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Synthetic Data Generation in Hybrid Modelling of Railway HVAC System

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Abstract **– This paper proposes a hybrid model (HyM) for a heating, ventilation and air conditioning (HVAC) system installed in a passenger train. This HyM fuses data from two sources: data taken from the real system and synthetic data generated using a physics-based model of the HVAC.**

The physical model of the HVAC was developed to include the sensors located in the real system and new virtual sensors reproducing the behaviour of the system while a failure mode (FM) is simulated.

Statistical features are calculated from the selected signals. These features are labelled according to the related FMs and are merged with the features calculated from the data from the real system. This data fusion allows us to classify the condition indicators of the system according to the FMs. The merged features are used to train a neural network (NN), which achieves a remarkable accuracy.

Accuracy is a key concern of future research on the detection and diagnosis of a multiple faults and the estimation of the remaining useful life (RUL) through prognosis. The outcome is beneficial for the proper functioning of the system and the safety of the passengers.

Keywords – Predictive maintenance, fault detection, railway, hybrid modelling, fault modelling, synthetic data.

I. INTRODUCTION

Diagnostics and prognostics are the main techniques of prognostics and health management (PHM). Diagnostic techniques identify a faulty component by detecting and isolating a fault; the relationship between the data taken from the system and their degradation identifies the faulty part based on a pre-selected failure mode (FM). Thus, diagnostics includes failure mode and effect analysis (FMEA) [1], [2]. Diagnostics starts once a fault or abnormal behaviour is detected. The aim of prognostics is to estimate the remaining useful life (RUL) by assessing the changes in the behaviour of the system over time. RUL estimation evaluates the accumulation of degradation and predicts the future health state. If there is evidence of a failure, information from data observed in diagnostics is analysed to identify and assess the damage before RUL estimation.

There are three main approaches to estimate RUL through prognosis [3]: data-driven approaches, model-based (physics-based) approaches, and hybrid model approaches (HyMAs). These approaches integrate engineering experience and expert knowledge, techniques used in the reliability domain.

A. Data-driven approaches

Data-driven approaches use mathematical models and weight parameters to predict the future state of a system. The prediction is calculated using data from the sensors embedded in the real system. There are many techniques, but they can be divided into two categories [4]. The first are artificial intelligence approaches, including neural networks (NNs) and fuzzy logic. The second are statistical approaches, including linear regression and hidden Markov model. These techniques can accurately predict RUL, but they need to be trained using a large amount of historical information taken from the operational data labelled to ease the extraction of data at different stages of system degradation. Research on data-driven approaches for fault diagnosis in HVAC chillers includes work by

Choi et al. [5] and Madhavi Namburu et al. [6]. More recently, data-driven methods were used for fault detection and diagnosis in air handling units by Montazeri and Mohamad Kargar [7]. Zhenxin Zhoy et al. [8] presented a comparison study of basic data-driven fault diagnosis methods for a system with variable refrigerant flow.

B. Model-based (physics-based) approaches

Model-based approaches or physics-based models estimate RUL, building mathematical models from the physical system to give a physical understanding of the monitored system [4]. These models incorporate such characteristics as material properties and thermodynamic and mechanical responses. At times, these approaches cannot be applied because they need too many resources, especially in complex systems or processes where some key parameters are difficult or impossible to obtain. Nevertheless, an accurate physics-based model is more effective than other approaches [9]. A dynamic model of an HVAC system for fault detection and diagnostics (FFD) was proposed by Bendapudi et al. [10]. Poon et al. [11] and Yul Chu and Avestruz [12] also developed model-based approaches.

C. Hybrid modelling

Hybrid modelling approaches combine model-based approaches and data-driven approaches. HyMAs reduce the amount of historical information required to train a data-driven model and the information needed for a robust model. Applications of hybrid models for fault detection include work by [13], [14], and [15].

This paper presents a methodology using hybrid modelling. The system studied and modelled is an HVAC system installed in a passenger vehicle of a train. It keeps the vehicle's interior within a comfortable temperature range, with an acceptable concentration of CO_2. A failure in this system directly affects people's comfort and safety; their safety is more important than efficiency or reliability. Previous work includes some dynamic models of HVAC systems and chiller systems for fault detection [16], [17].

The paper proceeds as follows. Section 2 describes the methodology of the proposed hybrid modelling. Section 3 describes the physics-based model developed for data generation. Section 4 explains the process to prepare the data for feature extraction. Section 5 takes and classifies features for training, validating, and testing the data-driven model. Section 6 discusses the results. Section 7 concludes the work and suggests future work to implement the proposed HyMA.

II. HYBRID MODELLING METHODOLOGY

The maintainers of the HVAC system under study are currently using approaches based on data, but they must use preventive maintenance for critical components because there is insufficient information to train the RUL estimation model. Maintainers replace critical components in early stages of degradation for safety, environmental, and economic reasons, thus complicating the obtention of run-to-failure data. The HyM is developed to overcome the lack of data. It improves the ability to detect FMs and reduces hidden FMs, metaphorically known as "black swans" [18].

The hybrid model of the HVAC system is developed in Matlab R2019b; the proposed methodology for training, validating, and testing is shown in Figure 1. A physics-based model is used to generate synthetic data in healthy and faulty states based on the operational modes being modelled. The physics-based model has sensors located in the real system and virtual sensors which depend on the data measured in the real system. These virtual sensors generate key features for the detection of faults. Thus, the measured data must be loaded in the physics-based model to simulate the response of the virtual sensors. The output of these simulations is recorded in a dataset which contains the data taken from the real system and the data obtained from the virtual sensors. The physics-based model can also generate synthetic data in healthy and faulty states by introducing the required inputs. Every simulation generates a timeseries of every signal selected; the data related to a simulation are individually saved in a table.

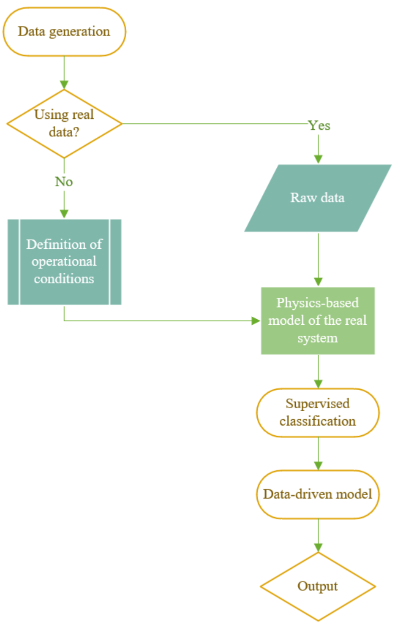

Fig. 1. Scheme of proposed methodology to build data-driven model

The data-driven models presented in this paper use supervised learning methods. Once the data are generated by the physics-based model and organised in a table, each simulation is labelled with a fault code indicating the presence of a fault and the type of fault. The features are then extracted from every signal loaded in the table. Thus, the features are related to a fault code and are used to train, validate, and test the data-driven model. The dataset containing the features related to a simulation is named the "fingerprint".

III. HVAC SYSTEM MODEL

The physics-based model of the HVAC installed in the passenger vehicle is separated into cooling subsystems, heating subsystems, ventilation subsystems, and vehicle thermal networking systems. The temperature and the concentration of CO_2 are managed by two ventilation subsystems, two cooling subsystems, and two heating subsystems. Table 1 contains the set of sensors used in the real system; these sensors are labelled "real" in Table 1.

A. Fault modelling

The FMs of the HVAC are detected by the sensors listed in Table 1. The model includes fault models for temperature, pressure, and CO_2 sensors. The sensors' drift fault is modelled by introducing an offset in the sensor model; the offset is controlled by a model variable able to indicate no sensor fault and faults at different stages of degradation. A fault in components is modelled by varying their nominal conditions. Before doing this, however, it is crucial to evaluate FMEA; this allows us to analyse the FM to be modelled, including its effects and causes. The physics-based model has defined virtual sensors used to improve the detectability of FMs. The problem is that the real sensors detect FMs which have the same effects but result from different causes. Hence, the virtual sensors defined for fault detection must be related to a particular FM and to the signals that can be fed into the model once the HyM is implemented. Table 1 contains the virtual sensors defined in the physics-based model; these sensors are labelled "virtual".

IV. DATA PREPARATION FOR FEATURE EXTRACTION

A. Physics-based model preparation

The physics-based model requires a set of inputs to generate synthetic data, such as atmospheric temperature, number of passengers in the vehicle, control of the heating and air conditioning subsystems, and position of the fresh air damper. These inputs directly affect the response of the model. The physics-based model is also configured with variables that control the presence and severity of different fault types. This allows the models to be trained using healthy and faulty data.

B. Synthetic data Generation

The algorithm developed for generating synthetic data has several different sections.

The first section creates arrays of simulation input objects to define different simulation scenarios. The arrays can be classified into two groups. The first is an array containing a variable that indicates a degradation in a component. Thus, some arrays are variables of degradation indicating the presence and severity of faults. The second set of arrays contains controlled noise introduced into physical variables related to inputs. The physics-based model simulates the same response as the real system with the same inputs. The noise related to a physical variable is controlled by analysing the range of values the input can achieve.

The second section of the algorithm selects random values of noise and degradation. A new array is created by combining the random values selected with the related model parameter.

The third section runs the simulations with the array created in the previous section. Hence, this section contains the functions that configure the simulation, generate data, and save the data into a document. This paper uses data from the sensors listed in Table 1.

C. Ensemble data

The fourth section of the algorithm reads the documents saved in the previous section and creates a dataset which contains in columns the parameters listed in Table 1 and in rows the results listed by simulation. The final column contains the fault code.

Table 1. List of parameters for feature extraction.

	Type
Temperature after compressor 1 – virtual	Signal
Temperature after compressor 2 – virtual	Signal
Temperature before compressor 1 – virtual	Signal
Temperature before compressor 2 – virtual	Signal
Pressure after compressor 1 – real	Signal
Pressure after compressor 2 – real	Signal
Pressure before compressor 1 – real	Signal
Pressure before compressor 2 – real	Signal
Pressure after filter – virtual	Signal
Pressure before filter – virtual	Signal
Real heat transfer – virtual	Signal
CO_2 level – real	Signal
Vehicle temperature – real	Signal
Impulsion temperature – real	Signal
Fault code	Condition Variable

Data are generated to train three data-driven models. One data-driven model is trained by data generated with five different faults: dust mass in filters 1 and 2, faults in evaporator fans 1 and 2, and CO_2 sensor faults. These components can have different levels of degradation and can appear combined or individually. Another data-driven model is trained to detect a fault of the CO_2 sensor. A third data-driven model is trained to identify different levels of dust mass fed into filters 1 and 2.

V. FEATURE EXTRACTION AND CLASSIFICATION

Features are extracted from the dataset structured in the previous section using the diagnostic feature designer toolbox of MATLAB R2019b.

A. Feature extraction

The diagnostic feature designer toolbox allows the extraction of the following statistical features from the dataset containing the signals listed in Table 1.

Mean:

$$\mu = \frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} x(t) \tag{1}$$

Standard deviation (second order moment):

$$\sigma = \sqrt{\frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} [x(t) - \mu]^2} \tag{2}$$

Root mean square (RMS):

$$RMS = \sqrt{\frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} [x(t)]^2} \tag{3}$$

Shape factor

$$SF = \frac{RMS}{\frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} |x(t)|} \tag{4}$$

Skewness (third order moment)

$$\gamma = \frac{\frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} [x(t) - \mu]^3}{\sigma^3} \tag{5}$$

Kurtosis (fourth order moment)

$$\kappa = \frac{\frac{\Delta t}{t_1 - t_0} \sum_{t=t_0}^{t1} [x(t) - \mu]^4}{\sigma^4} \tag{6}$$

Peak value

$$x_{peak} = \max\, |x(t)| \tag{7}$$

Crest factor

$$CF = \frac{x_{peak}}{RMS} \tag{8}$$

B. Feature classification

Once the features are extracted and classified, it is necessary to find the features that best distinguish the various faults. A rigorous features comparison is developed using raking algorithms, i.e., one-way ANOVA and Kruskal-Wallis. The former creates the features ranking by one-way analysis of variance, while the latter ranks features using the chi-square statistic of a Kruskal-Wallis test.

The scores obtained from the ranking algorithms are similar but not identical. Standard deviation, peak value, and RMS of the real heat transfer signal and shape factor and crest factor of the CO_2 level signal are the five features with the best scores obtained using the one-way ANOVA algorithm. This indicates these features are better able to distinguish between FMs in the data-driven model trained to detect multiple faults.

The five features best able to detect a fault in the CO_2 sensor are the mean, RMS, and peak value of the CO_2 level signal, and the shape factor of the impulsion temperature. The five key features for detecting the dust mass fed into the filters are the peak value of the real heat transfer signal, the shape factor of the pressure after filter signal, and the mean, RMS, and peak value of the CO_2 level signal.

C. Training and validation of the data-driven model

The rankings of features obtained from the two algorithms are quite similar. Thus, there is no relevant difference between features. The features with a score higher than one in the ranking generated by one-way ANOVA algorithm are exported to the classification learner tool in the three cases defined.

The classification learner toolbox is used to train models, explore data, select features, specify validation schemes, and evaluate results.

The exported data are used to train the following classifiers: decision trees (DTs), discriminant analysis, support vector machines (SVMs), logistic regression, k-nearest neighbours (k-NNs), Naïve Bayes (NB), and ensemble classification. The models avoid overfitting by applying cross-validation with five folds. These specifications are loaded to train and validate the three models:

(1) Using the data containing features extracted from five failure modes, the fine tree classifier obtains the highest accuracy. However, when the DT classifier is optimised, it reaches an accuracy of 41.1%, making the model unacceptable.

(2) The classifiers trained to detect a fault in the CO_2 sensor reach a remarkable accuracy. The classifiers with an accuracy higher than 94% are optimised. SVM classifiers obtain an accuracy of 100% after the optimisation. The DTs and NB are optimised as well, and both reach an accuracy of 98.7%. The classifier subspace KNN obtains an accuracy of 100%.

(3) The classifiers trained to detect the air filter in a faulty state also show high accuracy. SVM, ensemble, and k-NN are the classifiers optimised, obtaining 95.5%, 95.0%, and 95.0% accuracy, respectively.

D. Testing the data-driven models

The training is developed for the models with an acceptable accuracy after validation, models (2) and (3). The aforementioned classifiers for models (2) and (3) are tested using the same simulations. In this fashion, their confusion matrices can be directly compared, indicating the best model. Two hundred and fifty simulations are used to train, validate, and test each model. Thus, 250 simulations contain data when the CO_2 sensor is in healthy and faulty states. Another 250 simulations contain the presence of dust in the filters. Two hundred (80%) of each set of simulations are used to train and validate the models; the other 50 (20%) are used to test the models. Another 640 simulations are used to train and validate model (1), simulating five different faults of the system. This model is not tested because the results of validation do not warrant its use.

VI. RESULTS AND DISCUSSION

The paper develops models using both measured and synthetic data. The measured data are taken from an HVAC system in healthy condition. The synthetic data contain both healthy and faulty data. All synthetic data are generated by simulating noise in some inputs of the physics-based model.

A. First case: multiple fault detection

The multiple fault detection model is trained and validated with data labelled with the faults listed in Table 1. The proposed model uses five different faults and the healthy state of the system. These faults are dust mass in filters 1 and 2, faults in evaporator fans 1 and 2, and CO_2 sensor faults.

Six hundred and forty fingerprints are used to train and validate this model; 41.1% is the best accuracy obtained after validation. This accuracy is unacceptable; for this reason, the testing of this model is not presented in the paper.

Nevertheless, three of the five faults are modelled, analysed, and presented here. The analysis shows the signals best able to distinguish between FMs match for the three faults analysed. This, together with the definition of degradation of components from early stages, makes it difficult to distinguish between FMs using the same model.

B. Second case: CO_2 sensor degradation

Table 2 contains the results obtained after training, validating, and testing the model for CO_2 sensor faults. The classifiers with best accuracy after validation are listed in Table 2. The table also contains the data of the confusion matrix obtained after testing the classifiers.

The DT classifier achieves 61.9% true positives (TP), 100% true negatives (TN), 38.1% false negatives (FN) and 0% false positives (FP). Subspace k-NN and SVM properly classify 100% of the data used for testing, as shown in Table 2.

Table 2. Results of the data-driven model for detection of a fault in the CO_2 sensor.

	Accuracy	Testing			
		TP	TN	FP	FN
SVM	100%	100%	100%	0%	0%
DT	98.7%	62%	100%	0%	38%
NB	98.7%	0%	100%	0%	100%
k-NN	100%	100%	100%	0%	0%

C. Third case: Detection of dust in the filter

In the third case, the classifiers with the best accuracy after validation are listed in Table 3. The table shows the accuracy obtained after validation and the confusion matrix obtained after testing.

All the classifiers selected can correctly classify the fault, as shown in Table 3. Nevertheless, only SVM properly classifies one of the other FMs: 98% true negatives, and 2% false positives.

Table 3. Results of data-driven model for detection of dust in air filter.

	Accuracy	Testing			
		TP	TN	FP	FN
DT	100%	100%	100%	0%	0%
NB	96.5%	100%	100%	0%	0%
SVM	99.5%	100%	100%	0%	0%
Ensemble	100%	100%	100%	0%	0%
k-NN	99.0%	100%	100%	0%	0%

VII. CONCLUSIONS AND OUTLOOK

The paper proposes an HyM for an HVAC system located in a passenger vehicle of a train. A physics-based model is used to generate data by simulating different levels of degradation in some components of the HVAC. These data are used to train, validate, and test various basic data-driven methods for fault detection in the HVAC system. The data-driven methods trained for comparative purposes are DTs, discriminant analysis, SVM, logistic regression, k-NN, NB, and ensemble classification. The comparison is performed in three data-driven models:

(1) The physics-based model generates data by combining five different fault types: the presence of dust in the filters, faults in evaporator fans 1 and 2, and CO_2 sensor faults. The DT method achieves an accuracy of 41.1%, which is the best result after the validation of all classifiers. This unacceptable result shows the main challenge in the future of failure detection and diagnostics (FDD) in HVAC systems is to find efficient and accurate methods for systems with degradation in multiple components at the same time.

(2) Synthetic data related to a fault in the CO_2 sensor are generated by the physics-based model. These data are used to train, validate, and test SVM, DT, NB, and subspace k-NN methods. SVM and subspace k-NN can correctly classify 100% of the fingerprint used in the testing process.

(3) The last data-driven model is trained, validated, and tested using data taken from simulations where different amounts of dust mass are fed into filters 1 and 2. The virtual sensors, defined as real heat transfer and pressure after filter, provide key features to detect dust in the filter. DT, NB, SVM, and ensemble k-NN do not reach 100% accuracy after validation, but all are able to correctly classify 100% of the fingerprints used during the testing process.

The difficulties found in the fault diagnosis of multiple fault problems in the HVAC system suggest the need to develop a more efficient and accurate diagnostic method. Furthermore, when the FMs are individually analysed, the features that strongly define them are found to match. This, together with the shortage of sensors in the system, calls for the development of new virtual sensors able to give a physical understanding of the defined faults. Once multiple faults can be accurately detected, RUL estimation will be possible using prognostics. This will extend the useful life, reduce the life cycle cost, and improve the reliability and availability of the HVAC system.

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