Hybrid Data-Driven and Physics-Based Modelling for Prescriptive Maintenance of Gas-Turbine Power Plant

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Abstract. The methodology for prescriptive maintenance of complex technical systems is presented. The proposed methodology is based on a hybrid physics-based and data-driven modelling of complex systems. This approach integrates traditional physics-based simulation techniques such as finite-element modelling, finite-volume modelling, bond-graph modelling and data-driven models, with machine learning algorithms. Combined implementation of the both approaches results in the development of a set of reliable, fast and continuously updating models of technical systems applicable for predictive and prescriptive analytics. The methodology is demonstrated on the jet-engine power plant preventive maintenance case-study.

Keywords: Prescriptive analytics · Machine learning · Hybrid modelling · Jet-engine simulation

1 Introduction

1.1 Digital Twin Concept

Traditionally, PLM systems and tools are focused on the development and production stages of a product lifecycle, including design, testing, validation of the developed models and manufacturing. Since 1980–1990-s (the time of initiation of the PLM concept) huge amount of data have been generated that is used for the development and manufacturing of complex products in aerospace, automotive, machinery and other industries [1]. The use of CAD, CAE and digital manufacturing tools now is considered as a standard for the product development. Nowadays more and more attention is paid to the multi-level simulation of a product functionality to support the development process and to reduce the needed number of physical tests. Demand in numerical models is one of the main drivers of the PLM market growth.

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The high-level models, built using systems modelling languages (SysML), functional models, built in Modelica-oriented environments, finite-element and finite-volume models, built in FEA and CFD codes are managed using special modules in PLM systems called Simulation Data and Process Management modules.

All the mentioned above factors, together with increasing computing power led to introduction of the digital twin concept. Digital twin is an integrated set of virtual physics-driven models of a product, system or process which enables real-time monitoring and avoids problems before they occur with its physical counterpart and prevents downtimes [2]. Also, digital twin aims to reduce the cost of system testing and verification. Unlike ordinary virtual model, which describes the product without any imperfections, digital twin of the product represents a particular its instance at different stages of the lifecycle (testing, production, maintenance, disposal). The digital twin concept along with descriptions of the entire digital twin technology were presented and discussed in a number of research papers [3, 4].

1.2 Preventive Maintenance and Performance Optimization Using Digital Twins

Among other applications, digital twin should be used for prescriptive maintenance of a system or a product in operation. There are different ways to perform preventive maintenance of a functioning product (Fig. 1), including descriptive, diagnostic, predictive and prescriptive analytics.

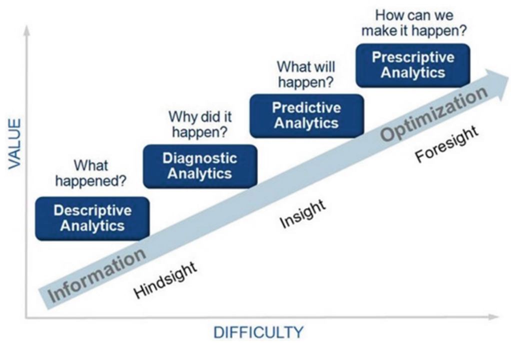


Fig. 1. The way to prescriptive analytics (courtesy of Gartner)

Descriptive and Condition-Based Maintenance

This type of maintenance became a widely-used option with automation and sensors cheapening. Instead of maintaining of the equipment based on a pre-defined schedule, the condition-based maintenance evaluates the asset's actual conditions to determine the need for the maintenance. Most of the modern machines have built-in sensors which provide real-time data transfer to centralized systems and help maintenance teams in maintaining of equipment before problems occur. Following IBM research, advanced maintenance teams have either adopted or are working towards implementing of condition-based maintenance programs to reduce cost and increase uptime.

Predictive Maintenance

The predictive maintenance is the next step further towards implementation of the condition-based maintenance. Once data is coming from the equipment in real-time or near real-time, advanced analytics are used to identify the asset's reliability risks that could impact business operations. By applying machine learning techniques and analytics to operational data, companies can act on these insights as part of a continuous improvement process. Companies with advanced processes and high-value equipment are rapidly adopting predictive maintenance solutions. But right now, these solutions aren't for everyone – they require firms to have condition-based processes in place and are usually data intensive.

Prescriptive Maintenance

The prescriptive maintenance is the next step in implementation of the condition-based maintenance. It uses advanced analytics to make predictions about maintenance, but the main difference is that prescriptive systems not only make recommendations but also act on recommendations, so it should be able to make decisions and be cognitive.

By evolving from time based, to condition based, to predictive and prescriptive maintenance, companies are evolving their maintenance systems from being simply efficient to becoming truly strategic.

One of the cornerstones of prescriptive analytics solutions is that it should be based on use of the maintained product's digital twin, which includes physics-based and data-driven models of a particular instance.

1.3 Hybrid Modeling Approach

The era of IIoT (Industrial Internet of Things) made a huge amount of data affordable, generated by technical systems during exploitation. Machine learning techniques became a very popular tool to build data-driven models and to predict failures or to optimize performance. These models are as efficient as the quantity and quality of data that is used to train them. The popularity of machine learning methods is so high, that sometimes a set of such data-driven models is also called a digital twin. This is not correct since the data-driven models are "blind" in sense of knowing the nature of processes, causes of defects and faults, etc. From another hand, physics-based models are usually quite slow and have to be adjusted to fit real-time data using verification experiments. An approach for overcoming of the described issues is presented below.

Fig. 2. Digital twin as a combination of data-driven and physics-based models

The general idea is in putting together the data-driven models with physics-based models in order to increase the benefits from digital twin as it's shown in Fig. 2. Despite its obvious advantage, quite few researches discuss the hybrid modelling approach to build digital twin. The hybrid approach to the digital twin development should include two-phase methodology for prognostics, where the first phase develops a physics-based model for both healthy and damaged conditions and the second phase computes the residuals when comparing the measurements with the simulation results [5]. These residuals are indicative of the state of the monitored instance, and the remaining useful life (RUL) can be computed by comparing the residuals with a predefined performance. A comprehensive review of different hybrid modelling approaches for the RUL estimation is presented in [6]. The authors of this paper propose to use the physics-model in order to simulate systems behavior with the presence of different types of defects and then use it for defect detection and identification. The scheme is shown on Fig. 3.

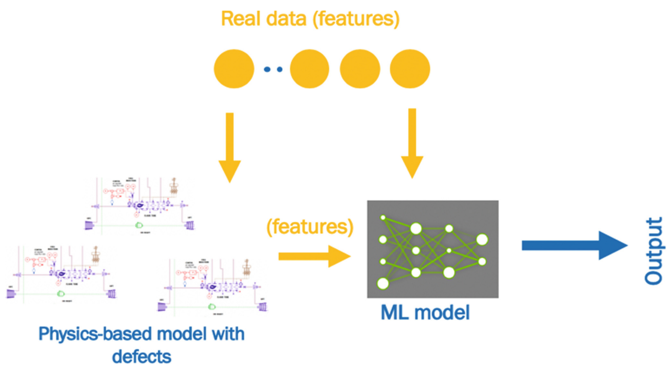


Fig. 3. Combined model of a system for its predictive analytics

2 Gas-Turbine Power Plant Condition Monitoring

In this paper, a hybrid modeling, using both data-driven and physics-based models for defects identification is presented using the example of a gas-turbine power plant monitoring. Mobile Gas Turbine Package FT8 Mobilepac, produced by Pratt & Whitney is about 25 MW jet-engine power plant, which can be mounted and commissioned in one day for emergency power generation.

There are dozens of subsystems which should be monitored and maintained, but this paper is focused on the particular subsystem of flame tubes of the combustion chamber (Fig. 4), which is located in the heart of the gas-turbine power plant – gas-engine.

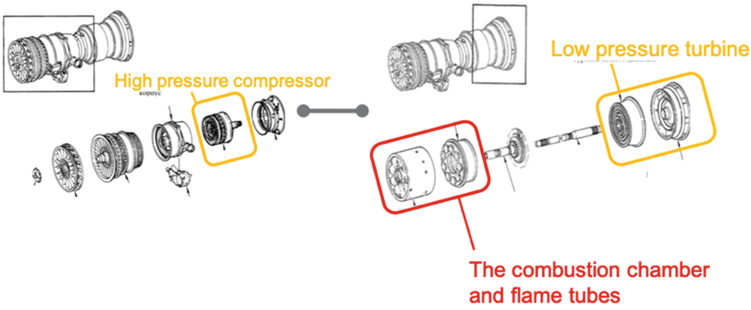


Fig. 4. Main parts of gas-engine

2.1 Data-Driven Model Description

To design data-driven model 25 features were used as presented in the Table 1.

Table 1. Features for machine learning model

Features		
Generated power	Pressure before low pressure compressor (LPC)	Power turbine (PT) rpm
Thermocouples 1–9 temperature	Pressure after high pressure compressor (HPC)	LPC rpm
Mean outlet gas temperature	Pressure after low pressure turbine (LPT)	HPC rpm
Fuel consumption	LPT outlet gas temperature	Environment temperature

One of the most important industrial tasks in the gas turbine prescriptive maintenance is detection of the flame tube breakage. It could be detected by the temperature profile of thermocouples, placed at the different distance from combustion chamber. The point is that the profile deviation could be caused by the different reasons (injector lags, hydraulic system malfunctions and so forth). Monitoring of the combustion process health is a method commonly used in the industry [7].

Initial data analysis has shown, that the correlation between such parameters as generated power, thermocouple temperatures, LPT and HPT rotary speed is more than 0.85. The correlation tab for the whole amount of the data is presented on the Fig. 5.

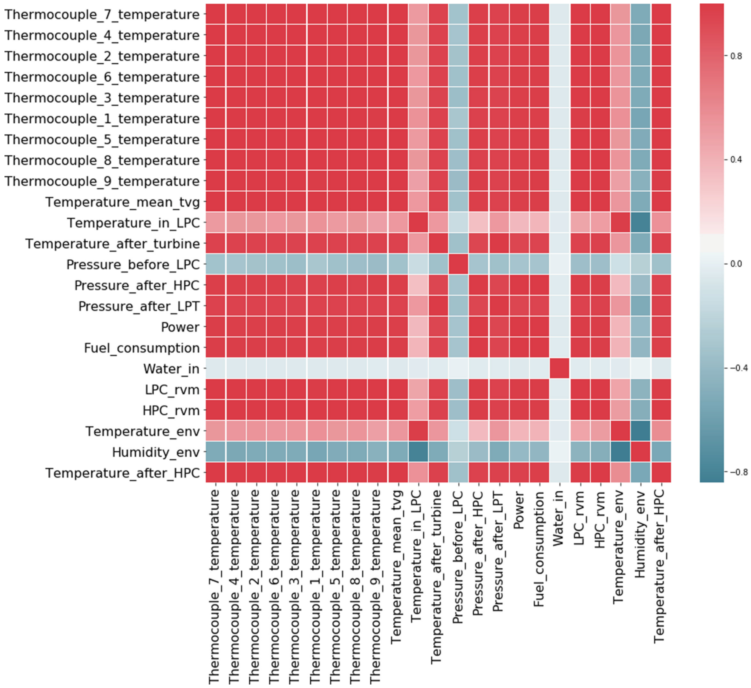
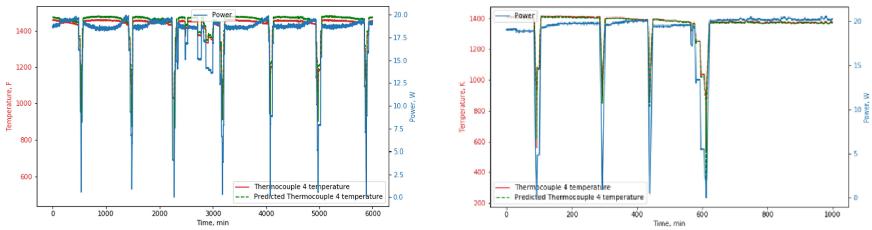


Fig. 5. Correlation tab for the data used in the machine learning model

As the turbine thermodynamics determines the turbine behavior [8] the artificial neural networks, which are well suited for non-linear dependencies, were used to predict the thermocouple temperatures. Training dataset consisted of 25 000 min of exploitation data (excluding the region where flame tubes were broken). The test results are shown on the Fig. 6.



a) b)

Fig. 6. Thermocouple "4" temperature prediction in the regions with broken flame tubes (a) and repaired flame tubes (b)

The best result was shown on the model with configuration of 4 hidden layers and totally 2459 parameters. The machine learning model solves the problem of an abnormal behavior detection, and answering the questions about condition of the tubes. With available amount of data, there is no opportunity to identify the reason of the breakage.

2.2 Physics-Based Modeling

The physics-based model was built to identify the cause of the defect and to enrich the results of the data-driven modelling with physical dependencies. Siemens LMS Amesim software was used to create the functional model of the gas turbine. Amesim is a software platform for multi-physical dynamical systems modelling, which uses bond-graph theory. The problem arises at the stage of detailed design, as the most important parameters for the modelling are usually unknown (compressors and turbine performance maps). To find out the performance map of the HPC the scaling of preloaded performance maps in the Amesim was used. The model of the compressor was used as it shown on the Fig. 7.

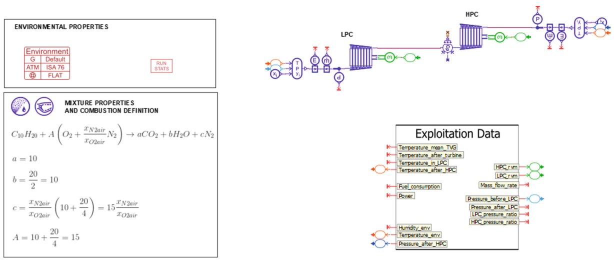


Fig. 7. Amesim model for compressor validation

Real exploitation data was uploaded to the Amesim model, which in conjunction with digitized LPC performance [9] allowed us to select HPC parameters. The results of the model simulation on the real exploitation data are shown on the Fig. 8.

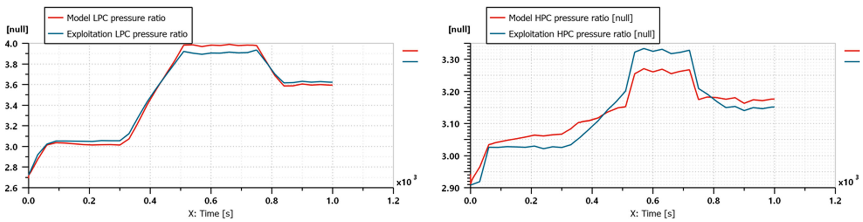
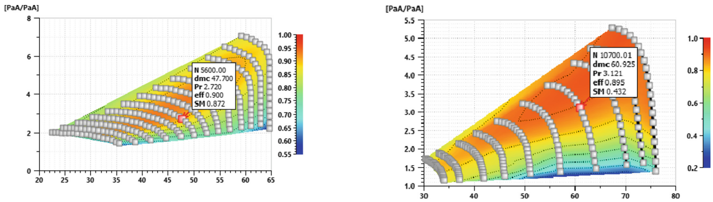


Fig. 8. Simulation data in comparison with exploitation data

The Fig. 9 represents performance maps of the compressors.



a) b)

Fig. 9. Performance map of the LPC (a) and HPC (b)

2.3 Using Physics-Based Model to Identify the Cause of Defect

For the flame tube breakage simulation, the full gas-engine Amesim model was created. It consisted of a compressors system and a combustion chamber models with real exploitation data uploaded (Fig. 10).

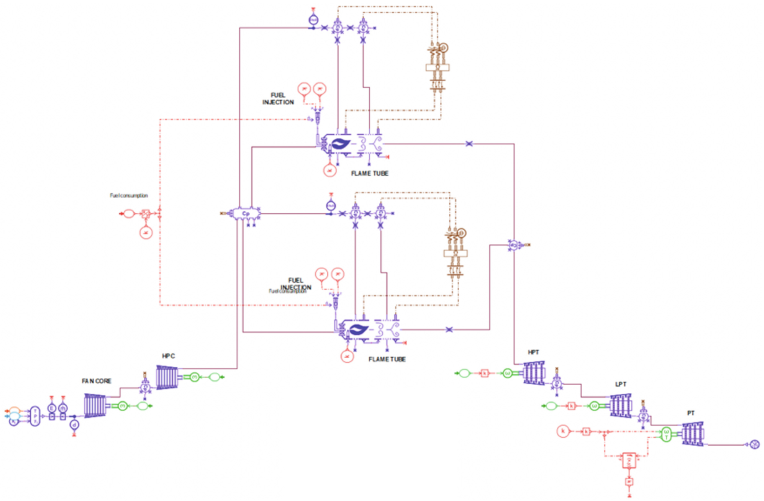


Fig. 10. Amesim model of the combustion chamber with the compressors system

We simulated the injector lag via variations of the fuel injected supply. The inverse task was solved by means of optimization in order to find which injector lag corresponds to the same thermocouples temperature difference as in the dataset, used for machine learning. It was found that the injector lag in flame tube #4 that was equal to 4% led to the difference in temperature of the thermocouples of about 50 °C (Fig. 11) that matched well the machine learning results.

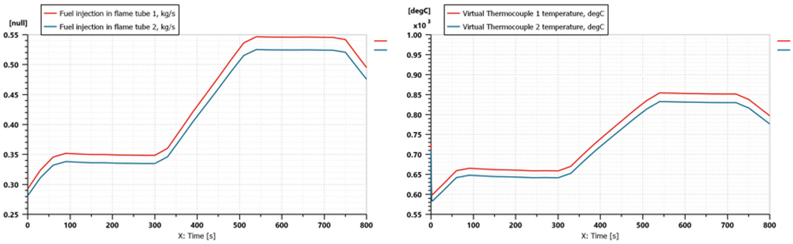


Fig. 11. Simulation of the lag in injector

Combining of applications of physics-based and data-driven models allowed not just to identify the problem in particular flame tube, but also to find out the reason of this defect and to prevent an expensive procedure of the tube replacement, by replacement of just the injector.

3 Conclusion

The approach of hybrid modeling for prescriptive analytics was tested on the gas-turbine flame tubes maintenance. The presented approach consists of two stages: implementation of the data analysis, development of a physics-based model, and its combination in order to identify the causes of anomalies and defects. The presented case study is devoted to the defect identification inside one of the flame tubes in the engine. By using simulation and machine learning modeling of the injector lag, which corresponds to the measured temperatures, the problem was identified and the injector has been replaced.

It's worth noting that, in most cases, there is no need to build a detailed 3D model of the investigated system for its predictive and prescriptive analytics. Usually, the functional model (built in Amesim, Modelica, etc.) can vastly improve the quality of prediction, made just on data analysis. Such models can be developed quite fast and don't need a lot of computational resources.

Our future work will be devoted to automatization of multiple simulations with various types of defects in order to add the datasets for machine learning and to identify the causes of defects and of the product's residual useful life.

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References

1. Terzi, S., Bouras, A., Dutta, D., Garetti, M., Kiritsis, D.: Product lifecycle management – from its history to its new role. Int. J. Prod. Lifecycle Manag. **4**, 360 (2010)
2. Madni, A.M., Madni, C.C., Lucero, S.D.: Leveraging digital twin technology in model-based systems engineering. Systems **7**(1), 7 (2019)

3. Schluse, M., Priggemeyer, M., Atorf, L., Rossmann, J.: Experimentable digital twins—streamlining simulation-based systems engineering for industry 4.0. IEEE Trans. Ind. Inform. **14**, 1722–1731 (2018)
4. Schluse, M., Rossmann, J.: From simulation to experimentable digital twins: simulation-based development and operation of complex technical systems. In: Proceedings of the 2016 IEEE International Symposium on Systems Engineering (ISSE), Edinburgh, UK (2016)
5. Leturiondo, U., Salgado, O., Galar, D.: Methodology for the physics-based modelling of multiple rolling element bearing configurations. Proc. Inst. Mech. Eng. Part K: J. Multi-body Dyn. **231**(1), 194–212 (2016)
6. Liao, L., K'ottig, F.: A hybrid framework combining data-driven and model-based methods for system remaining useful life prediction. Appl. Soft Comput. **44**, 191–199 (2016)
7. Weizhong, Y., Lijie, Y.: On accurate and reliable anomaly detection for gas turbine combustors: a deep learning approach. In: Annual Conference of the Prognostics and Health Management Society (2015)
8. Turan, O.: First law approach of a low bypass turbofan engine. J. Autom. Control Eng. **2**(1) (2014)
9. Monhardt, R.J., Richardson, J.H.: Design and test of the FT8 gas turbine low pressure compressor. In: The American Society of Mechanical Engineers, 89-GT-295 (1989)