Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 16 (2018) 75–82

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

7th International Conference on Through-life Engineering Services

Reliability Challenges for Automotive Aftertreatment Systems: a State-of-the-art Perspective

Morteza Soleimani[a]*, Felician Campean[a], Daniel Neagu[a]

[a]*Advanced Automotive Analytics Research Centre, University of Bradford, Bradford, BD7 1DP, United Kingdom*

Abstract

This paper provides a critical review and discussion of major challenges with automotive aftertreatment systems from the viewpoint of the reliability of complex systems. The aim of this review is to systematically explore research efforts towards the three key issues affecting the reliability of aftertreatment systems: physical problems, control problems and fault diagnostics issues. The review covers important developments in technologies for control of the system, various methods proposed to tackle NOx sensor cross-sensitivity as well as fault detection and diagnostics methods, utilized on SCR, LNT and DPF systems. This paper discusses future challenges and research direction towards assured dependability of complex cyber-physical systems.

Keywords: Aftertreatment system; reliability; control strategy; fault diagnostics; sensor cross-sensitivity

1. Introduction

Increasing customer demand for highly reliable products and assured compliance with environmental issues makes reliability and dependability engineering a significant engineering concern. The complexity of modern automotive systems is driven by the ubiquitous multidisciplinarity of the systems; most functional systems in a vehicle have embedded electronics and software that control the behaviour of the systems, increasingly connected with the other vehicle systems and the external environment. Developing and validation such system requires an integrated approach across the different engineering disciplines that are involved in their design and development.

Environmental concerns have caused emission legislation becoming more stringent for the automobile industry. For example, the NOx emission limits for light-duty vehicle have been reduced from 0.50 to 0.08 g/km within less than 15 years. Additionally, the particulate matter (PM) reduction is limited to 0.0045 g/km in Euro VI [1]. Automotive

* Corresponding author. *E-mail address:* m.soleimani@bradford.ac.uk

2351-9789
10.1016/j.promfg.2018.10.174

aftertreatment systems have evolved and become increasingly complex and sophisticated in the drive to efficiently meet the gaseous emissions targets. In the future it can be expected that emission control technology will have to face further pressures as the vehicle will be expected to meet the legislated emissions targets under all real world driving conditions and not just against the set reference emissions drive cycles, such as NEDC or FTP. This places significant challenges on aftertreatment systems development and integration, which will be required to demonstrate advanced and assured dependability properties, such as self-awareness and assurance.

A modern automotive aftertreatment system for a Diesel engine, illustrated in Figure 1, typically contains four different catalysts with different functions: (i) Diesel Oxidation Catalyst (DOC): oxidation of HC and CO into H2O and CO2, and NO into NO2; (ii) Diesel Particulate Filter (DPF): PM filtration; (iii) Selective Catalytic Reduction (SCR): NO and NO2 elimination; and (iv) Ammonia Slip Catalyst (ASC): excess ammonia (NH3) removal before the gases are released into the atmosphere. In order to increase the performance of the aftertreatment system and to meet the increasingly stringent emissions legislations, many exhaust system configurations integrate combinations of these technologies [2].

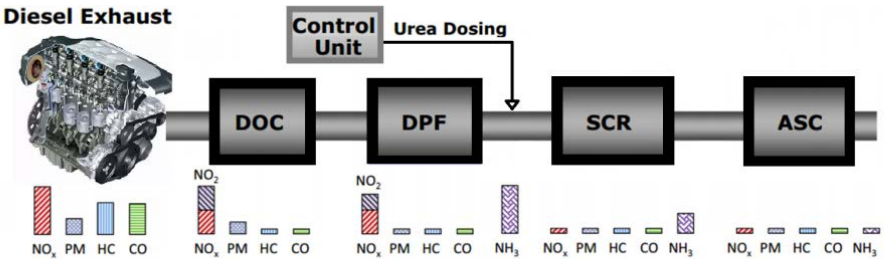

Fig. 1. *The standard Euro VI automotive aftertreatment system*

Several review papers have been published in recent years on automotive aftertreatment system, focussed on specific challenges, such as control issues i.e. [3, 4], or a specific component of the system, e.g. DPF [5, 6]. The main objective of this paper is to take a whole system view, considering the aftertreatment as a complex system, to systematically review the challenges and approaches and methods for reliability analysis and improvement. This provides a systematic view of the state of the art with reference value for scholars and practitioners alike, as well as informing future methodology development to tackle aftertreatment systems reliability and assurance challenges stemming from increasing complexity of connected cyber-physical systems.

The paper is structured as follows: section 2 identifies key reliability issues in aftertreatment systems, followed by a detailed review of control and decision-making methods (section 3), physical faults of the sensor and actuators (section 4), and current fault detection and diagnostics developments (section 5). The final sections of the paper provide an overall discussion along with conclusions and directions for future work.

2. Reliability Issues in Aftertreatment system

Figure 2 summarizes the classification of aftertreatment system reliability issues guiding the systematic review.

A robust control strategy plays an important role for the reliability of a system because it is the decision-maker. In an aftertreatment system, decision problems may occur because of software issues or incorrect inputs; software issues relate to the control strategy, whereas uncertainty about the inputs are linked to faults in the measuring process. The increase interdependence within the system leads to escalating complexity of the control system. For example, the SCR system control sophistication is induced by the requirement to manage a high NOx conversion efficiency while avoiding excessive dosing of diesel emission fluid (DEF) - that will cause ammonia slip.

The reliability of physical / hardware systems strongly depend on the working environment. The harsh operating conditions, especially high temperature and the presence of chemical reactions, are the main factors affecting the performance of hardware in aftertreatment system. Sensor faults and catalyst fault are the most significant physical problem in the system. Sensors have an important role in the system since their measured data are used in control unit as inputs and any fault in the sensors will have direct impacts on the function of the whole system. Dosing fault can be caused by both hardware problems and defect in controlling unit; physical problems, such as blockage on the injector nozzle or low DEF quality to fault in dosing command coming from control unit.

Fault diagnosis is one of the technologies to ensure the system reliability and safety. After detecting anomaly (monitoring and detection of abnormal conditions in the system operation), the task of fault diagnosis is the determination of the type of the fault, with as many details as possible such as the fault size, location and time of detection [7]. A number of issues must be considered when choosing particular fault detection method. The most important are: type of failures, description of process structure, process dynamics, available process signals, process complexity, available amount of process input-output data and process suitability for description in terms of rules. Early detection of faults can help avoid abnormal event progression and major failures. An aftertreatment system has complex subsystems comprising sensors, controllers and actuators, all of which are liable to various faults.

Given that these three classes of issues are interdependent with dynamic relationships, any problem in one sub-system can lead to influences on the function of others, rendering the overall system reliability problem very complex.

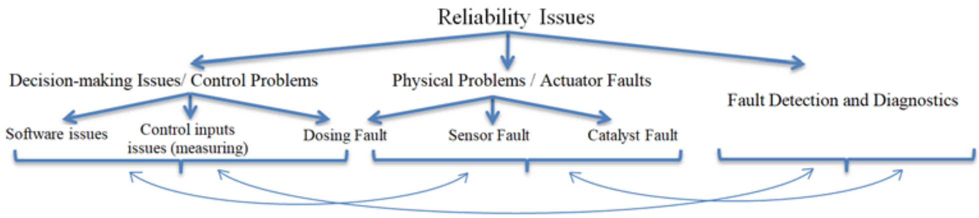

Fig. 2. Reliability issues in aftertreatment system

3. Decision-making Issues / Control Problems

Software reliability is an important factor affecting system reliability. It differs from hardware reliability in that it reflects the design perfection, rather than manufacturing perfection. Due to error in software by human action or discrepancy between computed, observed or measured value and specified value of some important reliability parameter may lead to fault in the software. An aftertreatment system consists of hardware and software; the later makes decisions according to the function of system and inputs. The control of aftertreatment system works based on the continual measurements of various factors which come from different sensors. For instance, dosing system in SCR works based on measured temperature, NOx, NH3, NO/NO2 ratio and so forth. Any problem in the inputs information will directly affect the system function. Therefore, it is vital to have a reliable control method both in terms of software and fault tolerance for inputs. Different control methods have been developed for SCR driven by the need to follow new emission legislations, which are discussed in the following.

3.1. Classic Control Methods

If operating conditions change only slowly, open-loop controllers are suitable solutions to the SCR control design problem [8]. Although this method is widely used and suitable for a nonlinear system, it requires significant calibration work and is inaccurate in transient states. Its main disadvantage is the high uncertainties because of the limitation in identifying all the reactions taking place on the SCR catalyst. Since these systems do not have a feedback mechanism, they can be inaccurate in terms of result output and hence they are unreliable.

Most aftertreatment control systems employ classical PI/ PID controllers. For an SCR system, the output feedback approach is not entirely convincing from a theoretical perspective. Because ammonia slip causes a sign reversal, the control loop can easily become unstable at high conversion. The basic control structure is only stable and feasible at low conversion where NH3 slip is rare. In order to reduce complexity, some papers combined classical PI control with a model-based approach [9]; however the performance is still less than ideal with this approach. As an advantage, it is more reliable than open loop methods.

3.2. Model-Based Control Methods

Model-Based Control (MBC) methods rely on a mathematical model of the system has to be developed, and based on the characteristics of the system the controller can be synthesized and analysed.

Generally, the main goals of a feedback controller are stability, reduced sensitivity to disturbances, and reduced effects of the most detrimental sources of error. The use of switching mode control was studied in [10] as an extreme form of state feedback.

The Extended Kalman Filter (EKF) is applied to the state estimation in SCR problem, estimating internal species concentration, ammonia slip and sensor cross-sensitivity [11]. EKF estimation performance is generally very good. It is a natural choice for combination with advanced control methods, both benefitting from the development of a high-fidelity, computationally efficient, control-oriented model. The availability of analytical Jacobians of the non-linear model also helps with convenient implementation. EKF requires the linearization of the nonlinear system. To tackle this deficiency, Unscented Kalman filter (UKF) and particle filter (PF) are recently used to input and state estimations in the SCR system; i.e. [12, 13].

3.3. Advanced Control Methods

For a more comprehensive approach, advanced control methods are being considered, that often include an element of online optimization. This allows compromises to be made between conflicting demands such as urea consumption, system degradation and efficiency [3].

In the multi-input multi-output systems that there are more than one control objective or constraint, model predictive control (MPC) is especially useful. For SCR, the research by McKinley and Alleyne [14] can be mentioned as the first example of the use of MPC. In another work [15], a linearized state-space SCR model was used in a standard unconstrained GPC-type formulation with NOx efficiency, NH3 slip, and urea dosing as controlled variable targets in the cost function, in addition to the urea input increment penalty term. Despite the noticeable advantages, MPC has two main disadvantages; computational efficiency and solution feasibility.

Adaptive control is suitable for solving nonlinear and uncertainty problems in the SCR system. The uncertainly is addressed in the controller, not in the estimator, and usually a global stability analysis is performed for the design. Herman et al. [16] proposed a closed loop PI controller, based on real time NH3 surface coverage computations, and using NH3 sensor feedback. Arsie et al [17] proposed the application of LS technique to adapt a NOx virtual sensor based on recurrent neural networks. The advantage of adaptive control schemes is that they can reduce the mismatch between the model and the actual system behaviour by adjusting the model parameters. This type of methods is confronted with the objection that the nonlinear dynamics are too complex to be solved reliably, efficiently, and safely; thus, the reliability issues arise which should be considered.

Minimization of simultaneously fuel consumption and emissions from combustion engines is a new field of research. In this case, the engine is considered as a part of the plant that is subject to control along with SCR with an integrated control approach. Mentink et al. [18] presented a design of an Integrated Emission Management strategy. The Integrated Emission Management functions as a supervisory controller, which determines the desired control settings for the different low-level controllers using online optimization.

The summary of reviewed references along with presented control techniques listed in table 1. The interested reader is referred to [3, 4] for more details regarding control strategies.

Table 1. Summary of reviewed references along with presented control techniques.

	Traditional Control Methods		*Model-Based Control Methods*		*Advanced Control Methods*		
	Open Loop Control	Close Loop Control (PI/PID)	State Feedback	State Estimation	Model Predictive Control (MPC)	Adaptive Control	Integrated Strategies
Reference	[8, 19]	[9, 19]	[10]	[11] [12] [13]	[9] [14, 15]	[16, 17, 20]	[18]

4. Physical Problems / Actuator Faults

Sensor fault, catalyst fault, wiring problems and actuator fault can be considered as the common hardware issues affecting the reliability of aftertreatment system. As aftertreatment system relies on the feedback from different sensors, the system reliability and control performance are likely to be affected by the sensor failure rates, sensor dynamic characteristics, and their interface circuits.

SCR is a complex subsystem of aftertreatment system and it comprises sensor, controller and actuator which are liable to various faults. Three major faults in the SCR system are outlet NOx sensor fault, dosing fault and SCR catalyst fault. Figure 3 shows the pertaining fault tree analysis.

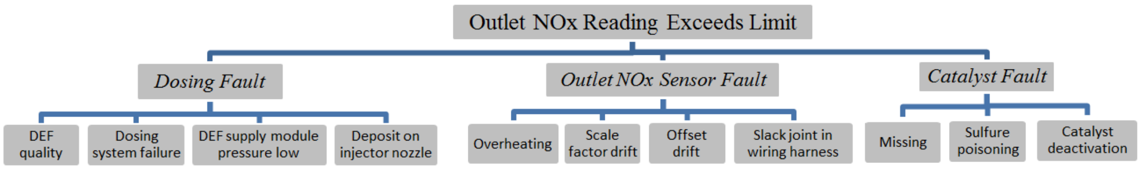

Fig. 3. *Fault tree analysis of the SCR*

NOx sensors play a key role in urea-SCR controls since they provide valuable information such as the NOx concentrations at the SCR inlet and outlet. The main drawback of current NOx sensors in mobile SCR application is that they carry high cross-sensitivity to the ammonia in the exhaust [21]. In practice, the cross-sensitivity factor of the NOx sensor can be calibrated as a function of exhaust temperature. Different NOx sensors may show different ammonia cross-sensitivity characteristics at the same exhaust temperature. Therefore, the ammonia cross-sensitivity factor needs to be experimentally calibrated for each NOx sensor [22].

Various methods have been proposed in to tackle the problem of the NOx sensor cross-sensitivity Jiang et al. [23] have investigated adaptive unscented Kalman filter (AUKF) to estimate the cross-sensitivity factor in the SCR system. AUKF has the advantages of sample calculation and the capacity to deal with nonlinear system. In reference [24], a design approach for a robust gain-scheduling mixed H2/H∞ observer is proposed in order to estimate the actual value of NOx concentration and non-constant cross-sensitivity factor. Ming and Junmin [25] introduced a method to estimate the actual NOx concentration and cross-sensitivity factor which utilized the stochastic character of EKF and an approximate cross-sensitivity factor model.

Basically, the common goal in all presented methods is to determine the NOx and NH3 concentrations at the outlet of the SCR system with solely a cross-sensitive NOx sensor. However, all the proposed methods have their weaknesses. For example, the method described in [26] requires active perturbation. Therefore, it can only be applied in static operations. The method proposed in [22] requires two NOx sensors with different and known cross-sensitivities. The observer suggested by [27] is very difficult to tune, and it has been validated in a simulation environment. The method described in [28] can only detect the presence of NH3, but its concentration cannot be determined. Up to now, a robust method for removing the NOx sensor cross-sensitivity with only one downstream NOx sensor has not yet been available.

Another problematic issue is the wiring and its connections problem because of high temperature within exhaust system. To cope with the wiring reliability problems, wireless sensor networks can be evaluated and its feasibility should be analysed. In addition, connectors should be kept to a minimum, selected, and installed to provide the maximum degree of safety and reliability. Although the main contributing factors in dosing faults are software and controlling problem, hardware and actuator problems can also be root causes. Catalyst, dosing and sensor faults are in a close relation to fault diagnostics issues and will be reviewed in more detail in the following section.

5. Fault Detection and Diagnostics

There are some basically similar classification for fault detection and diagnosis methods. In general, there are three basic methods for fault diagnosis, i) data-based, ii) model-based and iii) knowledge-based methods. Figure 4 illustrates fault detection and diagnosis methods derived from [7, 29].

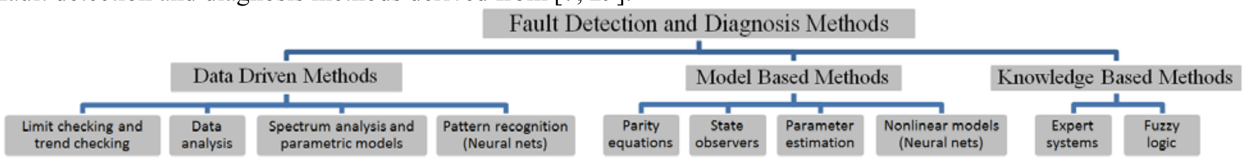

Fig. 4. *Divisions of fault detection and diagnosis methods*

Because of the importance of fault detection and diagnostics on the reliability of aftertreatment system, the main methods used for DPF, LNT, and SCR are reviewed in this section.

Pressure sensor combined with a flow measurement is the technology to meet the DPF leakage monitoring requirement. The main disadvantages of this method are limited performance due to the high tolerance caused by the sensor (because of noise factors), also the driving conditions under which the monitoring occurs. In 2008, Nieuwstadt and Brahma [30] investigated the ability of the model-based DPF leakage detection methods over the pressure sensor-based DPF leakage monitor. They presented the noise factors entering the relevant models and a numerical evaluation to assess the capability of the model-based leakage monitor under typical ranges of the noise factors. A research by Surve [31] proposed to correlate the pre and post-DPF temperature and pressure signals to define its transfer function characteristics for the baseline DPF behaviour. The method achieved a fault detection of lightly failed DPF not possible by current algorithms based on mean value pressure drop.

A simplified storage model that can be integrated into the existing control strategy for real-time LNT control and diagnosis was developed in [32] that captures the dynamics of NOx adsorption, reaction rate, and physical mass transfer process. Deactivation of the LNT catalysts is one type of fault that can compromise the NOx conversion efficiency if it is not properly monitored and compensated for. Thermal exposure during high load operating conditions or filter regenerations could also lead to the loss of activity, which is irreversible. Another cause of deactivation is related to the presence of sulphur in the fuel and lubricated oil due to the formation of sulfates on the catalyst surface that reduces the LNT storage capacity. Canova [33] described the development of a fault diagnosis procedure to detect and isolate sulphur poisoning, deactivation of the LNT catalyst storage sites due to thermal aging, and faults in the sensors, based on the parity equation approach and on the principle of analytical redundancy. They used a time-varying nonlinear ODE model of the LNT system to generate the residuals using the system model, through comparison of the predicted and measured values of selected variables.

Using parity equation residual generator, Chen and Wang [34] developed a model-based fault diagnosis system to detect and isolate the SCR system dosing fault and the outlet NOx sensor fault. In reference [35], an integrated on-board diagnosis and fault-tolerant control methods with experimental validation was developed for a urea injection fault in SCR. Diagnostics are performed by estimating and monitoring the injected urea mass flow with no need for a costly physical flow sensor. Kalman filter (KF) is formulated to further reduce the estimation noise and improve diagnostic robustness. An algorithm was developed to correct the NOx sensor reading by Wang et al. [36]. With considerable experimental data, they obtained the relationship between the cross-sensitivity factor and the temperature by employing the adaptive-network-based fuzzy inference system (ANFIS). Results revealed that the developed fuzzy inference system has prominent advantages on the reading correction performance compared with the existing extended Kalman filter (EKF). Recently, Aberg et al. [37] derived a single channel model for a heavy-duty SCR catalyst based on first principles. They considered heat and mass transfer between the channel gas phase and the wash coat phase. Results showed that the model predictive capabilities regarding NOx was highly affected by the assumption that the catalyst does not have any thermal mass and wash coat heat transfer. During steady state operation, as used for parameter estimation of the kinetic parameters, this did not lead to any error, since the temperature of the monolith is already at operating condition at the start of the test, and does not change throughout the test. Liu et al. [38] proposed an ensemble method based on a support vector machine (SVM) and genetic algorithm (GA) to establish the models for the prediction of upstream and downstream NOx emissions and NH3 slip. The utilized data for modelling were collected from a steady-state diesel engine bench calibration test. The conclusion was that the prediction accuracy of the SCR model could be improved by using an SVM, the parameters of which were optimized using a GA control strategies. Table 2 summarizes the reviewed references for fault detection and diagnostics methods.

Table 2. Summary of reviewed references along with their fault diagnostic techniques

		Data-driven methods		Model-based methods			Knowledge Based Methods
		Principal Component Analysis	*Pattern Recognition*	*Parity equations*	*State observers*	*Parameter estimation*	*Fuzzy logic*
SCR	*sensor fault*	[38]	-	[34]	-	-	[36]
	dosing fault	-	[36]	[34]	[35]	[35]	-
	catalyst fault	-	-	-	-	[37]	-
	LNT	-		[32] [33]			-
	DPF	-		[30] [31]			-

6. Discussion, Conclusions and Further Direction

This paper has presented a methodical review of the reliability of aftertreatment systems, taking a complex systems viewpoint, and providing a holistic view of the interconnected reliability challenges. The review has systematically considered the analytical techniques and methods employed to address and prevent the reliability issues across the sub-systems of the aftertreatment system. This addresses the limitations of previous studies which have focused on specific challenges for specific subsystems, thus contributing a valuable reference view of the state of the art.

This section presents a synthesis of the key issues arising from the systematic review of the aftertreatment systems reliability, and provides a view of the future challenges that scope out the direction for future research

SCR is a complex and highly nonlinear system and its chemical reactions are difficult and sensitive to control. Many researches have focused on improving its control, NOx conversion efficiency and NH3 slip prevention. As computer technologies advance, more computationally-intensive, high performance algorithms are expected to be employed for this nonlinear system. Some powerful control methods have been utilized in aftertreatment system such as MPC and integrated control approaches that are very attractive for this application. The main challenges in DPF are the accurate estimation of the soot and reliable regeneration control strategies. To comply with the future stringent emissions regulations, high efficiency DPF and SCR technologies are being required to effectively reduce PM and regenerating under all possible driving conditions, which in turn requires assured NOx sensors reliability.

Physics of failure as an approach for reliability prediction uses knowledge of a system's life-cycle loading and failure mechanisms to perform reliability modeling, design, and assessment. In particular, physics of failure is a key approach used by manufacturers of commercial products for reliability enhancement. This method can be used along with other similar methods in order to enhance the reliability of aftertreatment system. This approach is applicable especially in the case of SCR which has complex nonlinear structure.

Fault diagnostics technology has developed into a new discipline. On the basis of the operating principle of diagnosis objects, it integrates computer network, database, control theory, artificial intelligence and other technologies. Due to the complexity and nonlinearity of aftertreatment systems and also new developments in fault diagnosis technology a new procedure is required to synchronize with modern methods.

One of the most significant challenges from the perspective of complex system reliability is the interdependency for multi-component systems. Many researchers have pointed out that when it comes to developing reliability and failure prediction models for multi-component systems, the assumption of independence is unrealistic. In fact, it has proven that the independence assumption often leads to errors in estimating the system/component lifetimes in many real-world applications. Therefore, for the multi-component aftertreatment systems evaluation of this factor seems imperative, especially stochastic dependency which shows the influence of the state of a component on the lifetime distribution of other components.

Software reliability is dynamic and stochastic. It differs from the hardware reliability in that it reflects design perfection, rather than manufacturing perfection. In the reviewed literature for control of aftertreatment system, the researcher investigated and assessed the control issues through the design point of view (as mentioned in the advantages and disadvantages of each approach). From the application standpoint, these control strategies are completely relevant to estimate the reliability of the whole system in real applications. Therefore, a comprehensive effort is needed to evaluate software reliability because, in a modern system like aftertreatment system, there is a real-time interaction between hardware subsystem and software subsystem.

Reliability can be improved through fault tolerance. The most important method supporting fault tolerance/reliability is redundancy. Although the application of redundancy is always connected with an increase in cost and/or complexity, it can be a good way to increase the reliability of critical parts of this system.

Alternative sensing mechanisms other than the direct feedback from sensors can improve the system reliability. For example, the use of current information reconstruction or estimation schemes that can increase the fault tolerance against current sensor faults can be considered as a method to increase the system reliability.

The most important issue for a complex system reliability is to provide assurance for mission achievement. The development of the aftertreatment system will be expected to meet emerging legislation for real world driving emissions, along with customer expectations for highly reliable products. Taking a broader view of emissions legislation evolution, a likely demand for future aftertreatment systems is to provide assured self-certification. This means that the aftertreatment system could be expected to automatically certify failure-free mission, within dynamically variable operating conditions, and against variable targets received from the connected environment. This highlights the importance of design for reliability effort and methodology development and validation for aftertreatment system which will be operating as a cyber-physical system, addressing all the issues discussed in this review in an integrated approach with dependability and safety assurance methods. Given the dynamic complexity of the cyber-physical system, integration of big data and advanced machine learning methods will be an essential enabler for both assessment and validation of mission reliability. Integration of complex systems assurance with dynamic reliability methods underpinned by big data and machine learning is an evolving research area. This defines the approach we are taking in our current work towards the development and validation of an advanced framework for the healthcare of complex automotive systems.

Acknowledgement

The research presented in this paper is part of the Intelligent Personalised Powertrain Healthcare research project undertaken by the University of Bradford's Advanced Automotive Analytics research unit, in collaboration with Jaguar Land Rover.

References

1. *DieselNet. Summary of Worldwide Diesel Emissions Standards*. Available from: http://www.dieselnet.com/standards.
2. Chatterjee, D., et al., *Numerical simulation of DOC+ DPF+ SCR systems: DOC influence on SCR performance.* SAE International Journal of Fuels and Lubricants, 2009. 1(1): p. 440-451.
3. Skaf, Z., et al., *The state of the art in selective catalytic reduction control*. 2014.
4. Yuan, X., H. Liu, and Y. Gao, *Diesel engine SCR control: current development and future challenges.* Emission Control Science and Technology, 2015. 1(2): p. 121-133.
5. Guan, B., et al., *Review of the state-of-the-art of exhaust particulate filter technology in internal combustion engines.* Journal of environmental management, 2015. 154: p. 225-258.
6. Khair, M.K., *A review of diesel particulate filter technologies*. 2003, SAE Technical Paper.
7. Isermann, R., *Fault-diagnosis systems: an introduction from fault detection to fault tolerance*. 2006: Springer Science & Business Media.
8. Chi, J.N., *Control challenges for optimal NOx conversion efficiency from SCR aftertreatment systems*. 2009, SAE Technical Paper.
9. Song, Q., G. Zhu, *Model-based closed-loop control of urea SCR exhaust aftertreatment system for diesel engine*. 2002, SAE Technical Paper.
10. Shen, B., et al. *Applied research on diesel engine SCR system with the variable structure control theory*. in *Electrical and Control Engineering (ICECE), 2011 International Conference on*. 2011. IEEE.
11. Surenahalli, H.S., G. Parker, and J.H. Johnson, *Extended Kalman filter estimator for NH 3 storage, NO, NO 2 and NH 3 estimation in a SCR*. 2013, SAE Technical Paper.
12. Cao, E. and K. Jiang, *Adaptive unscented Kalman filter for input estimations in Diesel-engine selective catalytic reduction systems.* Neurocomputing, 2016. 205: p. 329-335.
13. Sun, K., et al., *A particle filter for ammonia coverage ratio and input simultaneous estimations in Diesel-engine SCR system.* PloS one, 2018. 13(2): p. e0192217.
14. McKinley, T.L. and A.G. Alleyne, *Model predictive control: a unified approach for urea-based SCR systems.* SAE International Journal of Fuels and Lubricants, 2010. 3(2010-01-1184): p. 673-689.
15. Chiang, C.-J., et al. *Model predictive control of SCR aftertreatment system*. in *Industrial Electronics and Applications (ICIEA), 2010 the 5th IEEE Conference on*. 2010. IEEE.
16. Herman, A., et al., *Model based control of SCR dosing and OBD strategies with feedback from NH 3 sensors.* SAE International Journal of Fuels and Lubricants, 2009. 2(2009-01-0911): p. 375-385.
17. Arsie, I., et al., *Neural network models for virtual sensing of NOx emissions in automotive diesel engines with least square-based adaptation.* Control Engineering Practice, 2017. 61: p. 11-20.
18. Mentink, P., et al., *Experimental demonstration of a model-based control design and calibration method for cost optimal Euro-VI engine-aftertreatment operation*. 2013, SAE Technical Paper.
19. Willems, F., et al., *Is closed-loop SCR control required to meet future emission targets?* 2007, SAE Technical Paper.
20. Chen, P. and J. Wang, *Estimation and adaptive nonlinear model predictive control of selective catalytic reduction systems in automotive applications.* Journal of Process Control, 2016. 40: p. 78-92.
21. Frobert, A., et al., *About cross-sensitivities of NOx sensors in SCR operation*. 2013, SAE Technical Paper.
22. Chen, P. and J. Wang, *A novel cost-effective robust approach for selective catalytic reduction state estimations using dual nitrogen oxide sensors.* Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2015. 229(1): p. 83-96.
23. Jiang, K., E. Cao, and L. Wei, *NOx sensor ammonia cross-sensitivity estimation with adaptive unscented Kalman filter for Diesel-engine selective catalytic reduction systems.* Fuel, 2016. 165: p. 185-192.
24. Zhang, H., J. Wang, and Y.-Y. Wang, *Removal of NOx sensor ammonia cross sensitivity from contaminated measurements in Diesel-engine selective catalytic reduction systems.* Fuel, 2015. 150: p. 448-456.
25. Hsieh, M.F. and J. Wang. *An extended Kalman filter for NO x sensor ammonia cross-sensitivity elimination in selective catalytic reduction applications*. in *American Control Conference (ACC), 2010*. 2010. IEEE.
26. Schar, C.M., C.H. Onder, and H.P. Geering, *Control of an SCR catalytic converter system for a mobile heavy-duty application.* IEEE Transactions on Control Systems Technology, 2006. 14(4): p. 641-653.
27. Zhang, H., J. Wang, and Y.-Y. Wang. *Robust mixed* $\mathcal{H}_2/\mathcal{H}_\infty$ *gain-scheduling observer design for removal of NO x sensor ammonia cross sensitivity in selective catalytic reduction systems*. in *American Control Conference (ACC), 2013*. 2013. IEEE.
28. Upadhyay, D. and M. Van Nieuwstadt, *Robust Separation of Signal Domain From Single Channel Mixed Signal Output of Automotive Urea Based Selective Catalytic Reduction Systems.* Journal of Dynamic Systems, Measurement, and Control, 2014. 136(1): p. 011012.
29. Frank, P.M., *Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy: A survey and some new results.* automatica, 1990. 26(3): p. 459-474.
30. van Nieuwstadt, M. and A. Brahma, *Uncertainty analysis of model based diesel particulate filter diagnostics.* SAE International Journal of Commercial Vehicles, 2008. 1(2008-01-2648): p. 356-362.
31. Surve, P.R., *Diesel particulate filter diagnostics using correlation and spectral analysis.* 2008.
32. Wang, X., et al., *Lean NOx trap storage model for diesel engine aftertreatment control and diagnosis.* Transactions of the ASABE, 2006. 49(6): p. 1687-1693.
33. Canova, M., et al., *Model-based fault detection and isolation for a diesel lean NOx trap aftertreatment system.* Control engineering practice, 2010. 18(11): p. 1307-1317.
34. Chen, R. and X. Wang, *Model-Based Fault Diagnosis of Selective Catalytic Reduction Systems for Diesel Engines.* SAE International Journal of Passenger Cars-Electronic and Electrical Systems, 2014. 7(2014-01-0280): p. 449-453.
35. Wang, Y.-Y., et al., *Model-based fault detection and fault-tolerant control of SCR urea injection systems.* IEEE Transactions on Vehicular Technology, 2016. 65(6): p. 4645-4654.
36. Sun, Y., et al., *Detection of urea injection system faults for SCR systems*. 2012, SAE Technical Paper.
37. Åberg, A., et al., *Parameter estimation and analysis of an automotive heavy-duty SCR catalyst model.* Chemical Engineering Science, 2017. 161: p. 167-177.
38. Liu, B., et al., *Modeling and Multi-Objective Optimization of NOx Conversion Efficiency and NH3 Slip for a Diesel Engine.* Sustainability, 2016. 8(5): p. 478.