict one, that in this specific circumstance starts over-predicting the CO concentration. Similarly, Figure 8 shows the behavior of the nowcaster for the sensor MA02DX during ten days, i.e. November 14th to November 24th 2019.

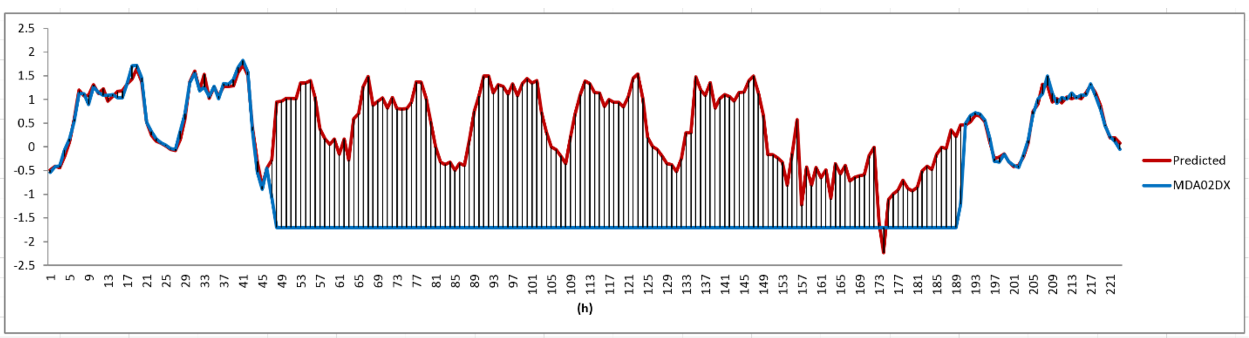

Figure 8. Normalized MDA02 DX signal November 14th 2019 to November 24th 2019: actual (blue) and predicted (red).

Notably, in the selected sample the prediction of the nowcaster returns to the actual value of the sensor signal after the maintenance intervention as such giving a further evidence of the robustness of the multivariate learner.

5.1 Proposed Improvements

The regressor models created are a start point that well implemented could be a robust predictive learner, making possible to have a reliable forecast of breakdowns. So the future steps of this preliminary work are improve the algorithm with more data for managing real time tunnel safety, giving the possibility to organize maintenance activities before a system failure occurs, for avoiding the adoption of compensatory measures now necessary during the failure of a plant, to ensure tunnel operation with an equal level of safety (ALARP criterion). Moreover, it would be convenient to create a single model by type-category of sensor (no longer for each sensor of the same category) by extending the input data to different road tunnels.

6. Conclusions

About nowcasting is possible to conclude that the presence of a fault (where the intervention of the maintenance technician is recorded) is detected by the models created for the sensors. For the period 24/03 - 25/03 we hypothesized a malfunction of the communication system as more than one sensor was involved but the plots do not show a flattening of the signal curve. To improve the performance, future work will be aimed at gathering at least one year of data, in order to include a greater number of cases and phenomena typically associated with seasonality.

References

European Parliament and Council. Directive 2004/54/EC. Official Journal of the European Union. L.167, Bruxelles, Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32004L0054, April 2004.

Konstantinos A. Kirytopoulos,. Quantitative risk analysis for road tunnels complying with EU regulations. Journal of Risk Research 13(8):1027-1041, December 2010.

ZeyuWangRavi S.Srinivasan, A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models, Renewable and Sustainable Energy Reviews Volume 75, August 2017, Pages 796-808.

L.H. Chiang, E.L. Russell, R.D. Braatz, Fault Detection and Diagnosis in Industrial Systems. Part of the Advanced Textbooks in Control and Signal Processing book series, 2001.

Basak, Sanchita, Ayman, Afiya, Laszka, Aron, Dubey, Abhishek ; Leao, Bruno, Data-driven detection of anomalies and cascading failures in traffic networks, Annual Conference of the PHM Society 2019.

Hongm Wang, Tian-You, Jin-Liang Ding, Martin Brown, Data Driven Fault Diagnosis and Fault Tolerant Control: Some Advances and Possible New Directions Volume 35, Issue 6, June 2009, Pages 739-747

Kaile Zhou, Chao Fu, Shanlin Yang. Big data driven smart energy management: From big data to big insights. Renewable and Sustainable Energy Reviews, Elsevier, 20 July 2015.

IDC. 2011 Digital universe study: extracting value from chaos. ⟨http://www. emc.com/collateral/analyst-reports/idc-extracting-value-from-chaos-ar.pdf⟩; 2011

Yanqing Duana, John S.Edwards, Yogesh KDwivedi, Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda, International Journal of Information Management Volume 48, October 2019, Pages 63-71 2019

Mirza Golam Kibria, Kien Nguyen, Gabriel Porto Villardi, Ou Zhao, Kentaro Ishizu, Fumihide Kohima, Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-Generation Wireless Networks, Digital Object Identifier 10.1109/ACCESS.2018.2837692, May 17, 2018.

Momoh JA. Smart grid design for efficient and flexible power networks operation and control. In: Proceedings of the power systems conference and exposition, 2009 PSCE'09 IEEE/PES. IEEE; 2009. p. 1–8

Alf J. Isakssona, Iiro Harjunkoski, Guido Sand. The impact of digitalization on the future of control and operations. Computers and Chemical Engineering 114 (2018) 122-129.

Amin M. Challenges in reliability, security, efficiency, and resilience of energy infrastructure: Toward smart self-healing electric power grid. In: Proceedings of the power and energy society general meeting-conversion and delivery of electrical energy in the 21st century, 2008 IEEE. IEEE; 2008. p. 1– 5.

Altın M, Goksu O, Teodorescu R, Rodriguez P, Jensen B-B, Helle L. Overview of recent grid codes for wind power integration. In: Proceedings of the 2010 12th international conference on optimization of electrical and electronic equipment (OPTIM). IEEE; 2010. p. 1152–60.

Zhou K, Yang S, Shen C, Ding S, Sun C. Energy conservation and emission reduction of China's electric power industry. Renew Sustain Energy Rev 2015;45:10–9.

Aalami H, Moghaddam MP, Yousefi G. Modeling and prioritizing demand response programs in power markets. Electr Power Syst Res 2010;80:426–35.
Marina Paolanti, Luca Romeo Andrea Felicetti, Adriano Mancini Emanuele Frontoni, Machine Learning approach for Predictive Maintenance in Industry 4.0. IEEE/ASME International Conference on Mechtronic and Embedded Systems and Applications, MESA, 2018.
Subana Shanmuganathan (2016) Artificial Neural Network Modelling: An Introduction. Artificial Neural Network Modelling pp 1-14, 4 February 2016.
Andrew McAfee and Erik Brynjolfsson. Big Data: The Management Revolution, From the Magazine Available: https://hbr.org/2012/10/big-data-the-management-revolution, Oct. 2012.
PIARC, Available: https://tunnelsmanual.piarc.org/en/operation-and-maintenance-maintenance/maintenance-equipment.
Christian Kuhn, Ferdinand Kaschewski, Jan Gläser, Christoph Seewald, Condition Monitoring in road tunnels, Virtual Conference 'Tunnel Safety and Ventilation', December 2020.
Farahani, B.V.; Barros, F.; Sousa, P.J.; Tavares, P.J.; Moreira, P.M. A railway tunnel structural monitoring methodology proposal for predictive maintenance. Struct. Control Health Monit. 2020, 27, e2587.
Jimenez, J.J.M.; Schwartz, S.; Vingerhoeds, R.; Grabot, B.; Salaün, M. Towards multi-model approaches to predictive maintenance: A systematic literature survey on diagnostics and prognostics. J. Manuf. Syst. 2020, 56, 539–557.
Quatrini, E.; Costantino, F.; Di Gravio, G.; Patriarca, R. Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. J. Manuf. Syst. 2020, 56, 117–132.
Motaghare, O.; Pillai, A.S.; Ramachandran, K.I. Predictive Maintenance Architecture. In Proceedings of the 2018 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), Madurai, India, 13–15 December 2018; pp. 1–4.
Zeyu Wang, Ravi S.Srinivasan, A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models, Renewable and Sustainable Energy Reviews
Volume 75, August 2017, Pages 796-808.
Konstantinos A. Kirytopoulos, Athanasios Rentizelas, Ilias P. Tatsiopoulos, Quantitative risk analysis for road tunnels complying with EU regulations, December 2010 Journal of Risk Research 13(8):1027-1041 DOI:10.1080/13669877.2010.494331.
Evangelos C. Alexopoulos, Introduction to Multivariate Regression Analysis, HIPPOKRATIA 2010, 14 (Suppl 1): 23-28, December 2010.
Saad Hikmat Haji, Adnan Mohsin Abdulazeez, Comparison of optimization techniques based on gradient descent algorithm: a review, Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq, 2021.
C.Caruso, F.Quarta, Interpolation methods comparison, Computers & Mathematics with Applications
Volume 35, Issue 12, June 1998, Pages 109-126.
Samson Sifael Kiware, Detection of Outliers in Time Series Data, a thesis submitted to the faculty of the graduate school, Marquette University, Available: https://core.ac.uk/download/pdf/67758994.pdf, May 2010
S. Gopal Krishna Patro, Kishore Kumar Sahu, Normalization: A Preprocessing Stage. Available: https://arxiv.org/ftp/arxiv/papers/1503/1503.06462.pdf, 2015.
Mark Plutowski, Halbert Whit, Selecting Concise Training Sets from Clean Data, IEEE Transactions on Neural Networks 4(2):305-18, February 1993.
Tichy, T.; Broz, J. Reliability Diagnostics of Technological Equipment, CTU FTS Research Report for Technology Agency of the Czech Republic; Project No. TH04010481; CTU FTS: Prague, Czech Republic, 2020.

Biography

Rossana Coccia is Ph.D student in Industrial and Management Engineering, Sapienza University Rome. Her research activities are based on methodologies for the evaluation of infrastructure assets based on data analysis and AI.

Alessandro Corsini is Full Professor, Department of Mechanical and Aerospace Engineering, Sapienza University Rome. The scientific research activity has developed since 1991, without solution of continuity. The researches carried out followed different fields of study in the field of energy systems and the fluid environment and machines, and have been carried out within academic realities and research institutions national (i.e., COFIN, ENEA, CNR), and international (i.e., collaborations with DLR, Leicester University (UK), Rice University (USA), BUTE (HU), & e). A significant part of the work was then carried out in the context of industrial research programs and applied with the collaboration of leading operators in the energy and industrial machinery sector (i.e. Enitecnologie and ENI Spa, Faggiolati Pumps Spa, Fieni Sri, Flakt Woods Ltd, Flakt Solyvent AB, Flakt Solyvent Ventee & e) or at the service of public administrations and ministerial bodies (i.e. Provincia e Municipality of Latina, Ministry of the Environment and Land and Sea Protection, & e).

Fabrizio Bonacina is Ph.D. in Industrial and Management Engineering. His research activities are based on the use of Data Intensive Analytics techniques on Sensor Network, with particular attention to connectivity analysis methods, Graph Modeling, Complex Network Analysis, Clustering and Supervised Learning.

Mara Lombardi is Associate Professor, Sapienza University of Rome. She obtains a PhD in Materials and Raw Materials Engineering. She carries out numerous assignments both in the University field and for important national and international Bodies / Structures. She is engaged in teaching activities for various Degree Courses of the Faculty of Civil and Industrial Engineering of Sapienza: SAFETY ENGINEERING, TRANSPORT SYSTEMS ENGINEERING, ENVIRONMENTAL AND TERRITORY ENGINEERING - Latina office and SECURITY ENGINEERING AND CIVIL PROTECTION . She has participated she has been and is responsible for several research projects at national level both university and financed by public and private bodies, such as the Municipality of Rome, ATAC, INAIL, Start-up 3-FASE srl, Municipality of Siena and Autostrade per l'Italia SpA. The research activity focuses on: Fire Safety Engineering, geostatistical analysis and modeling, risk analysis in relation to human behavior, RAMS approach, risk analysis for complex systems, network security road and railways and occupational safety. He is currently chairman of the Degree Course in Safety and Civil Protection Engineering, of the start-up Sapienza "Security 4.0" and a member of the CCTS (CNVvF) and of the CTR (CNVvF, Lazio Regional Directorate). She is the author of publications written both individually and in collaboration, many of which are international in character and book chapters.

Lorenzo Ricciardi Celsi Ph.D received his Ph.D. degree in Sciences et Technologies de l'Information et de la Communication, Specialité Automatique from Université Paris-Saclay, Paris, France, in 2018. His research interests include cooperative control methodologies for multiagent systems, and applied research in artificial intelligence and robotics. Since 2020, as R&D Manager, he has been the scientific responsible for the Joint Research Project initiative at ELIS Innovation Hub, pursuing technology transfer from academia to industry.

Natale Marco Pellicanò is Responsible for the Operation of the 3rd Section (BO) of AUTOSTRADE PER L'ITALIA S.p.A.

Novella Zangheri is technical director of AUTOSTRADE PER L'ITALIA S.p.A. She has been working within the Tunnel Safety Plan for plant adaptation and since 2016 in the central plant maintenance and monitoring coordination structure.

Nicola Savini is working in the central plant maintenance and monitoring coordination structure and since 2016 is head of tunnel security pursuant to legislative decree 264/06 for several tunnels managed by AUTOSTRADE PER L'ITALIA S.p.A.

Fabio Santucci is Software Engineer and is working in the video and tunnel systems structure for MOVYON (Autostrade Tech S.p.A.)

Samuel Salini is R&D specialist for the Data Management stream at MOVYON (Autostrade Tech S.p.A.).

Marzia Malavisi is R&D specialist for the Structure Health Monitoring at MOVYON (Autostrade Tech S.p.A.).