CHEMICAL ENGINEERING TRANSACTIONS

VOL. 33, 2013

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at: www.aidic.it/cet

Guest Editors: Enrico Zio, Piero Baraldi

**ISBN** 978-88-95608-24-2; **ISSN** 1974-9791

DOI: 10.3303/CET1333174

# A Generic Diagnosis and Prognosis Framework: Application to Permanent Magnets Synchronous Machines

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In the context of electrification of aeronautical actuation systems, aircrafts manufacturers intend to supervise more and more the health state of equipment during their service life. Authors propose a generic modeling framework to represent systems functional behavior and health evolution through time. A health assessment method is then built based on this framework. Throughout the paper Permanent Magnet Synchronous Machines are used as an illustration.

## 1. Introduction

The objective of health state supervision is to increase the operational availability of systems, and to organize efficient maintenance management for safety and economic reasons. In this purpose diagnosis and prognosis are performed to determine the current and future health state of mechanical, electrical, and hydraulic equipment.

Many authors, such as Isermann et al. (2005), Kothamasu et al. (2006) and Vachsevanos et al. (2007), propose methods for diagnosis. Some authors are getting interested in prognosis (see Gebraeel and al. (2009), Onori et al. (2012) and Voisin et al. (2009)). Very few authors such as Bregon et al. (2012) begin to study the integration of framework for both diagnosis and prognosis. We would like to emphasize that diagnosis and prognosis are both health assessment and could be performed in a very similar way. It seems to us that they could be thought and designed simultaneously. Most importantly diagnosis and prognosis could then be coupled in order to feed each over. Besides, we consider that a generic method, adaptable for different kinds of equipment (and any kind of equipment model, that may be physics or experience based, continuous, discrete or hybrid), would be more consistent than existing methods dedicated to only one kind of equipment.

To standardize diagnosis and prognosis into one formal method of health assessment, we propose a generic modeling framework. It is made of two parts. First a structural and functional model enables representing nominal and faulty behavior of complex systems. It also describes the functional interaction between components. Then an ageing model allows representing the system degradation through time thanks to the knowledge available about its ageing, from physical laws or experience. It also shows the effect of damaged components on others, and the propagation of ageing-related performance losses through the system. The evolution of the machine health state in nominal case and during faults initiation and progression is modeled. In our definition, health state represents both the degradation level and the functional losses and performance of the system.

A health assessment method based on this generic modeling framework is proposed. It is meant to evaluate the health state of any complex system at any time of its life. This method comprises two modules: the detection and diagnosis module evaluates the current health state, and the prognosis module assesses the future health state and computes the remaining time before failure.

Permanent Magnet Synchronous Machines (PMSMs) illustrate this method. They are subject to critical progressive faults such as short-circuits that are successfully modeled by the proposed framework. The health assessment method is then implemented on healthy and faulty simulated PMSMs. In this example our algorithms allow assessing current and future health state of the machines.

Please cite this article as: Vinson G., Ribot P., Prado T., Combacau M., 2013, A generic diagnosis and prognosis framework : application to permanent magnet synchronous machines, Chemical Engineering Transactions, 33, 1039-1044 DOI: 10.3303/CET1333174

## 2. The generic modeling framework

### 2.1 The functional network

The functional model is based on Ribot et al. (2009). A component $C^i$ is part of a system $\Sigma = \{C^1,\ldots,C^n\}$. $C^i$ environment is $\varepsilon^i$. Physical quantities or information that circulate through the system are modeled with parameters p. $p^{i,j}$ in $P^i$ is the $j^{th}$ parameter of component $C^i$. The conversion of physical quantities by the system are modeled as mathematical relationships $ar^{i,l} \in A^i$ between parameters.
The goal of a component is to provide elementary functions $Fu^{i,k}$ in $FU^i$. Physical quantities corresponding to the results of functions are output parameters $op^{i,\cdots}$ in $OP^i$. Functions are defined by manipulating relationships:

$$ar^{i,k}(p^{i,j},\ldots,p^{i,l}) = 0 \ ; \quad op^{i,k} = Fu^{i,k}(ar^{i,k}(p^{i,j},\ldots,p^{i,l})) \tag{1}$$

The set of parameters appearing in the function definition is the function support $Supp(Fu^{i,k})$. Components are grouped into system in order to achieve system goal functions $Fu^{\Sigma}$ as a combination of components functions. Components have physical quantities in common which is modeled by exchange ports between them. This is modeled by the structure st of the system. Two parameters structurally connected always have the same value v(p,t).
Parameters that are not output parameters are divided into two categories:

- input parameters $ip^{i,\cdots}$ in $IP^i$ whose value is forced by $\varepsilon^i$ through the structure
- private parameters $pp^{i,\cdots}$ in $PP^i$ that are intrinsic to one component and are not structurally connected with any other parameters.

The set of values that is said possible for the parameters is called their rank r(p) in $R^i$. System definition is:

$$\Sigma = \left\{C^1, C^2,\ldots, C^n\right\} \ ; \ C^i = \left\langle P^i, A^i, R^i \right\rangle \ ; \ P^i = IP^i \cup OP^i \cup PP^i \tag{2}$$

This functional model is applied to a PMSM (Figure 1), composed of two components: stator and rotor. Stator is structurally connected to environment through supply voltages $U_{ab}$ , $U_{bc}$, $U_{ca}$, and to rotor through phase currents $I_a$, $I_b$, $I_c$, and induced voltages $E_a$, $E_b$, $E_c$. Its private parameters are phase resistances $R_a$, $R_b$, $R_c$, and inductances $L_a$, $L_b$, $L_c$. Rotor is also structurally connected to the environment through electromagnetic couple $C_{em}$ and speed $\Omega$. Relationships between those parameters are well known. Stator function $Fu^s$ is the production of a balanced system of currents at given frequency and magnitude. Goal function $Fu^g$ is to produce a stable speed.

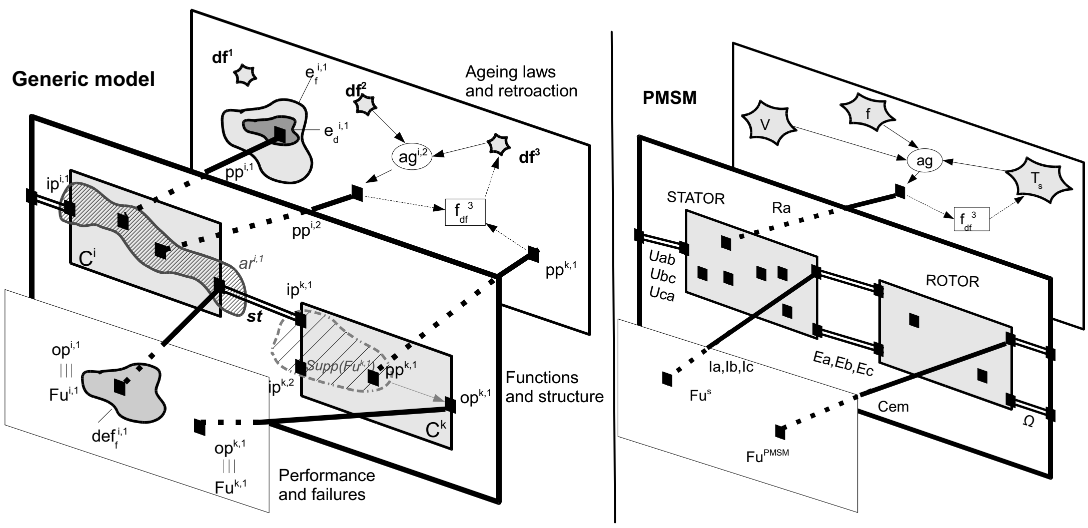


*Figure 1: The proposed modelling framework (left) and PMSM model based on it (right)*

### 2.2 The ageing network

During its life a component is damaged because of thermal, electrical, mechanical, or chemical stresses. Damage is cumulative; it is usually zero at the beginning of component's life and increase in time. Only maintenance operation can result in a damage decrease. Private parameters allow representing the component damage evolution (Ribot et al. (2009)). The damage $e^{i,j}$ cumulated during a period of time is defined as the distance dist between the private parameters values $pp^{i,j}$. To every private parameter $pp^{i,j}$ corresponds one kind of damage $e^{i,j}$. The initial private parameter value is noted $pp_0^{i,j}$ and then:

$$v(pp^{i,j},t) = pp_0^{i,j} + e^{i,j}(t) \quad ; \quad e^{i,j}(t) = dist(\ v(pp^{i,j},t),pp_0^{i,j}) \tag{3}$$

Stresses are modeled as damaging factors df. The ageing law $ag^{i,j}$ expresses the relationship between damage $e^{i,j}$ and damaging factors $\{df^i_1,df^i_2,\dots\}$ values:

$$e^{i,j}(t) = ag^{i,j}(df^i_1, df^i_2,...,t) \tag{4}$$

A damaged component has a more negative impact on its environment than a healthy one, so damaging factors possible values or ranks r depend on components damage. There is a retroaction of the system health state on itself through the function $f_{df}$:

$$r(df^i_l) = f_{df}(pp^{1,1},...,pp^{n,m}) \tag{5}$$

The functional network - input, output, and private parameters - models exchanges and transformation in the system when the goal of these transformations is to accomplish a functional goal. The ageing network - damaging factors and private parameters - models the system damage evolution in time. Private parameters allow a coupling of these two networks (Figure 1).
For our application with PMSM, possible damage is inter-turns short-circuit. It is modeled as a diminution of the short-circuited phase resistance $R_a$. Damage is defined as $e(t) = |R_{a,opt} - R_a(t)|$. Damaging factors are supply voltage magnitude V and frequency f and stator temperature $T_s$. The chosen ageing law for short-circuits is $ag(t)=1.45.10^5.exp(-\lambda(t))$ where $\lambda$ is a function of damaging factors $T_s$, V and f. Inter-turns short-circuits cause an increase in the stator temperature, which is modeled as a relationship $f_{df}$ giving $T_s$ temporal value as a function of $R_a$ value, and shows the retroaction effects.

**2.3 How ageing decreases useful life duration**

Parameters nominal values are set by the user according to the application. A function performance depends on its output parameter value. The loss of performance $def^{i,k}(t)$ of the function $Fu^{i,k}$ is defined similarly as damage: it is the distance dist between the optimal output parameter $op^{i,k}_{opt}$ and the actual value $v(op^{i,k},t)$. Ageing usually induces a decrease in performance since modification of private parameters values of $Supp(Fu^{i,k})$ may lead to a modification of the output parameter value $v(op^{i,k},t)$. When the distance is greater than a given failure threshold $def^{i,k}_f$, the function is said failed and its availability Av is null:

$$def^{i,k}(t) = dist(v(op^{i,k},t), op^{i,k}_{opt}) \quad ; \quad def^{i,k}(t) \geq def^{i,k}_f \Rightarrow Av(Fu^{i,k},t) = 0 \tag{6}$$

The failure of one component function may lead to a failure in a structurally connected component, since it changes its input parameter value. This is the propagation in loss of performance (Figure 2). Thresholds are set for the damage value $e^{i,j}(t)$ according to the effect the damage has on the performance loss $def^{i,k}$ of the function $Fu^{i,k}$. Thresholds calculation considers there is one and only one damage on the component. When damage is progressive degradation thresholds $e^{i,j}_d$ are defined to quantify the degradation level before the fault. The fault thresholds $e^{i,j}_f$ is the value of damage that makes the function $Fu^{i,k}$ non available. When the damage of one private parameter exceeds the given fault threshold, the parameter is said faulty.

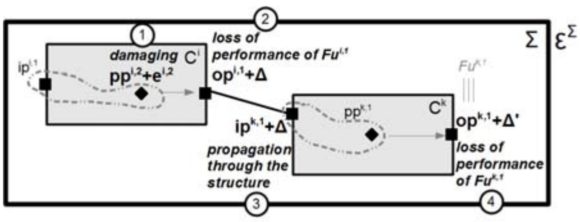


*Figure 2: Ageing and loss of performances propagation through the structure*

A component (resp. a system) is said to be at the end of its useful life when at least one of its functions (resp. of the goal functions) is not available. Then the remaining useful life $RUL^i$ (resp. $RUL^\Sigma$) goes from 1 to 0. A maintenance operation is needed. At any time the remaining time to fault is $t_{RUL}$.
In the application, the stator function performance loss is the distance between optimal and actual phase currents, considering the three parameters of signal s: frequency f(s), phase Φ(s) and magnitude |s|.
The goal function performance loss is similar but with the electromagnetic torque signal. Inter-turns short-circuits cause a loss of performance in $Fu^s$ which is propagated to $Fu^g$ through the structural connection between stator and rotor.

**2.4 Modeling the anticipated behaviors of the system**

The functional and the ageing models of the components have been presented. They represent the evolution of the components behavior. This behavior is modeled by the configuration- the component external solicitations - and the mode – its health state. Configuration may be normal if all input parameters values are into the user expected rank for normal use $r_n(ip)$, or abnormal otherwise. Regardless of configuration, three kinds of health modes are defined.
The nominal mode $m_n^i$ is a mode where all damage values are below the lowest degradation threshold $e_{d1}^{i,\dots}$, usually at the beginning of the system life. Parameters ranks are $r_n(p)$. The degraded modes $m_d^i$ are the one where at least one damage is greater than the lowest degradation threshold $e_{d1}^{i,\dots}$ but all damages are below the fault threshold. Parameters ranks are $r_{dk}(p)$ where dk is the $k^{th}$ degradation level threshold. The faulty modes $m_f^i$ are the one where at least one damage value is greater than the fault threshold. Parameters ranks are $r_f(p)$. Finally unknown modes are the one that have not been anticipated. Equations (9) (10) (11) define the health modes $m_n^i$, $m_d^i$ or $m_f^i$ that may represent a component $C^i$ at a time t.

$$\begin{cases} (C^i,t) \equiv m^i{}_n(t) \Leftrightarrow \left\{ \forall p^{i,k} \in PP^i, e^{i,k}(t) \le e^{i,k}{}_{d1} \right\} & (7) \\ (C^i,t) \equiv m^i{}_d(t) \Leftrightarrow \left\{ \exists pp^{i,j} \in PP^i, e^{i,j}{}_{dk} \le e^{i,j}(t) \le e^{i,j}{}_{dk+1} \text{and}\, \forall p^{i,l} \in PP^i \cup OP^i, v(p^{i,l},t) \in r_{dk}(p^{i,l}) \right\} & (8) \\ (C^i,t) \equiv m^i{}_f(t) \Leftrightarrow \left\{ \exists pp^{i,j} \in PP^i, e^{i,j}(t) \ge e^{i,j}{}_f \text{and}\, \forall p^{i,l} \in PP^i \cup OP^i, v(p^{i,l},t) \in r_f(p^{i,l}) \right\} & (9) \end{cases}$$

Every component has a trajectory in the space of health modes, based on the evolution of damages. This evolution is from healthy to degraded and faulty. Health mode impacts configuration: a degraded/faulty component may lead to an abnormal configuration of a structurally connected component.
These definitions are expandable to systems. System modes $m_x^\Sigma = \langle m_{x1}^1, \dots m_{xn}^n \rangle$ in $M^\Sigma$ are composed of components modes being consistent with each other's. The set of possible system modes $M^\Sigma$ is defined in Ribot and al. (2009). System is in abnormal configuration when at least one input parameter structurally connected with the environment is not-nominal. System health mode is nominal when every component modes are nominal, degraded/faulty when at least one component mode is degraded/faulty. Functions availabilities are a result of configuration and health mode.
For example, PMSM's components are in nominal mode when PMSM is still completely healthy. When a short-circuit is initiated but has no important consequences on performance, stator is in degraded mode. If the short-circuit implies enough turns to seriously decrease the stator performance (because of changes in currents phase and magnitude), the stator function is no more available and the stator is in fault mode. Stator and rotor are structurally connected, the input phase currents of the rotor are no more nominal, and the rotor is then in abnormal configuration, but still in nominal mode. In this scenario the PMSM mode is first nominal then degraded and then faulty.

## 3. The health assessment module

The health assessment module is composed of a diagnosis and a prognosis module described hereby.

**3.1 Diagnosis**

Local diagnoses are realized thanks to observations obs(p,t) (parameters measurement with sensors), the modes knowledge, and the structure. Indicators $\rho^i_x$ in $Rho^i$ are created by removing every non observable parameter from relationships $ar^{i,\dots}$ They take specific values in every mode. Local diagnosis outputs the components and system current mode $m^i_x$ and health state that represent a component at the current time t. Health state is defined as $HS^i(t) = \langle E^i(t), AV^i(t) \rangle$ where $E^i$ is the vector of all damages values and $AV^i$ is the vector of functions availabilities. The global diagnosis $\Delta^\Sigma(t)$ is the set of possible system modes $m^\Sigma{}_x(t)$ and health states $HS^\Sigma(t)$ that well represent the system current behavior. It is a fusion of local diagnoses, consistent with the damaging factors observation. Diagnosis algorithm is presented Figure 3.

$$\Delta^i(t) = \left\{ \left\langle m^i{}_x(t), HS^i(t) \right\rangle, \forall \rho^i{}_y, v(\rho^i{}_y, t) \in r^i{}_x(\rho^i{}_y) \right\} \tag{10}$$

$$\Delta^\Sigma(t) = \left\{ \left\langle m^\Sigma{}_x(t), HS^\Sigma(t) \right\rangle \right\} \tag{11}$$

**with** $m^\Sigma{}_x(t) \in \left(\Delta^1(t) \times ... \times \Delta^n(t)\right) \cap M^\Sigma$, $E^\Sigma(t) = \left[\left[E^1(t)\right]^T ... \left[E^n(t)\right]^T\right]^T$, $AV^\Sigma(t) = \left[\left[AV^1(t)\right]^T ... \left[AV^n(t)\right]^T\right]^T$

The PMSM's diagnosis results are presented in Vinson et al. (2012). A short-circuit indicator $A_{sc}$ is designed based only on phase currents that are observed. Its value depends on the short-circuit presence and gravity, assessed by the resistance $R_a$ value.

**Diagnosis**

**Input : {obs(p,t)}, $\{\rho^i{}_x\}$, st**
**Output : $\Delta^\Sigma(t)$**

FOR ALL $C^i \in \Sigma$
  FOR ALL $m^i{}_x$
    Calculation of every $v(\rho^i{}_y,t)$
    IF $v(\rho^i_y, t) \in r^i_x(\rho^i_y)$
      FOR ALL $p^{i,j} \in$ PPi U OPi
        Estimate $v(p^{i,j},t)$,
        Deduce $e^{i,j}(t)$ and $Av(Fu^{i,j},t)$
      $HS^i(t) \leftarrow \langle E^i(t), AV^i(t)\rangle$
      $\Delta^i(t) \leftarrow \Delta^i(t) \cup \{\langle m^i{}_x(t), HS^i(t)\rangle\}$
FOR ALL $m_x^\Sigma \in (\Delta^1(t) \times … \times \Delta^n(t))$
  IF $m_x^\Sigma \in M^\Sigma$
    IF $(v_{obs}(df^k{}_l) \in r_x(df^k{}_l)$ for all $df^k{}_l)$
      Calculate $AV^\Sigma(t)$
      $HS^\Sigma(t) \leftarrow \langle E^\Sigma(t), AV^\Sigma(t)\rangle$
      $\Delta^\Sigma(t) \leftarrow \Delta^\Sigma(t) \cup \{\langle m_x^\Sigma(t), HS^\Sigma(t)\rangle\}$
FOR ALL $\{\langle m_z^i, HS^i\rangle\} \in \Delta^1(t) \times … \times \Delta^n(t)$
  IF no exist $m_x^\Sigma$ | $m_z^i \in m_x^\Sigma$
    $\Delta^1(t) \leftarrow \Delta^1(t) \setminus \{\langle m_z^i, HS^i\rangle\}$

**Prognosis**

**Input: $\Delta^\Sigma(t)$, $\widehat{\varepsilon^\Sigma}$, {ag}, $\{f_{df}\}$**
**Output: $\pi^\Sigma(t)$, $t_{RUL}$**

$t_{RUL} = \infty$, $k \leftarrow 1$
FOR ALL $\Delta^\Sigma(t)$
  $\pi^\Sigma(t) \leftarrow \Delta^\Sigma(t)$
  WHILE ( RUL ≠ 0 )
    FOR ALL $C^i$
      FOR ALL $df^i{}_l$
        Calculate $v(df^i{}_l,t) = f_{df}(pp^{i,1},…)$
      FOR ALL $p^{i,j} \in$ PPi U IPi
        Estimate ip evolution from $\widehat{\varepsilon^i}$
        Estimate $t_1{}^{i,j}$ from $e^{i,j} = ag^{i,j}(df^i{}_{1},…)$
    $\widehat{t_k{}^i} \leftarrow \min(t_1{}^{i,j})$
    Diagnose Σ at time $\widehat{t_k{}^i}$
    $\pi^\Sigma(t) \leftarrow \pi^\Sigma(t) \cup \{\Delta^\Sigma(\widehat{t_k{}^i})\}$
    RUL $\leftarrow RUL^\Sigma(\widehat{t_k{}^i})$
    $t \leftarrow \widehat{t_k{}^i}$
    $k \leftarrow k+1$
  $t_{RUL} \leftarrow \min(t_{RUL}, t)$

*Figure 3: Diagnosis and prognosis algorithms*

### 3.2 Prognosis

In our work prognosis is adaptive; it is performed at any detection of a change of mode. In order to consider propagations and retroactions, local and global prognoses are simultaneously computed. The temporal projection for prognosis involves a decrease in the available knowledge on the system compared to diagnosis. Indeed observations are replaced with future projection of some parameters. Future values come from the knowledge of the future system configuration $\varepsilon^\Sigma$ for input parameters, and from ageing laws {ag} for private parameters. The prognosis also takes as input retroaction laws $\{f_{df}\}$, and diagnoses. It outputs a temporal prediction of mode changes and evolution of components and system health states. Prognosis algorithm is presented on Figure 3. Prognosis is represented as a sequence of system diagnoses $\Delta^\Sigma$ at every predicted times of mode changes. Prognosis $\pi^\Sigma$ at current time t is :

$$\pi^\Sigma(t) = \left\{ \Delta^\Sigma(t), \Delta^\Sigma(t_1), \Delta^\Sigma(t_2), ... \right\} \tag{12}$$

For the application, there is only one possible kind of damage, so damage thresholds and loss of performance thresholds match exactly. The remaining useful life is defined from the damage fault threshold, and prognosis consists in $t_{RUL}$ estimation.

The algorithms are run with a fictive scenario (see 2.4). Results are presented on Figure 4. The PMSM runs from time $t_0$ under constant supply voltage and frequency. A first prognosis is made at time $t_0$ to forecast the remaining useful life duration $t_{RUL}$ considering the absence of fault on the PMSM. The short-circuit indicator $A_{sc}$ is regularly computed from observations (phase currents sensors), which allows estimating damage evolution e(t). At time $t_{sc}$ a short-circuit is initiated (modelled as a decrease in the equivalent phase resistance $R_a$ value). It is well detected and diagnosed at time $t_1$ with the degradation threshold $e_d$ crossing. The stator temperature $T_s$ value is re-estimated knowing the fault presence and gravity. At this same time $t_1$, the prognosis module updates the prediction of $t_{RUL}$. At $t_2$ a second threshold $e_p$ is detected to be crossed and the second level of short-circuit gravity is diagnosed. Updated $t_{RUL}$ is predicted. In this example, diagnosis and prognosis are well performed and fulfil their objectives.

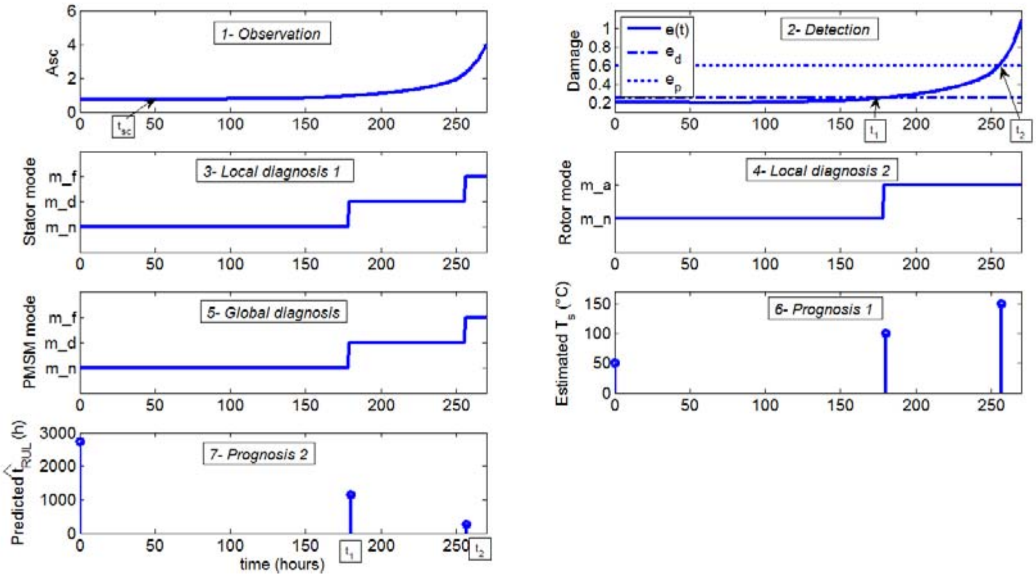


*Figure 4: Results from the health assessment module on a simulated PMSM short-circuit scenario*

## 4. Conclusion

The proposed generic modeling framework represents systems functional behavior and health evolution through time. The diagnosis and prognosis module based on it allows assessing the current health state, forecasting its future evolution, and computing the remaining time to fault. Results obtained on a PMSM short-circuit evolution realistic scenario are convincing. Further work consists in the application of this method on several applications including a real PMSM.

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