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MACHINE INTEGRATED HEALTH MODELS FOR CONDITION-BASED MAINTENANCE

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Preliminary notes
Machines undergo degradation as a result of both technical factors and non-technical factors that increase the potential for failures and deteriorate their health condition, and there is growing interest in new methods for health condition assessment. Currently, the inherent health of a machine is evaluated by monitoring of the data acquired by sensors. In other words, the evolution of the inherent health depends only on the evolution of technical factors, and therefore does not comprehensively represent the overall condition of the machine. This study introduces the concepts of "inherent health" and "integrated health" as well as their relationship. On the basis of inherent health assessment, the integrated health considers the non-technical factors related to the age, working conditions, and maintenance of a machine. By integrating a sequential imperfect maintenance policy into the maintenance strategy based on the integrated health conditions, the maintenance effectiveness is also considered. Through comprehensive assessment and real-time detection of the integrated health condition, this model may be used to support machine health management and maintenance decision-making. In case studies, the obvious differences between inherent health and integrated health are expected to appear under certain circumstances.

Keywords: *inherent health, integrated health, maintenance, proportional degradation model, proportional health recovery model*

Integrirani modeli zdravlja stroja kod održavanja temeljenog na stanju

Prethodno priopćenje
Strojevi su podložni degradaciji zbog tehničkih kao i ne-tehničkih faktora koji im povećavaju mogućnost kvarova i pogoršavaju njihovo stanje zdravlja. Zbog toga raste zanimanje za nove metode procjenjivanja zdravstvenog stanja. Sada se inherentno zdravlje stroja procjenjuje praćenjem podataka koje pružaju senzori. Drugim riječima, razvoj inherentnog zdravlja ovisi jedino o razvoju tehničkih čimbenika te stoga ne daje sveobuhvatnu informaciju o stanju stroja. Ovaj rad uvodi koncepte "inherentnog zdravlja" i "integriranog zdravlja" kao i njihovu povezanost. Na osnovu procjene inherentnog zdravlja, integrirano zdravlje uzima u obzir ne-tehničke faktore koji se odnose na starost, radne uvjete i održavanje stroja. Učinkovitost održavanja se također razmatra integrirajući sekvencijalnu nesavršenu politiku održavanja u strategiju održavanja koja se zasniva na integriranim zdravstvenim uvjetima. Sveobuhvatnom procjenom i otkrivanjem u stvarnom vremenu stanja integriranog zdravlja, ovaj se model može koristiti kao podrška upravljanju zdravljem stroja i donošenju odluke o održavanju. U analizi pojedinih slučajeva, očekuje se da će se očite razlike između inherentnog zdravlja i integriranog zdravlja pojaviti u određenim uvjetima.

Ključne riječi: *inherentno zdravlje, integrirano zdravlje, održavanje, proporcionalni model degradacije, proporcionalni model obnavljanja zdravlja*

1 Introduction

Currently, innovations in such areas as reactive maintenance (Fail and Fix, FAF) and predictive maintenance (Predict and Prevent, PAP) have been driven by the demands for a reduction in maintenance costs and for an increase in equipment availability [1]. Increasingly sophisticated sensors are installed on machines to a larger degree while the speed of computers continues to increase in great leaps. Under these circumstances, condition-based maintenance (CBM) has emerged as a more appropriate and efficient tool for achieving near-zero breakdown time. CBM is a maintenance program that recommends maintenance actions based on the information collected through health condition monitoring [2 ÷ 7]. Accordingly, there is a growing interest in methods for health condition assessment, in which health management programs play an important role. In much of the literature, a series of data-driven methods such as the self-organising Map (SOM), the cerebella model articulation controller (CMAC), logistic regression, statistical pattern recognition, and the Gaussian mixture model (GMM) have been proposed for machine health assessment [8 ÷ 12]. However, most of these methods concentrate on performance degradation assessment using the condition-monitoring data acquired by various sensors in standard working condition but do not consider the effects of non-technical factors. Therefore, the assessment result for "inherent health" can only indicate the current performance level in standard working condition and is not comprehensive in representing the overall health condition of a machine.

In order to more clearly present the existing problem, it is necessary to explore the concepts of "inherent health" and "integrated health" as well as their relationship. The evolution of the health condition of a machine is under the influence of the evolution through time of various factors. The technical factors refer to the machine itself factors being determined in the machine design process; they mainly include machine structure, performance characteristic, and reliability and so on, and they can be represented by the condition monitoring data acquired by sensors. The non-technical factors refer to the objective influencing factors that the machine inevitably suffers in service, such as age, maintenance activities and working conditions. Considering the lack of a unified definition of machine health condition, this study discusses the concepts of "Inherent Health" and "Integrated Health".

Inherent health can be defined as the health condition of a machine evaluated by the condition-monitoring data acquired by various sensors in standard working condition, it is considered from the point of view of standard working condition. Then, integrated health can be defined as the health condition of the machine derived by the comprehensive integration of the inherent health assessment result and relative influencing factors, e.g. different maintenance activities, increasing age, and varying working conditions, it is considered from the point of view of objective influencing factors. Therefore, according to its concept, the integrated health depends on four important factors [13]: (1) technical factors, representing the inherent health; (2) age; (3) working conditions, both environmental and operational; and (4) maintenance activities.

Age refers to an internal process in the machine in which gradual deterioration takes place, and each consecutive stage brings the machine closer to failure or breakdown [14 ÷ 18]. During operation, different operational conditions exist among various machines. Thus, certain machines spend much of their useful life in full-load operation, while others work under part-load conditions. Moreover, different environmental conditions may apply to machines. Thus, certain machines are located in severe environments, e.g. under high temperature and radiation exposure, while others remain in mild environments. In addition, the machines undergo many different maintenance activities and thus may deteriorate at different rates after such maintenance actions. These effects must be considered when developing a health assessment model [19 ÷ 22].

The integrated health assessment process is conditioned by different maintenance activities, each consecutive stage of the age and the various types of environmental and operational variables along with the inherent health process. In other words, the inherent health is only a single factor or a baseline for integrated health. Therefore, the integrated health of a machine at the different stages of age and subject to variable working conditions (environmental and operational) can evolve and vary along with its inherent health.

In this paper, an integrated health model is proposed that considers the parameters related to the age, the working conditions and the maintenance effectiveness of a given machine and allows the quantification of the different effects that the important parameters have on the integrated health condition. The parameters of the model may be obtained from the available machine degradation data and the engineering information. In simulation examples, the important differences between inherent health and integrated health may appear under certain circumstances. In this work, the results of several sensitivity studies are also analysed. This model may be used to support health management and maintenance decision-making for machines.

2 Proportional degradation model: considering age and working conditions

Such factors as the age, the operational and the environmental conditions, obviously affect the machine health condition and must be introduced into the integrated health assessment model. A proportional degradation model (PDM) is proposed as a tool to integrate the above factors into the machine integrated health assessment model.

The main feature of the PDM is the existence of the inherent health of a machine as influenced by a vector of covariates, often called explanatory variables. The effect of the explanatory variables consists of modifying the inherent health degradation of a machine.

Let z be a $q\times1$ vector that contains q covariates. In our case, the covariates represent the machine age and working conditions, and, in this work, q = 3: age (AG), environmental conditions (EC), and operational conditions (OC). Each covariate may assume either discrete or continuous values. Herein, the integrated health function in the PDM is given:

$$H_{\mathrm{r}}(t)=H_{\mathrm{r}}(0)-\psi(z)\left[H_{\mathrm{r}}(0)-H_{\mathrm{i}}(t)\right],\ t\geq0. \tag{1}$$

Where $H_{\mathrm{r}}(t)$ and $H_{\mathrm{i}}(t)$ represent the integrated health and inherent health at time t, respectively; $H_{\mathrm{r}}(0)$ and $H_{\mathrm{i}}(0)$ are respectively the initial integrated health and inherent health at the moment of machine installation, and are both equal to 1; and $\psi(z)$ is a link function that depends on the explanatory variables in vector z. The explanatory variables are linked to the inherent health degradation by $\psi(z)$, which satisfies $\psi(0)$ = 1 and $\psi(z) > 0$ for all z. When a link function satisfies these conditions, then z = 0 implies that the non-technical factors are not considered. In this work, we assume that a common mathematical model employed as the link function is the log-linear form with the following expression:

$$\psi(z)=\mathrm{e}^{\beta^{\mathrm{T}}z}, \tag{2}$$

where β is a $q\times1$ vector of regression coefficients corresponding to the q explanatory variables, and β^{T} is the transpose of β. In our case, $\psi(z) > 1$, and the explanatory variables increase the degradation of the inherent health proportionally to the evolution of the integrated health. Three coefficients (q=3), β_{AG}, β_{EC} and β_{OC}, corresponding to the age, the environmental and the operational conditions, respectively, are included in Eq. (2) to yield:

$$\psi(z)=\mathrm{e}^{\beta_{AG}\cdot AG+\beta_{EC}\cdot EC+\beta_{OC}\cdot OC}. \tag{3}$$

3 Proportional health recovery model: considering the maintenance effectiveness

3.1 Imperfect maintenance

In this work, the maintenance strategy based on integrated health condition is assumed by integrating the integrated health condition and a sequential imperfect maintenance policy into the CBM strategy, i.e. whenever the integrated health falls below the predetermined threshold, an imperfect maintenance event is triggered and performed. Thus, the effects of maintenance activities on the integrated health must be considered.

When the machine is properly maintained, its health condition lies somewhere between "as good as new" (GAN) and "as bad as old" (BAO), and this is known as "imperfect maintenance" [23, 24]. We propose that the maintenance can be classified according to the degree to which the integrated health condition of a machine is restored by the maintenance in the following way:

a) Perfect maintenance: Replacement of a failed machine by a brand new machine represents a perfect repair. This type of activity could be modelled by considering the GAN model.

b) Minimal maintenance: Certain activities consist of a simple visual inspection or test that does not involve major maintenance or repair actions. This type of activity could be modelled by considering the BAO model.

c) Imperfect maintenance: Certain activities involve a partial replacement or an adjustment, and these activities partially renew the machine.

Therefore, it is clear that imperfect maintenance is a general maintenance strategy that can include the two extreme cases: minimal and perfect maintenance. Although they are not considered in this paper, adverse effects associated with maintenance activities also have been analysed [25 ÷ 28].

In this paper, a proportional health recovery (PHR) model is proposed that introduces the improvement effects of the maintenance activities depending on an effectiveness parameter, which assumes that each maintenance activity restores the integrated health proportionally.

3.2 Proportional health recovery (PHR) model

The effect of the age and the working condition is introduced into integrated health assessment model using the PDM, and subsequently, the maintenance effect is taken into account in integrated health evolution model by introducing the factor ε, which varies between 0 and 1, and adopting the specific model of imperfect maintenance, PHR.

This work makes several assumptions, which are as follows: a) In comparison to the time elapsed between consecutive maintenance activities, the time in which the machine is "down" due to maintenance activities is so short that it can be considered negligible; and b) Maintenance activities are performed only when the integrated health falls below a predetermined threshold (health threshold), and the corrective (preventive) maintenance is replaced by this integrated health condition-based maintenance strategy.

In this PHR model, each maintenance activity proportionally restores the deteriorating integrated health of a machine by a factor of ε, and ε ranges on the interval [0, 1]. If $\varepsilon = 0$, the PHR model simply reduces to the BAO condition, while if $\varepsilon = 1$, it denotes GAN. Therefore, this model is a natural generalisation of both the GAN and BAO models that accounts for imperfect maintenance.

Suppose that t_i is the time at which the machine undergoes the maintenance number i, and T_i is the time interval between the $(i-1)^{\text{th}}$ and the i^{th} maintenance. hr_i^+ and hi_i^+ represent the integrated health and inherent health of a machine immediately after the i^{th} maintenance event, respectively. $hr_i(t)$ is the integrated health of a machine with time t after the $(i-1)^{\text{th}}$ maintenance event; $hi_i(t)$ is the inherent health with time t after the $(i-1)^{\text{th}}$ maintenance event. Particularly, $hi_i(t)$ is not only calculated by condition-monitoring data acquired by sensors, but can also be predicted based on the data in the previous maintenance intervals. $\psi(z_i)$ is the link function, and $\boldsymbol{z}_i$ is a vector of covariates that represents the age and the working conditions of the machine during the i^{th} maintenance interval, ε_i represents the effectiveness of the i^{th} maintenance activity.

Thus, in the first maintenance interval, the integrated health of a machine evolves as:

$$0 \le t \le t_1,\ hr_1(t) = 1 - \psi(z_1)\left[1 - hi_1(t)\right], \tag{4}$$

$$hr_1^- = hr_1(t_1),\ hr_1^+ = 1 - (1-\varepsilon_1)\cdot(1 - hr_1^-). \tag{5}$$

In the second maintenance interval:

$$t_1 \le t \le t_2,\ hr_2(t) = hr_1^+ - \psi(z_2)\left[hi_1^+ - hi_2(t)\right], \tag{6}$$

$$hr_2^- = hr_2(t_2),\ hr_2^+ = 1 - (1-\varepsilon_2)\cdot(1 - hr_2^-). \tag{7}$$

Then, in the general case, in the m-th maintenance interval:

$$t_{m-1} \le t \le t_m,\ hr_m(t) = hr_{m-1}^+ - \psi(z_m)\left[hi_{m-1}^+ - hi_m(t)\right], \tag{8}$$

$$hr_m^- = hr_m(t_m),\ hr_m^+ = 1 - (1-\varepsilon_m)\cdot(1 - hr_m^-). \tag{9}$$

Here, we set hT as the integrated health threshold. Whenever the integrated health falls below the hT, a maintenance activity is triggered and performed. That is,

$$hr_1^- = hr_2^- = \ldots = hr_m^- = hT, \tag{10}$$

$$hr_1(t_1) = hr_2(t_2) = \ldots = hr_m(t_m) = hT. \tag{11}$$

Thus, $t_1, t_2, ..., t_m$ can be derived from Eqs. (4) ÷ (11), and decisions on the maintenance interval $T_1, T_2, ..., T_m$ can be made such that the maintenance interval can be predicted accordingly.

3.3 The evolution of integrated health

As shown in Eqs. (8) and (9), the integrated health at a given time can be expressed as a function of its integrated health as restored from the last maintenance activity (maintenance effect) minus the evolution of its integrated health degradation in the period elapsed since the last maintenance (the effects of the age and the working condition).

Let $hr_m(t, \varepsilon, Z)$ be the evolution of the integrated health with time t for the period between two consecutive maintenance activities, $m-1$ and m. The parameter ε is a set $\{\varepsilon_1, \varepsilon_2, ..., \varepsilon_{m-1}\}$ that represents the effectiveness of each maintenance activity performed until the instant t, and Z is a set $\{z_1, z_2, ..., z_m\}$, the element $\boldsymbol{z}_i$ is a vector of covariates that represents the age and the working conditions of the machine during the i^{th} maintenance interval. Thus, after the $(m-1)^{\text{th}}$ maintenance event, the evolution of the integrated health of the machine can be generalised as (see Fig. 1):

$$hr_m(t, \varepsilon, Z) = hr_{m-1}^+ - \psi(z_m)\left[hi_{m-1}^+ - hi_m(t)\right], \tag{12}$$

$$hr_m^- = hr_m(t_m),\ hr_m^+ = 1 - (1-\varepsilon_m)\cdot(1 - hr_m^-). \tag{13}$$

In conclusion, the non-technical factors (including the age and the working conditions) are considered by the PDM, and thus integrated health assessment can be achieved. By integrating the sequential imperfect maintenance policy into the maintenance strategy based on the integrated health condition, the effect of the maintenance is also introduced into the integrated health evolution model by the PHR model. This process is shown in Fig. 2.

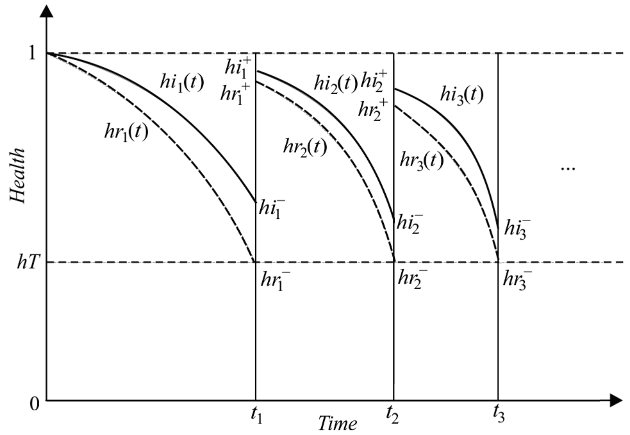

Figure 1 Evolution of integrated health and inherent health

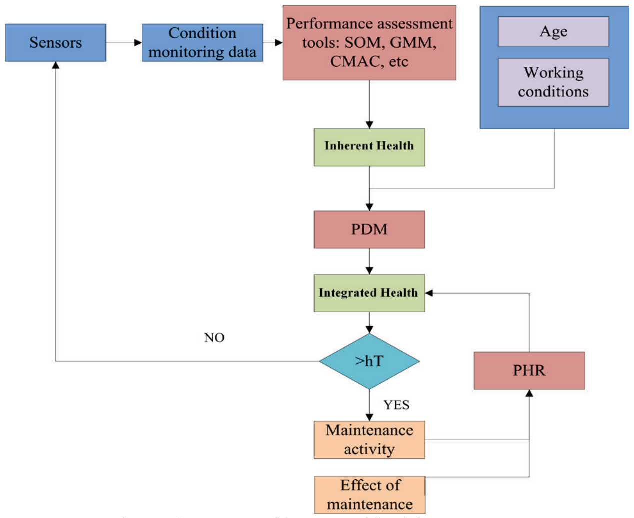

Figure 2 Process of integrated health assessment

4 Case studies

To intuitively demonstrate the process of integrated health assessment and to prove the rationality of the proposed model, we present simulation examples. First, the inherent health of a machine was evaluated using the available degradation condition-monitoring data acquired by sensors in a standard working condition. To take into account the effects of the age, the working condition, and particularly the maintenance, the evolution of the inherent health after each maintenance activity was simulated by imitating the existing inherent health. Thus, a comparison between the inherent health and the integrated health can be realised.

To simply the relationship between the integrated health and the inherent health, it is assumed that:

(1) The maintenance strategy based on integrated health condition is performed, i.e., a maintenance activity is performed only when the integrated health reaches the threshold hT .

(2) The effectiveness of each maintenance activity is equal to a constant value ($\varepsilon_k = \varepsilon$) that ranges from 0 to 1.

(3) The time in which the machine is "down" due to the maintenance activity is negligible when compared to the operational time of the machine.

(4) Deteriorations of the working conditions are applied.

Table 1 Parameters for the PDM and PHR model

Parameter	Value
ε	0,6
hT	0,7
$\psi(z_i)$	$1+\dfrac{i}{13}$

In addition, Tab. 1 shows the values for the parameters ε, hT, and $\psi(z_i)$, which are temporarily assumed for the simulation of the health assessment model. Regarding the evolutions of the inherent health and the integrated health of the machine under different ε, hT, and $\psi(z_i)$, it is summarized as follows:

When the maintenance effectiveness ε increases (e.g. 0,5; 0,55 or 0,6), the recovery degree of the integrated health increases. Thus, the machine reaches the threshold at a delayed speed, and its maintenance intervals increase accordingly.

Whenever the integrated health arrives at the predetermined threshold (e.g. 0,7), a maintenance activity is performed. If the threshold is set higher, the integrated health reaches that threshold earlier, so that each maintenance interval gets shorter. A high threshold indicates a more conservative maintenance strategy resulting in frequent maintenance activities and high maintenance costs.

As aforementioned, different ages and working conditions can be transformed into different link function values $\psi(z_i)$. In this study, for the purpose of simplification, we assume that the $\psi(z_i)$ remains constant (e.g. 1,1; 1,2 or 1,3) throughout the entire process. However, $\psi(z_i)$ actually varies along with time t during machine operation. When the link function value increases, this means that as the age increases and the working conditions (both environmental and operational) deteriorate, the integrated health condition deteriorates more severely. As a result, the integrated health will reach the threshold more quickly, and each maintenance interval, which normally grows shorter, can be derived from the evolution of the integrated health curve.

However, because of the lack of the data needed to estimate the parameters for link function, in this work, for the purpose of simplification and health evolution simulations, we temporarily suppose $\psi(z_i)=1+\dfrac{i}{13}$, which approximately simulates the increasing age and the deteriorating working conditions of the machine along with the maintenance interval i. In practice, $\psi(z_i)$ depends on the accurate parameter estimation of the coefficients β_{AG}, β_{EC} and β_{OC} (e.g. the maximum likelihood method), as well as the reasonable quantification of the age (AG) and the working conditions (OC and EC).

4.1 Inherent health assessment and simulations

First, wavelet packet decomposition is employed for extracting the energy feature vectors from the available degradation condition-monitoring data of a machine, the condition-monitoring data is vibration signal acquired from a rotating machine by a vibration acceleration sensor, with a motor speed of 2000 rev/min and a sampling frequency of 20 000 Hz. Then, Self-organising map (SOM) neural network is used for transforming the energy feature vector samples into Minimum Quantisation Error (MQE), which will be normalised into inherent health (ranging from 0 to 1, which indicates unacceptable and normal machine performance, respectively). Due to the page limitation, the detailed process about the energy feature extraction and SOM-based MQE calculation can refer to the relevant literature [8 ÷ 11].

The results are shown as the blue points in Fig. 3. The results are discrete points, and thus they do not facilitate the subsequent calculation and analysis of integrated health. Therefore, in this case, an 8-variate Gaussian function is applied to fit the discrete results:

$$f(x)=\sum_{i=1}^{8} a_i \mathrm{e}^{\frac{-(x-b_i)^2}{c_i^2}}. \tag{14}$$

From Fig. 3, we observe that the fitting results in the red curve are consistent with the trend of the original inherent health. This fitting of inherent health results can be denoted as $hi(t)$.

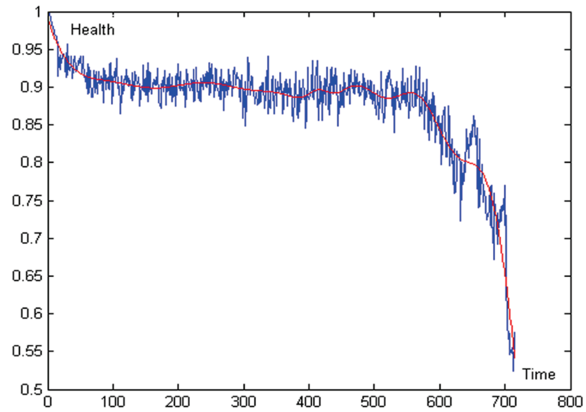

Figure 3 Evolution of the existing inherent health and fitting results from a machine (T in h)

To demonstrate the effects of the age, the working conditions, and especially the maintenance on the integrated health assessment and evolution, the evolution of the inherent health after each maintenance activity was simulated sequentially by imitating the existing inherent health curve $hi(t)$.

Normally, each point of the inherent health can be assessed on-line by the condition-monitoring data acquired from the machine, which may be more accurate than the simulation curve. However, limited to the current experimental conditions and engineering application conditions, it would be difficult to obtain the actual inherent health curves for the corresponding integrated health calculation before the subsequent k-step maintenance activities take place. In this case, the authors use the initial inherent health curve from before the first maintenance activity to simulate the subsequent evolution of the inherent health after a series of pre-designed maintenance activities.

The simulation process is depicted as follows:

Step 1: After the first maintenance activity, locate the starting point p_1 of the updated inherent health hi_1^+ in the existing inherent health curve $hi(t)$.

$$0 \le t \le t_1,\ hi_1(t)=hi(t),\ hi_1^- = hi_1(t_1),$$
$$hi_1^+ = 1-(1-\varepsilon_1)(1-hi_1^-)-\gamma_1,\ hi_1^+ = hi(p_1) \rightarrow p_1.$$

Step 2: According to p_1 and $hi(t)$, simulate the inherent health curve $hi_2(t)$ in the second maintenance interval. After the second maintenance activity, locate the starting point p_2.

$$t_1 \le t \le t_2,\ hi_2(t)=hi(t-t_1+p_1),\ hi_2^- = hi_2(t_2),$$
$$hi_2^+ = 1-(1-\varepsilon_2)(1-hi_2^-)-\gamma_2,\ hi_2^+ = hi(p_2) \rightarrow p_2.$$

Step 3: Simulate the inherent health curve $hi_3(t)$, and locate the starting point p_3.

$$t_2 \le t \le t_3,\ hi_3(t)=hi(t-t_2+p_2),\ hi_3^- = hi_3(t_3),$$
$$hi_3^+ = 1-(1-\varepsilon_3)(1-hi_3^-)-\gamma_3,\ hi_3^+ = hi(p_3) \rightarrow p_3.$$

Step m: Simulate the inherent health curve $hi_m(t)$ in the m^{th} maintenance interval, and locate the starting point p_m.

$$t_{m-1} \le t \le t_m,\ hi_m(t)=hi(t-t_{m-1}+p_{m-1}),\ hi_m^- = hi_m(t_m),$$
$$hi_m^+ = 1-(1-\varepsilon_m)(1-hi_m^-)-\gamma_m,\ hi_m^+ = hi(p_m) \rightarrow p_m.$$

where $\gamma_1, \gamma_2, ..., \gamma_m$ are correction factors influenced by the incompleteness of the fault diagnosis and the maintenance work, the run-in status, and other uncertainties of the machine, these uncertainties follow a Gaussian distribution with zero mean. Through the above iteration steps, after each maintenance activity, the evolution of the inherent health can be simulated. By adjusting the maintenance effectiveness ε, the corresponding changes in the evolution can be achieved.

4.2 Results of the inherent health and the integrated health simulations

Fig. 4 shows the simulation result of the evolution of the inherent health and the corresponding calculation result of the integrated health; the related parameter settings are shown in Tab. 1. The simulation results are consistent with the theoretical analysis results, as shown in Fig. 1. Therefore, it may be inferred that our simulation and theoretical analysis conform to the reality. Tab. 2 lists the maintenance intervals derived from the evolution of the integrated health, and it is found that the maintenance intervals show a decreasing trend, which can be interpreted as: with the consecutively growing age and deteriorating working conditions, the integrated health degradation accelerates and reaches the health threshold more quickly, at which point the appropriate maintenance actions should be taken. This result is entirely consistent with the previous Assumption (4).

Table 2 Trend of maintenance intervals under the parameter settings in Tab. 1

T1	686
T2	307
T3	111
T4	105
T5	103
T6	99
T7	95
T8	93
T9	90
T10	87
T11	84
T12	81
T13	78

5 Conclusions and future work

Currently, the traditional reactive or blindly preventive maintenance strategies are gradually being replaced by condition-based maintenance (CBM). In this strategy, the health condition assessment is considered to be a key prerequisite for CBM strategy.

This paper notes that the health condition is influenced by both technical and non-technical factors. Because the inherent health only concentrates on technical factors, it is not comprehensive for representing the overall health condition of a machine. Therefore, this paper introduces a new concept of integrated health considering effects of the age, the working conditions, and the maintenance. Through the PDM, the inherent health and such non-technical factors as age and working conditions (both environmental and operational) are fully integrated, and thus the integrated health assessment can be achieved. Moreover, a sequential imperfect maintenance policy is integrated into the maintenance strategy based on the integrated health condition. Thus, the effect of the maintenance is taken into account in the integrated health evolution model using the PHR model.

With the proposed comprehensive integrated health assessment and evolution method, both the CBM and PAP (Predict and Prevent) are able to play their roles. As suggested early in this paper, an important application of the model may be to support health management and maintenance decision-making.

Further research must be carried out on this integrated health model: first, only the case in which the maintenance effectiveness is kept constant has been analysed in this paper. Therefore, it seems of interest to further analyse the case where maintenance effectiveness is able to vary during the different maintenance intervals. Second, we plan to sequentially acquire on-line degradation measurements that are representative of the entire life cycle during which a series of maintenance activities are performed and thus further validate the proposed models via a real case. Third, the question of how to reasonably quantise the factors of working conditions and maintenance effectiveness for accurate expression of $\psi(z_i)$ and ε still remains. Most importantly, there may be further possible improvements or optimisations for the maintenance tasks through the integration of information regarding the integrated health condition prediction, mission planning, risk and cost.

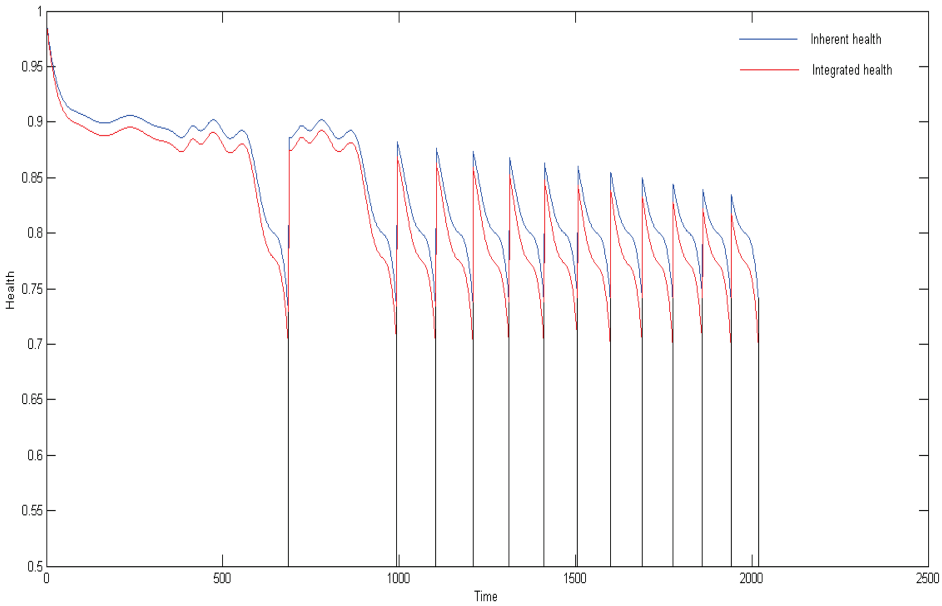

Figure 4 Simulation results of the inherent health and integrated health (T in h)

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