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A Hybrid Bond Graph Model-based – Data Driven Method for Failure Prognostic

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Abstract

Failure prognostic builds up on constant data acquisition and processing and fault diagnosis and is an essential part of predictive maintenance of smart manufacturing systems enabling condition based maintenance, optimised use of plant equipment, improved uptime and yield and to prevent safety problems. Given known control inputs into a plant and real sensor outputs or simulated measurements, the model-based part of the proposed hybrid method provides numerical values of unknown parameter degradation functions at sampling time points by the evaluation of equations that have been derived offline from a bicausal diagnostic bond graph. These numerical values are computed concurrently to the constant monitoring of a system and are stored in a buffer of fixed length. The data-driven part of the method provides a sequence of remaining useful life estimates by repeated projection of the parameter degradation into the future based on the use of values in a sliding time window. Existing software can be used to determine the best fitting function and can account for its random parameters. The continuous parameter estimation and their projection into the future can be performed in parallel for multiple isolated simultaneous parametric faults on a multicore, multiprocessor computer.

The proposed hybrid bond graph model-based, data-driven method is verified by an offline simulation case study of a typical power electronic circuit. It can be used to implement embedded systems that enable cooperating machines in smart manufacturing to perform prognostic themselves.

Keywords: Unknown parameter degradation; bicausal diagnostic Bond Graphs; parameter estimation; repeated trend projection; failure prognostic; remaining useful life; uncertainties; predictive maintenance.

1. Introduction and motivation

Failure prognostic is of essential importance beyond fault diagnosis for safety critical engineering systems and processes, for supervision, automation and condition based maintenance (CBM) of industrial processes, predictive maintenance, and for all kinds of emerging autonomous intelligent operating mobile systems such as unmanned aerial vehicles, or for cyber physical systems. Based on continuous monitoring of the state of health (SoH) of an engineering system and by estimating the ongoing degradation of component behaviour, failure prognostic enables predictive maintenance of industrial processes, or the reconfigurable fault tolerant control (FTC) of intelligent autonomous systems. With regard to an industrial plant, predictive maintenance enables a longer lifetime of process components, increased safety, a more efficient use of ressources, and a reduction of costs. Predictive anomaly identification based on real-time data, monitoring degradation, detecting precursors to failure, and predicting the remaining useful life (RUL) of components and subsystems becomes even more important for complex systems in industry 4.0 smart manufacturing as the increased range of interaction between intelligent autonomous machines and system interdependencies have an influence on process faults and failures. For predictive maintenance in an industry 4.0 framework it is therefore essential that cooperating machines equipped with sensors, in-situ self-monitoring and prognostic capabilities issue warnings with confidence intervals when they are about to operate out of admissible tolerances and that maintenance alarms are automatically set by the system.

If pronostic applied to a mobile autonomous system suggests, for instance, the failure of an actuator or a critical state of charge (SoC) of the battery of a drone in the near future, the control or the mission of the unmanned aerial vehicle can be changed to avoid all kind of possible damage.

Fault detection and isolation (FDI) as a prerequisite for failure prognostic has been a major subject in research and in var-

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ious application fields since some decades. Data-driven as well as physics model-based approaches to FDI with their pros and cons have been reported in the literature. More recently, combinations of both approaches are increasingly addressed [9].

As to fault isolation, a question is how many sensors are to be placed in which locations in order to isolate a maximum of potentially faulty system components. Various approaches to the sensor placement problem have been reported in the literature [10, 1, 6, 3].

Once, an incipient fault due to a trending parameter has been diagnosed, a question is how long a system may safely continue its operation despite the presence of the incipient fault before the increasing affect of the fault on the dynamic system behaviour may lead to a component or even a system failure. Clearly, constant monitoring of system health and a repeated prediction of the time to failure, or the remaining useful life, i.e. failure prognostic is clearly of technical and economical importance. In comparison to fault diagnosis it is still a rather young, still developing research subject.

To anticipate the RUL as of a current time instant t_P, it is necessary to know the degradation behaviour of a fault over time. To that end, one may try to develop a model of the progressing damage starting from first physical principles. Difficulties, however, may be that the degradation process is not fully understood or that not all needed parameters of a degradation model can be determined.

Other options may be to obtain a degradation model from offline accelerated life tests [7] and to use the results in online health monitoring for the prediction of the RUL [12], or to assume that a potential degradation function candidate is a member of a certain class of functions and to adapt the unknown parameters of the function by curve fitting. As measured signals carry noise, a RUL has to be considered a stochastic quantity.

As systems may operate in various modes, the degradation behaviour may change from mode to mode making it necessary to change to another class of potential degradation functions [13], [2, Chap. 6].

The physics model-based part of the proposed approach uses a diagnostic bond graph (DBG) for the acquisition of degradation data. To that end, known system input signals and measurements provided by sensors are not used to evaluate analytical redundancy relations (ARRs) but to estimate the magnitude of faulty parameters at each sampling time point. Equations for the magnitude of a trending faulty parameter are obtained from a bicausal diagnostic bond graph. That is, given known system inputs and either measurements from a real system or simulated measurements, the purpose of the bicausal DBG model is to numerically determine an unknown parameter degradation function by estimating the numerical values of a faulty parameter at sampling time points.

The numerical values of an unknown degradation function are determined over a sliding time window of fixed size and are used in the data-driven part of the approach for failure prognosis. For each time window, the data-driven part of the approach identifies a mathematical function over the time window and projects it into the future to obtain an estimate of the current RUL. As a result, a sequence of RUL estimates is obtained

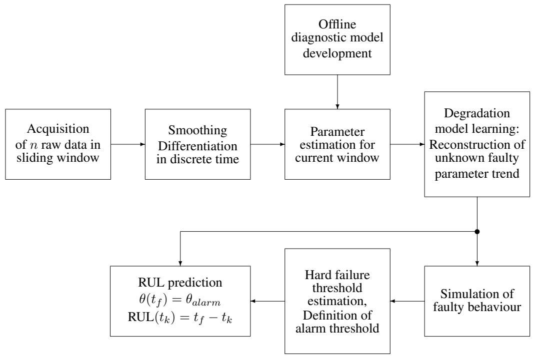

Fig. 1. Scheme of the proposed hybrid bond graph model-based – data-driven approach

with values that tend to zero as the considered faulty component reaches its end of life (EOL). Fig.1 displays the scheme of the proposed hybrid bond graph model-based – data-driven method.

The approach is explained by means of a simple boost (step-up) converter, a typical power electronic circuit used in various applications such as in battery power systems, DC motor drives, in wind power systems, or in the connection of solar panels to a utility grid. Results are verified by an offline simulation study. Moreover, various uncertainties in failure prognostic are addressed.

2. Bond Graph model-based online estimation of an unknown degradation trend

Parametric degradation means that the deterioration of the dynamic behaviour of an engineering system is attributed to the fact that some of its parameters increasingly deviate from their nominal values with time following a function of which an exact analytical expression is mostly unknown.

One way to approximate a degradation trend may be to develop a physics model based on first principles. The physics of a degradation process, however, may not be fully understood or values for some parameters of the developed degradation model may not be available.

A data-driven approach may select an analytical degradation function from an appropriate class of functions and adapt its unknown parameters by curve fitting.

The approach proposed in this paper determines a time series for an unknown degradation function by parameter estimation.

To that end, a bicausal bond graph is used in this paper. Bicausal Bond Graphs (BGs) were introduced in [8]. They extend the concept of computational causality by allowing that both power co-variables, effort and flow of a bond attached to a power port of an element, may be inputs into the element. Accordingly, they may be used for parameter estimation and thus can be used for setting up an equation that determines the degradation function $\Phi_\theta(t)$ of a faulty element parameter $\Theta(t)$ at sampling time instances t_i. Bicausal bond graphs have been used for FDI, e.g. in [17]. However, to the best of the author's

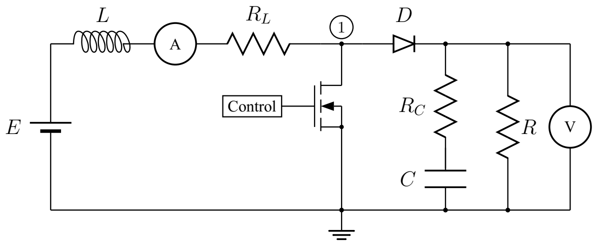

Fig. 2. Circuit schematic of an open loop boost converter with a load resistor *R*

knowledge, they have not been used in failure prognostic for the determination of numerical values of unknown degradation functions as proposed in this paper.

2.1. Following causal paths in a bicausal diagnostic Bond Graph

In a bicausal diagnostic bond graph, detectors representing sensors are in inverted causality because they provide known measurements into the diagnostic model. The two conjugate power signals into the port of a faulty element can be determined by following causal paths from sources providing known input signals and from detectors in inverted causality to the port of an identified faulty element. That is, both power variables in the element's constitutive equation are known, while the faulty trending parameter at the current sampling time point is unknown. The constitutive law results in a possibly implicit equations that determines the unknown parameter value. The approach is explained by means of a small power electronic circuit and is verified by an offline simulation study in the next section.

2.2. Application to a power electronic circuit

Consider the circuit schematic of an open loop boost converter in Fig.2. It is assumed that the converter used, e.g. in power generation plants, operates in continuous conduction mode (CCM) with a sensor for the inductor current i_L and a sensor of the output voltage V. A fault in this electronic component may lead to a failure in a power distribution system and to a degradation of its performance.

If the MOSFET transistor and the diode are modelled as two conversely commutating ideal switches Sw : s_i, $i = 1, 2$, then the circuit immediately transforms into the DBG in Fig. 3. If the small equivalent series resistance, R_C, of the capacitor is neglected and if variables are averaged over the switching period, then the circuit may be presented by the DBG in Fig. 4, in which d denotes the duty ratio.

In the following, two general cases are considered and illustrated by means of the small boost converter circuit. Firstly, it is assumed that the parameter of a resistive load element is deteriorating with time. The other scenario is that the parameter of a storage elements progressively deviates from its nominal value. For both cases it is shown how the numerical values of the respective unknown degradation function can be estimated

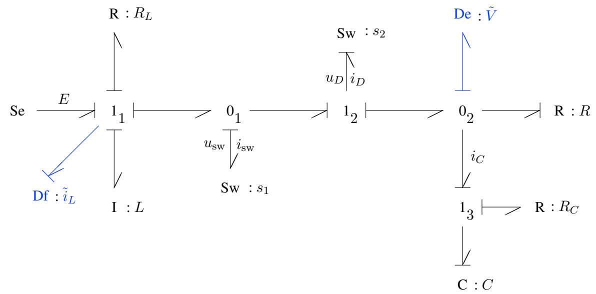

Fig. 3. DBG of the boost converter in Fig. 2 [4]

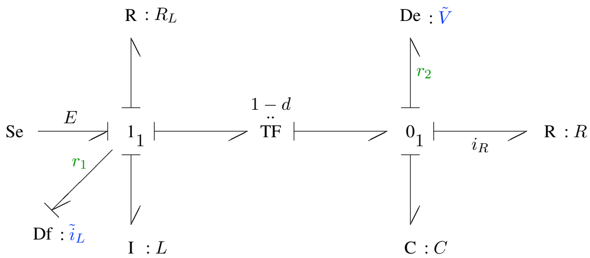

Fig. 4. Averaged DBG of the boost converter in Fig. 2

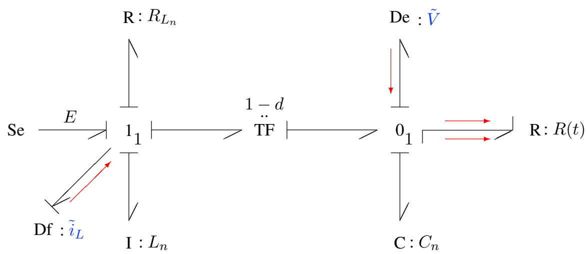

Fig. 5. Averaged bicausal DBG of the boost converter with a trending resistance $R(t)$

by means of known system inputs and measured values or simulated measurements.

2.3. Estimating the unknown degradation of a resistance

Assume that the cause of an abnormal dynamic behaviour has been isolated and is attributed to a resistance R that is increasingly deviating from its nominal value R_n with time, i.e. $R(t) = R_n + \Phi_R(t)$. Given monitored measurements, the task is to estimate the time-varying resistance $R(t)$. Accordingly, the bond attached to the port of the R-element is replaced by a bicausal bond as depicted in Fig. 5. As can be seen from the bicausal DBG in Fig. 5, there is a causal path from the flow detector Df : $\tilde{i}_L$ and another one from the effort detector De : $\tilde{V}$ to the power port of the R-element. The tilde denotes (filtered) measurements obtained from the real system or simulated measurements. As both port variables are determined by real measurements or simulated data provided by sensors into

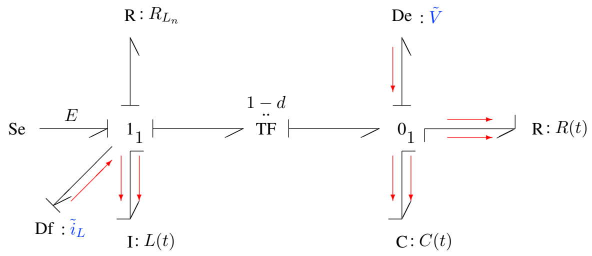

Fig. 6. Averaged bicausal DBG of the boost converter with trending parameters $R(t), C(t), L(t)$

the DBG model, the time evolution of the resistance $R(t)$, i.e. numerical values of the degradation function $\Phi_R(t)$ can be computed. In order to show that the approach is applicable in the case of nonlinear elements, a general nonlinear constitutive law $\tilde{V} = R(t) f_R(\tilde{i_R})$ is assumed for the load resistor. From the bicausal DBG, one obtains

$$\tilde{i_R} = (1-d)\tilde{i}_L - C_n \frac{d\tilde{V}}{dt} \quad (1)$$

$$\tilde{V} = R(t) f_R(\tilde{i_R}) = (R_n + \Phi_R(t)) f_R(\tilde{i_R}) \quad (2)$$

and as a result an implicit algebraic equation for the unknown degradation function $\Phi_R(t)$.

$$f_R(\tilde{i_R})\Phi_R(t) = \tilde{V} - R_n f_R(\tilde{i_R}) \quad (3)$$

Note that the computation of the degradation function values requires the differentiation in discrete time of the measured voltage $\tilde{V}$.

2.4. Estimating the unknown degradation of a storage parameter

In the bicausal DBG of Fig. 6, the bond attached to the power port of the C-element has also been turned into a bicausal bond. As a result, there are causal paths from the two detectors to the C-port so that the numerical values of a decaying capacitance $C(t)$ could be determined. However, these causal paths are not disjoint from the ones to the R-port so that it cannot be decided whether an abnormal dynamic system behaviour is caused by a degradation of the resistance R or of the capacitance C. This is not surprising, because both elements are in parallel, the voltage drop across both elements is the same. As addressed in [3], another junction with an additional detector attached to it is to be inserted for isolation if both elements are faulty. Therefore, the following case assumes that only the capacitance trend follows an unknown degradation function, i.e. $C(t) = C_n + \Phi_C(t)$. It is assumed that the constitutive equation of the C element may be nonlinear.

$$q_C = C(t) f_C(\tilde{V}) = (C_n + \Phi_C(t)) f_C(\tilde{V}) \quad (4)$$

The causal paths from the flow detector Df : $\tilde{i}_L$ and from the effort detector De : $\tilde{V}$ to the C-element in the DBG of Fig. 6 yield

$$\dot{q}_C = (1-d)\tilde{i}_L - \frac{\tilde{V}}{R_n} \quad (5)$$

Substitution of (5) into (4) gives the following implicit equation for the degradation function $\Phi_C(t)$.

$$f_C(\tilde{V}(t))\Phi_C(t) = \int_{t_{f_2}}^{t} \dot{q}_C(\tau)d\tau + \Phi_C(t_{f_2})\tilde{V}(t_{f_2}) - C_n f_C(\tilde{V}) \quad (6)$$

where t_{f_2} denotes the time instant when the incipient fault exceeds an (adaptive) fault threshold and thus is detected. That is, $\Phi_C(t) \neq 0$ for $t > t_{f_2}$. Below that threshold the value of the capacitance may vary. However, a robust fault detection is insensitive to small parameter deviations from their nominal values in order to avoid false alarms.

Finally, as can be seen from the bicausal DBG in Fig. 6, there are another two causal paths from the detectors to the inductor with a faulty inductance $L(t) = L_n + \Phi_L(t)$. The causal path from the voltage detector to the inductor is not disjoint from the causal path to the resistor R : R and the one to the capacitor. That is, these parametric faults cannot be isolated without inserting an additional detector.

If it is only the inductor that has become faulty as of a time instant t_{f_1}, then similar to the computation of $\Phi_C(t)$ above, one obtains for the unknown degradation function $\Phi_L(t)$ from the bicausal DBG

$$\begin{aligned}\tilde{u}_L = \frac{d}{dt}(L f_L(\tilde{i}_L)) &= \frac{d}{dt}[(L_n + \Phi_L(t)) f_L(\tilde{i}_L)] \\ &= E - R_{L_n}\tilde{i}_L - (1-d)\tilde{V}\end{aligned} \quad (7)$$

or

$$\Phi_L(t)\tilde{i}_L(t) = \int_{t_{f_1}}^{t} \tilde{u}_L(\tau)d\tau + \Phi_L(t_{f_1})\tilde{i}_L(t_{f_1}) - L_n f_L(\tilde{i}_L) \quad (8)$$

where t_{f_1} denotes the time instant when the onset of an incipient fault in the inductance is detected. The integration in (6), (8) may be performed by means of the trapezoidal rule. Note that in the case of a storage element no measurements need to be differentiated.

3. Offline simulation case study

The above determination of a capacitance degradation function $\Phi_C(t)$ at sample time points shall be verified in an offline simulation. The parameters of all other passive elements are assumed to keep their nominal value. Real measurements are replaced by simulated ones obtained from a behavioural BG model of the faulty circuit. The BG model may be considered a digital twin of the real circuit used to study the effect of the capacitance decay. Capacitor leakage is a typical fault. In [11], it is reported that electrolytic capacitors in power electronic systems have a higher failure rate than other system components. In this study, it is assumed that the decay of the capacitance deliberately introduced into the BG model is exponentially with time according to the function

$$C(t) = \begin{cases} C_n & t < t_0 \\ \frac{1}{5}C_n + \frac{4}{5}C_n e^{-\lambda(t-t_0)} & t \geq t_0 \end{cases} \quad (9)$$

That is, as of time instant t_0 the capacitance reduces exponentially with $t \to \infty$ to one fifth of its nominal value C_n.

Table 1. Parameters of the averaged DBG model in Fig. 4

Parameter	Value	Units	Meaning
E	12.0	V	Voltage supply
L	1.0	mH	Inductance
R_{L_n}	0.1	Ω	Resistance of the coil
C_n	500	μF	Nominal capacitance
R_n	5.0	Ω	Nominal load resistance
T_s	10^{-3}	s	Switching time period
d	0.45	–	Duty ratio
t_f	5	ms	Capacitance starts decline
λ	500	s^{-1}	Rate of decline

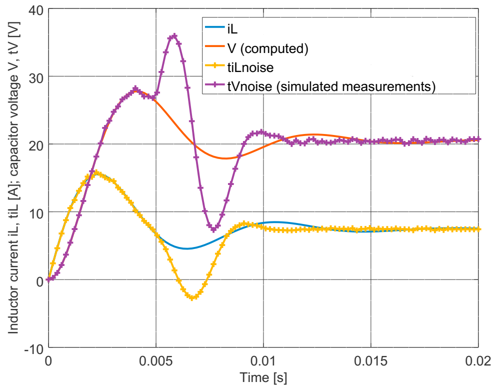

Fig. 7. Effect of the capacitor degradation as of $t_f = 0.005s$ on the inductor current $\tilde{i}_L$ and the capacitor voltage $\tilde{V}$

The objective of the simulation is to recover this degradation from available simulated measurement data $\tilde{i}_L$ and $\tilde{V}$ provided by a model with variables averaged over the switching period. Although averaging results in some smoothing, measurement noise is taken into account by adding 1% Gaussian noise to the output signals of the BG model. In a bicausal DBG, measurement uncertainties can be represented by modulated sinks.

The simulation performed by the free software GNU Octave 4.4.1 uses the parameters given in Table 1. The effect of the capacitance degradation on the inductor current $\tilde{i}_L$ and the capacitor voltage $\tilde{V}$ is displayed in Fig. 7 in which the tilde is substituted by the letter t prefixing the variable name. Simulated noisy measurements are obtained by means of the Octave function `randn()`.

```
tV = tV + 0.01*tV .* randn(linspace(tV))     (10)
```

That is, the distribution of the generated random numbers is normal with zero mean and a variance equal to 1. The noisy signals have been smoothed by a Savitzky-Golay filter [19] (Octave function `sgolayfilt()`). In case the resistor R : R is faulty, the derivative of the simulated measurement $\tilde{V}$ is needed (cf. Eq. 3). Differentiation and smoothing can also be carried out by a Savitzky-Golay filter. The result is displayed in Fig. 8.

Fig. 9 finally displays the recovered decay $rC(t)$ of the capacitance $C(t)$. As can be seen, the time evolution of the recovered capacitance $rC(t)$ is sufficiently close to the decay of the capacitance $C(t)$ deliberately introduced into the behavioural model of the circuit.

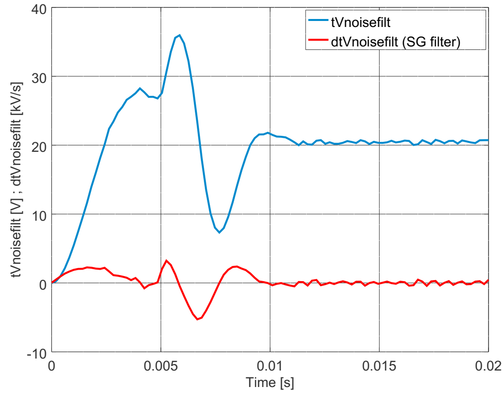

Fig. 8. Filtered noisy capacitor voltage tVnoisefilt and its derivative dtVnoisefilt

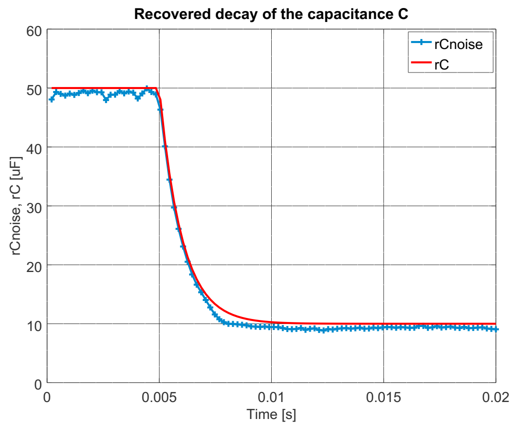

Fig. 9. Recovered capacitance rC(t), rCnoise(t)

4. Data-driven failure prognostic

4.1. Data acquisition phase

As explained and illustrated in Section 2, equations for unknown parameter degradation functions for resistive as well as storage elements can be directly derived from a bicausal diagnostic bond graph by following causal paths from sources and detectors in inverted causality to the port of a faulty element. That is, inputs to these equations are only known control inputs and measurements. Numerical values of an unknown parameter degradation function can be computed at sample time points online concurrently to the health monitoring of a real system and the constant measurement of signals. As soon as n measured values of each needed signal are available and stored in a buffer, the (filtered) trend of a faulty parameter $\Theta(t)$ can be approximated up to a time instant t and can be projected into the future to see when it would intersect with a failure threshold.

Once computed numerical values of an unknown function of the degradation of parameter Θ_i are available, they may be treated like degradation data of a feature extracted from measurement data. Direct measurement of degradation is often not possible without being invasive or destructive. The concurrent computation of a time-series of degradation data by an evaluation of equations derived offline from a bicausal diagnostic BG can be considered the data acquisition phase.

4.2. Learning a mathematical degradation model

Given n available degradation data $\Phi_\Theta(t_i^k)$, $i = 1, \ldots, n$ obtained from filtered real measurements or simulated measurements in the current k^{th} sliding time window w^k that are stored in a buffer of fixed size, a number of basic mathematical models, i.e linear, exponential, or power models with parameters to be determined may be tested to see which one fits best the data in the current window w_k. This task of learning a mathematical model can be carried out e.g. by commercial software such as Weibull++ [14] or by the Matlab Predictive Toolbox [21] and can be performed in parallel on a multiprocessor, multicore computer. As an evaluation criterion for the best fit, the root mean square error (RSME) may be used.

4.3. Projection and RUL estimation

The degradation function $\Phi_\Theta(t)$ found can then be used to determine a time point t_f^k at which the time evolution of the faulty parameter $\Theta(t)$ intersects with a given failure level threshold. The time span from the current time t_c^k (current age of the system) to the time instant t_f^k where the time evolution of the parameter $\Theta(t)$ obtained from degradation data in the k^{th} window w^k intersects with a failure level threshold (end of life, EOL^k) gives an estimate of the remaining useful life RUL^k.

$$\mathrm{RUL}^k := t_f^k - t_c^k \tag{11}$$

With progressing time new filtered degradation values of parameter Θ_i become available while some older values drop out of the buffer. That is, time windows overlap. For a new time window w^k, the two steps, i.e. the determination of the best fit degradation model and its extrapolation are repeated.

As time has advanced, i.e. the system has become older, that is, t_c^k takes a new value and the intersection with the failure level threshold gives a new time to failure value. As a result, one obtains a new value for the RUL. Repeating these steps while time is progressing results in a sequence of k RUL estimates $\mathrm{RUL}^k(\Theta_i)$ which ultimately converge to zero as a component reaches its EOL. This two step prognosis procedure consisting of a regression analysis of the degradation data in a window w^k and an extrapolation that provides an estimate of the time to failure can be carried out simultaneously for multiple degradation mechanisms that do not compete, and in parallel on a multicore, multiprocessor computer. The global system-level RUL is then the infimum of all component RULs.

4.4. Failure prognostic for hybrid systems

An advantage of a repeated identification of a mathematical model for the degradation is that in case of a hybrid model for each system mode of operation a possibly different degradation behaviour can be taken into account. In systems represented by a hybrid model, degradation of a component in ON mode may stop when the component switches into OFF mode. An example may be the mass flow through an increasingly contaminated valve. As long as the valve is open, its discharge coefficient, c_d, decreases with time. Clearly, when the valve is switched off, i.e. when this system component becomes inactive, then the last value of the discharge coefficient before closure is retained, degradation is stopped as long as the valve is in OFF mode, i.e. the decline of the time evolution $c_d(t)$ becomes zero. That is, extrapolating the time evolution of the faulty parameter from the current sliding window does provide no RUL estimate. In that system mode, the system behaviour is not affected by the faulty valve and nothing can be said about the RUL.

4.5. Accuracy of failure projection

The determination of numerical values of an unknown degradation function $\Phi_\Theta(t)$ at sample time points and the projection of $\Theta(t)$ into the future requires a sufficient number of degradation data in the current window w^k in order to accurately identify the parameters of a potential degradation model. The amount of available degradation data, i.e. the size of the sliding window, affects the uncertainty in the values of the degradation model parameters and has an effect on the estimation of the time to failure. Commercial software such as Weilbull++ [14] can compute upper and lower bounds for the RUL with a certain confidence level. In order to meet given accuracy requirements for the parameters of the degradation model to be fitted, the size of the sliding window may vary. The boundaries for the RUL become more narrow, they build a converging cone, as the sliding time window moves on, i.e. the identification of a best fit degradation model, its extrapolation and the prediction of the time to failure must be more accurate as a faulty component approaches its EOL.

4.6. RUL estimation for the boost converter example

In the case of the capacitance degradation considered in Section 3, fitting of degradation data in each window gives the same exponential function $C(t)$. Its intersection with a fictitious failure threshold level C_{crit} gives the same time to failure t_f if noise is neglected. Let α, β, γ be the identified parameters of the exponential function $\Phi_C(t)$ fitting the degradation data in a window. Then for $t_c = t_0$ the time to failure t_f is determined by the condition

$$C(t_f) = \alpha C_n + \beta C_n e^{-\gamma(t_f - t_0)} = C_{\mathrm{crit}} \tag{12}$$

Solving for t_f gives

$$t_f = t_0 - \frac{1}{\gamma}\left(-\ln\beta + ln\left(\frac{C_{\mathrm{crit}}}{C_n} - \alpha\right)\right) \tag{13}$$

Equation 13 indicates that the time to failure and the RUL, $\mathrm{RUL}(C, t_0) := t_f - t_0$ depend on the fitting parameters and the critical level C_{crit}. The ground truth RUL is obtained for $\alpha = 1/5$, $\beta = 4/5$ and $\gamma = 500$. These fitting parameters, $C_{\mathrm{crit}} = 2/5\, C_n$ and $t_c = t_0 = 5\, ms$ yield $t_f = 2.77$ ms. Fig. 10 depicts the true RUL.

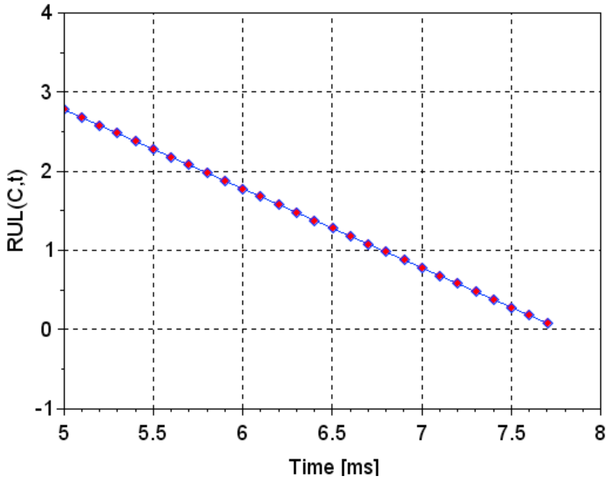

Fig. 10. True RUL of the decaying capacitance $C(t)$

5. Uncertainties in hybrid failure prognostic

There are some uncertainties linked to the proposed non-residual model-based approach to failure prognostic.

5.1. Modelling uncertainties

First, the bicausal BG model from which equations for unknown degradation functions are derived relies on modelling assumptions. Some features of a system or a process may not be fully understood, approximated, neglected, or modelled in a simplified manner. Model parameters may be uncertain. Numerical computation may start from an uncertain initial system state.

5.2. Measurement uncertainties

Entries into the equations derived from the DBG are measurements that are random and carry noise besides known control inputs. Sensors may be biased. That is, appropriate filtering of acquired raw measured data is needed that keeps essential information. A well known digital low-pass filter well-adapted for smoothing raw measurement data and for its differentiation in discrete time is the Savitzky-Golay (SG) filter widely used in various applications since a long time [19]. Its implementation is available in software such as Octave and Matlab.

The SG-filter fits a polynomial $P(t_i) = \sum_{j=0}^{n} a_j\, t_i^j$ of low order n to M observed equally spaced time series data in a moving symmetric window of length $N = 2M + 1$ around a reconstruction point by minimising the least square error.

$$\varepsilon_n = \sum_{j=-M}^{M} (P(t_i) - y(t_i))^2 \tag{14}$$

where $y(t_i) = x(t_i) + w(t_i)$ denotes the time series data of the observed noisy signal, $x(i)$ the time series data to be estimated, and $w(i)$ noise assumed to be independent and identically distributed with zero mean and variance σ^2. The reconstruction of the centered point needs future values, which means some delay.

To achieve sufficient smoothing, the polynomial order is generally chosen much smaller than the length of the window. However, low order polynomials will oversmooth sharp changes in the observed time series data so that there is a trade-off between smoothing and signal distortion. An increase of the window length, i.e. the number of samples, results in a decreased variance estimation but entails an increase of the bias error at the same time. That is, the two tuning parameters of the SG-filter will have to be chosen with care. There are no general guidelines how to choose the filter parameters as the result of the filter depends on the characteristics of a signal to be smoothed. In [16], the authors design a SG-filter by using Chebyshev orthogonal polynomials and give a closed form formula for the optimal window length in the sense of minimizing the mean square error for SG-filters of arbitrary order.

5.3. Statistical and environment uncertainties

Repeated measurements provide a set of distributed values of a sensor signal at a sampling point t_i. Unforeseen environmental changes may entail changes of operating conditions.

5.4. Degradation model uncertainties

As the fault estimation of a trending parameter $\Theta(t)$ at sample time points t_i in the k^{th} sliding time window w^k uses measurements, the values of the incipient fault, i.e. the degradation $\Phi_\theta(t)$ at each sample time instant are random with a probability density function (pdf). Accordingly, the parameters of a best fit degradation function are also to be considered random parameters with a mean value and a pdf which affects the prediction of the k^{th} time to failure t_f^k (EOL^k) and the estimation of RUL^k. The question then is which type of probability density functions are suited for approximation and how to choose their parameters. In the Matlab Predictive Maintenance Toolbox, the exponential degradation model to fit data of a health indicator $h(t)$ extracted from measured data is defined as

$$h(t) = a + \alpha\, exp(\beta t + \epsilon - \frac{\sigma^2}{2}) \tag{15}$$

[22] where

$h(t)$	:	health indicator as a function of time
a	:	intercept term considered constant
α	:	lognormal-distributed parameter
β	:	Gaussian-distributed parameter
ϵ	:	Gaussian white noise yielding $\mathcal{N}(0, \sigma^2)$

so that the expectation value $E[h(t)]$ is

$$E[h(t)] = a + \alpha\, exp(\beta t)\ . \tag{16}$$

5.5. Prediction uncertainties, prognostic metrics and risk assessment

The result of a long term RUL prediction is not a single value but a pdf. A pdf of initial conditions is propagated forward. Let

$\varphi(\theta\,|\,t)$ be the pdf of the trending parameter Θ at time instant t, then the probability $\pi[\Theta(t)]$ that the magnitude of $\Theta(t)$ is less than the failure threshold Θ_{FT} is

$$\pi[\Theta(t)] = \int_0^{\Theta_{FT}} \varphi(\theta\,|\,t)d\theta \tag{17}$$

As has been shown in [18], the RUL pdf may not be normal even if the trending parameter at sample time points t_i is normally distributed.

The prognostic metric called $\alpha - \lambda$ accuracy determines whether at a given time point t_λ the prediction accuracy is within desired accuracy levels specified by α and expressed as a percentage of the true RUL at time instant t_λ [20]

$$\pi[RUL(t_\lambda)]_{\alpha^-}^{\alpha^+} = \int_{\alpha^-}^{\alpha^+} \varphi(\theta\,|\,t = t_\lambda)d\theta \geq \beta \tag{18}$$

where

λ	: $t_\lambda = t_p + \lambda(t_{EoL} - t_p)$, $0 \leq \lambda \leq 1$
t_p	: time point of the first prediction
$\varphi(\theta\|t = t_\lambda)$	: probalility density of the trending parameter θ at t_λ
$\pi[RUL(t_\lambda)]_{\alpha^-}^{\alpha^+}$	: total probability of the predicted $RUL(t_\lambda)$ between $\alpha^- = RUL_*(t_\lambda) - \alpha RUL(t_\lambda)$ and $\alpha^+ = RUL_*(t_\lambda) + \alpha RUL(t_\lambda)$
$RUL_*(t_\lambda)$	: ground truth RUL
β	: minimum acceptable probability mass

As the RUL is not a single value but is random with a pdf and an expectation value $E[RUL]$, risk management introduces a so-called maximum allowable probability of failure (PoF), i.e. a maximum acceptable level of risk of equipment failure to support maintenance decisions and corrective actions. The choice of a PoF value depends on the plant to be operated and on various aspects. The time instant at which this level is reached is called Just-in-Time-Point t_{JITP} [5] and gives rise to the introduction of the so-called lead-time interval

$$t_{LTI} := t_{JITP} - t_P \tag{19}$$

where t_P denotes the prediction time. Corrective maintenance actions must be taken before $t_{LTI} < E[RUL]$ elapsed. Such maintenance actions make sure that a plant does not operate beyond a maximum allowable PoF.

5.6. Failure threshold

Prediction of the time to failure clearly depends on the failure threshold that has been set. With insufficient a priori knowledge, the choice of an alarm threshold below the EOL failure threshold ensuring a safety margin is uncertain so that for a failure threshold a pdf has to be assumed. A proper choice of an alarm threshold is crucial as the intersection of an extrapolated degradation trend provides a time instant t_{alarm} at which a decision on the action be to taken must be made.

For the sake of simplicity, it is assumed that the rate of degradation behaviour of a trending parameter $\theta^1(t)$ does not change from one sliding time window to the subsequent one. Once a best fit mathematical model $r\theta^1(t) = \theta_n^1 + \Phi_\theta^1(t)$ for the trend of an incipient fault $\theta^1(t)$ has been identified, the faulty behaviour of the system can be simulated. To that end, θ_n^1 is replaced by $r\theta^1(t)$ in the computation of the nominal state space model. Let y be an output signal that indicates the failure of a component or of the system. For instance, if in a hydraulic system a valve is completely congested, then there is no outflow which may entail that the system does no longer perform its intended function. In electronic systems, a current through a component persistently equal to zero as of some time instant t_{EoL}, or a battery voltage that has reached a critical minimal value indicates its failure. As a result, the system functionality may be reduced or may even cease. Let

$$\dot{\boldsymbol{x}} = \mathbf{f}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}) \tag{20}$$

$$y = g(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{\theta}) \tag{21}$$

be a state space model derived from a bond graph in integral causality, where $\boldsymbol{x}$ denotes the state, $\boldsymbol{u}$, the vector of known control input signals, and $\boldsymbol{\theta} = (r\theta^1(t), \theta_n^2, \ldots, \theta_n^p)$ the parameter vector. Then the condition

$$y(t_{EoL}) = y_0 \,, \tag{22}$$

where y_0 denotes a value characterising failure, determines the time instant of failure, t_{EoL}, and $r\theta^1(t_{EoL})$ is an estimate of the hard failure threshold θ_{FT}^1. Accordingly, an alarm threshold θ_{alarm} with a safety margin to θ_{FT}^1 can be chosen.

5.7. Onset of the degradation and start of the prediction

Furthermore, there is a time delay between the occurrence at time instant t_{oc}, the detection of an incipient parametric fault at t_D, and the start of the prediction at t_P. In [15] a correction time t_C is obtained by subtracting a margin from t_D that guarantees that the system is in a fault mode at time t_C.

A parameter value $\theta(t)$ deviating from its nominal value θ_n must not only touch constant fault thresholds, $a = \theta_n \pm 3\sigma_0$, with σ_0 denoting the standard deviation of θ, before the onset of degradation, or touch time dependent adaptive fault thresholds, but must increasingly deviate from these boundaries with time in order to be identified as a progressive fault. As a result, it takes some time until the first sliding window can be filled with degradation data.

6. Advantages of the proposed hybrid method

The proposed combined bond graph model-based, data-driven failure prognosis method has the following advantages.

The computation of numerical values of an unknown degradation function in the data acquisition phase by evaluating an equation derived from a bicausal DBG at sample time points can be performed in parallel for multiple simultaneous parametric faults concurrent to the constant monitoring of a real process.

For the fitting of measured degradation data in each consecutive window, w^k, pertaining to a faulty component, the mean value of random parameters of various potentially appropriate basic mathematical functions can be computed in parallel by means of existing software. A criterion such as the root square mean error (RSME) can single out the best fitting function among a set of potential candidates.

The repeated identification of a best fit degradation model for consecutive time windows w^k enables to account for possible changes of the degradation behaviour from window to window that may be due to changes of the system mode of operation or may be caused by changes in the system's environment.

Extrapolating a faulty parameter trend $\Theta(t)$ from each window w^k results in a sequence of RUL values $\mathrm{RUL}(\Theta,\ t_k)$ that tend to zero for $t_k \rightarrow t_{EoL(\Theta)}$.

Conclusion and outlook

The paper proposes a hybrid bond graph-model based – data driven method for failure prognostic. It is assumed that incipient faults have been detected and isolated. A novel BG based method to sensor placement problem that aims to isolate a maximum number of parameters has been proposed in [3].

As to the model-based part of the approach, this paper shows that by following causal paths in a bicausal DBG from detectors in inverted causality and from independent sources of system input signals to the power port of a possibly nonlinear element with the parameter $\Theta(t_i)$ at sample time instant t_i identified as faulty, i.e. $\Theta(t_i) = \Theta_n + \Phi_\Theta(t_i)$, an equation can be established that determines the numerical values of the unknown parametric degradation function $\Phi_\Theta(t)$ at t_i.

Data-driven identification of a best fit degradation model uses known control input signals and sampled values of measured output signals and may require the differentiation of some signals in discrete time. Therefore, sophisticated preprocessing of measured raw signal data is needed. For smoothing raw measured data and their differentiation in discrete time, the Savitzky-Golay algorithm may be used.

In the failure prognostic part of the proposed approach, the parameters of a degradation model that fit measured data in the current sliding time window are considered random with a mean value and a probability density function. This affects the projection of a parameter degradation trend into the future towards the intersection with a failure threshold.

The proposed hybrid method can be implemented in embedded systems that enable cooperating machines in smart manufacturing systems or power electronic devices equipped with sensors to determine health indicators such as vibration in an aging machine or heat development in systems on circuit and to perform fault diagnosis and failure prognostic themselves, to communicate results with collaborating subsystems and operators via smart human interfaces and to support prognostic and health management of complex cyber physical systems.

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