

Remaining Useful Life Prediction of a steam generator based on Control Chart X-Rm, Area-Threshold and Markov models

Predicción de la Vida Útil Restante de un generador de vapor basado en la Carta de Control X-Rm, el Área-Límite y los modelos Markov

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ABSTRACT

The condition-based maintenance (CBM) uses fault diagnosis and prognosis methods to characterize system future behavior and to advise some efficient maintenance strategies. The purpose of this work was modelling the Remaining Useful Life (RUL) of a steam generator used in a Thermoelectric Power Plant. The method consists of identifying early failure symptoms through the control chart X-RM; and the automatic recognition of non-random variation patterns, to generate the area-threshold (A_{Th}) as a health indicator (HI). The transition between degradation states was simulated using Continuous-Time Markov Chain (CTMC) models. The sampling was taken from on a real-time data acquisition system. As a result, the RUL was simulated with adequate predictive performance, the maximum deviation from active time was 22 h. Predicted *versus* actual plot for the superheated steam temperature achieved slope 0,81, intercept 41, 20, R^2 99,64 % and Mean Squared Error (MSE) 39,56; on the other hand, for the condenser pressure resulted $m = 0,878$, $n = 45,149$, R^2 99,83 % and MSE = 30,98. Once the RUL is simulated, effective actions must be taken to avoid emergency shutdowns.

Keywords: control chart, markov chain models, remaining useful life.

RESUMEN

El mantenimiento basado en la condición (CBM) utiliza métodos de diagnóstico y pronóstico de fallas para caracterizar el comportamiento futuro de un sistema y recomendar algunas estrategias eficientes de mantenimiento. El propósito de este trabajo fue modelar la vida útil restante (RUL) de un generador de vapor de una planta termoeléctrica. El método consiste en identificar síntomas tempranos de falla a través de la carta de control X-RM; y el reconocimiento automático de patrones de variación no aleatorios, para generar el área-umbral (A_{Th}) como un indicador de salud. La transición entre los estados de degradación se simuló mediante modelos Cadenas Markov de Tiempo-Continuo (CTMC). El muestreo se realizó mediante un sistema de adquisición de datos en tiempo real. Como resultado, se simuló el RUL con adecuado desempeño predictivo, la desviación máxima del tiempo activo fue de 22 h. El gráfico valores observados *versus* predichos para la temperatura del vapor sobrecalentado presentó pendiente (m) 0,81, intercepto (n) 41,20, R^2 99,64 % y error cuadrático medio (MSE) 39,56; por su parte, para la presión del condensado resultó $m = 0,878$, $n = 45,149$, R^2 99,83 % y $MSE = 30,98$. Una vez que se simule el RUL se deben adoptar acciones efectivas para evitar paradas de emergencias.

Palabras clave: carta de control, cadena Markov, vida útil restante

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Introduction

Scheduling maintenance cycles on the electrical grid is a complex activity. It is influenced by the quality and durability of the equipment components, maintenance effectiveness, environmental conditions, costs, electrical system availability and potential failures. ^(1,2)

The condition-based maintenance (CBM) uses fault diagnosis and prognosis methods to characterize system future behavior and to advise some efficient maintenance strategies. Fault diagnostics includes detection methods of abnormal behavior in the system, as well as revealing its causes and locations. These methods can be classified into model-based methods, data-driven methods, and hybrid methods. Fault prognosis refers to predicting the fault evolution over time and thus accurately estimating the remaining useful life (RUL) and the end-of-life (EOL)

of the affected component or subsystem. RUL is defined as the length of time a machine can operate before tool replacement or repair. ^(3,4,5,6)

Model-based methods involve the development of mathematical models (physical, statistical, probabilistic) based on state observers and systems knowledge, to simulate the behavior of the equipment and machinery under normal and faulty conditions to provide RUL estimate. Common models are Non-Linear Drift Wiener Degradation Model, hidden Markov model (HMM) and Markov Chains (MCs). ^(4, 7, 8)

On the other hand, data-driven methods utilize only the available data from sensory measurement, which are used to train the learning algorithms to estimate RUL. Among the techniques are discussed: univariate and multivariate statistical process control ^(9,10), Principal Component Analysis (PCA), Bayesian prognostics methods, and Projection to Latent Structures (PLS). ⁽¹¹⁾

Both data-driven and model-based approaches have their advantages and disadvantages. Therefore, the combination of different approaches into a hybrid method provides very good prognosis results.

In the field of CBM, Markovian-based models proven useful in optimizing the periodicity of maintenance schedule without exceeding a specific degradation boundary in the system. These are used to model the apparent-time transition rate from one degradation states of equipment to another state. Hence, the optimal schedule policies can be formulated using a dynamic programming method. ^(12,13)

Maintenance decision-making methods based on Markov models have been performed for equipment ^(6,9), manufacturing ⁽¹⁴⁾, buildings ⁽¹²⁾, and electric power systems ⁽¹⁵⁾ in different degradation stages of the systems. These are combined with statistical process control charts, deep learning (DP) and Machine learning (ML) techniques to improve predictive capability.

The purpose of this work was modelling the Remaining Useful Life (RUL) of a steam generator in a thermoelectric power plant. Fault diagnosis was performed from the boiler pressure (P_v), superheating steam temperatures (T_v), and condenser pressure (P_v^*), using individuals and moving range (X-MR) chart, decision rules and test zones, to generate the area-threshold as a health indicator (HI). The condition-base degradation was modelled using Markov Chain models. The method was validated considering performance evaluation metrics.

Materials and methods

The research was made at a Cuban Thermoelectric Power Plant (TPP), the phases and steps are represented in figure 1. ^(16,17)

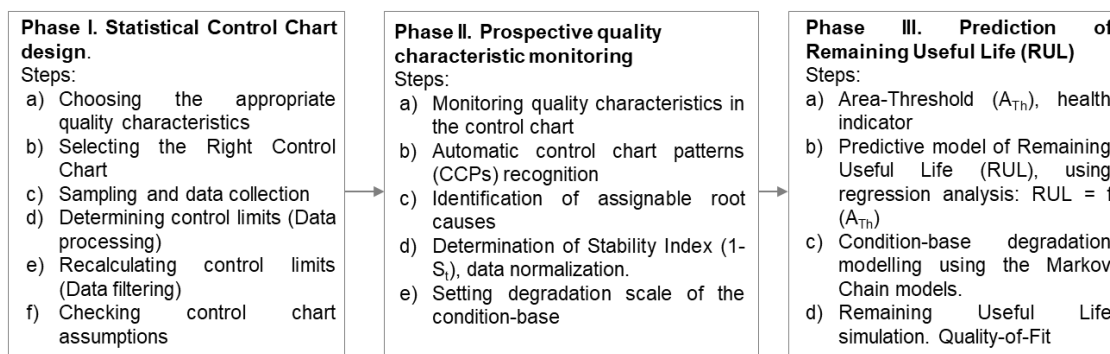


Fig. 1 - Schematic representation of the procedure

Statistical Control Chart design

From phase I, quality characteristics were: boiler pressure (Pv), the superheating steam temperature before the fourth reheat stage (Tv), and the condenser pressure (Pv*), these variables are fundamental to increasing the thermal efficiency of a power cycle. An Individual and moving range (X-MR) chart was selected because these variables are continuous and automated inspection and measurement technology is used ⁽¹⁸⁾. Data were obtained every two hours for 13 months of operations using Supervisory Control and Data Acquisition (SCADA) System. The sample size was determined for a normal distribution, using $Z=1.96$, two-sided test, 95% confidence level. Pv was selected as the guiding variable. ⁽¹⁷⁾

The control limits on the Individual-X chart were derived from the average, mean range and standard deviation. After analyzing the possible assignable causes, measurement points beyond the control limits were removed from the data set. The elimination and recalculation process were repeated while one or more points exceeded the new limits. Assumption of normality was checked by graphical (visual) and numerical (statistical) methods using StatGraphic Centurion v.19.0.

Prospective quality characteristic monitoring

Regarding phase II, a software application was performed for the automatic control chart patterns (CCPs) recognition. Western Electric Co. rules (WECO) (1956), Nelson's test (1984) and AIAG rules (2005) were used ^(19,20,21). This application consisted of a decision tree (DT), trend and dispersion statistics, and shape features ^(16,17). Subsequently, stability index (1-S_t) was determined (1). ⁽¹⁸⁾

$$(1 - S_t) = 1 - \frac{SP_{Rul}}{TP} \quad (1)$$

where SP_{RUL} is the number of special points indicating special - cause variation without double count, and TP is the number of total points, both in the same period. Degradation scale of the condition-base was set from an excellent to unacceptable state according to Stability Index (table 1).

Table 1- Degradation scale of the condition-base according to Stability Index

State	(1-S _i)	State	(1-S _i)	State	(1-S _i)
Excellent (E)	1	Acceptable (A)	0.7 - 0.8	Very Low (VL)	0.4 - 0.5
Very Good (VG)	1 - 0.9	Tolerable (T)	0.6 - 0.7	Poor (P)	0.3 - 0.4
Good (G)	0.8 - 0.9	Low (L)	0.5 - 0.6	Unacceptable (U)	< 0.3

Remaining Useful Life Prediction

From phase III, the area-threshold $A_{Th}(t)$ was determined between the functions $f(t)=1$ and $(1-S_t)$ by the definite integral for each variable P_v , T_v , and P_v^* (2).⁽¹⁷⁾

$$A_{Th}(t) = (1 - a) \cdot (t_2 - t_1) + \frac{b}{2}(t_1^2 - t_2^2) \quad (2)$$

where a is intercept and b is slop of $A_{Th}(t)$.

Three predictive models were performed to determine initial Remaining Useful Life, RUL(0), by Linear Regression (LR) and Multiple Linear Regression (MLR). On the other hand, the transition probability of the condition-based degradation was simulated using Continuous-Time Markov Chains (CTMC) models. The Area-threshold $A_{Th}(n)$ was then assumed, and RUL(0) was determined. The quality of predictions was assessed by comparing the expected and actual behavior of $A_{RUL}(t)$. The algorithm was applied in four cycles of continuous operation (figure 2).

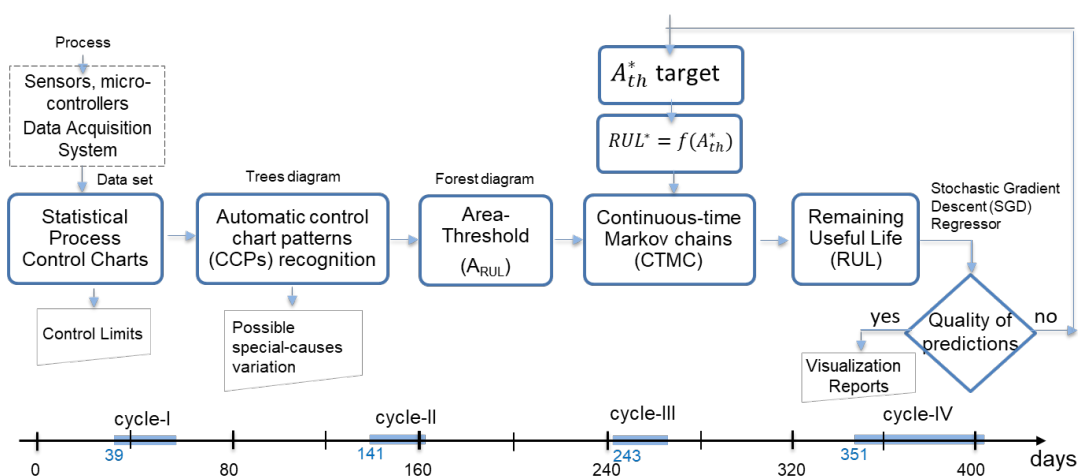


Fig. 2 – Schematic representation of RUL prediction

Markov Chains models

A continuous-time Markov Chain (CTMC) can be defined by a list of states, transition probability Matrix-P, the state vector at time initial $v(0)$, and a set of holding time parameters $\lambda_1 \dots \lambda_k > 0$ that are the exponential waiting time in each state. ⁽²²⁾

The transition Matrix-P shows the probability of change in income class from one generation to the next. This has several features: It is square, all entries are between 0 and 1, and the sum of the entries in any row must be one.

$P(t)$ satisfies the Chapman-Kolmogorov equation (3).

$$P(t) = e^{Qt}, t \in \mathbb{R}_+ \quad (3)$$

where the right-hand side is the Taylor expansion (4).

$$e^{Qt} = \sum_{k=0}^{\infty} \frac{t^k}{k!} Q^k \cong I_d + \frac{t}{1!} Q + \frac{t^2}{2!} Q^2 + \frac{t^3}{3!} Q^3 + \dots \quad (4)$$

where I_d is the corresponding identity matrix, and Matrix-Q defines a relationship between the rates of change of the transition probabilities, this can be used to generate the whole system ($P(t)$, $t \geq 0$) (5).

$$Q = (q_{ij}), i, j \in \mathbb{S} \quad (5)$$

Matrix-Q is the infinitesimal generator or generator of the process, $\mathbb{S}$ is the state set, q_{ij} is the rate at which transitions occur from state i to state j , q_{ij} is (6).

$$q_{ii} = - \sum_{j=0, j \neq i}^{\infty} q_{ji} \quad (6)$$

Generator-Q was obtained from (7)-(8)

$$Q = \lambda_i (P - I_d) \quad (7)$$

$$Q = [\lambda_1 \quad \lambda_2 \quad \dots \quad \lambda_n] \left(\begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \dots & P_{mn} \end{bmatrix} - \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} \right) \quad (8)$$

The following properties are valid for any generator Q (9):

$$\begin{aligned} q_{ii} &\leq 0 \text{ for all } i \in \mathbb{S} \\ q_{ij} &\geq 0 \text{ for all } i, j \in \mathbb{S} \text{ such that } i \neq j \\ \sum q_{ij} &= 0 \text{ for all } i, j \in \mathbb{S} \end{aligned} \quad (9)$$

The state vector at time t, $v_i(t)$ is (10)

$$v_i(t) = v(0) e^{Qt} \quad t \in [0, \infty) \quad (10)$$

If $\pi = [\pi_0, \pi_1, \pi_2, \dots, \pi_n]$ is the limiting distribution of the Markov chain, irreducible and aperiodic, when the chain has reached its steady-state (limiting) distribution satisfy the properties (11)-(12).

$$\pi_j = \sum \pi_i P_{ij} \quad i, j \in \mathbb{S} \quad (11)$$

$$\sum \pi_j = 1 \quad (12)$$

Markov chains parameters

The distribution of income classes was calculated from the stability index and the degradation scale (table 1). For its part, the outcome classes distributions were obtained by computing the transition from one income class to other, via software algorithm, e.g., $E \rightarrow E$, $E \rightarrow VG$, $E \rightarrow G$... The procedure was performed for four stable operating cycles, so the average values are represented in figure 3.

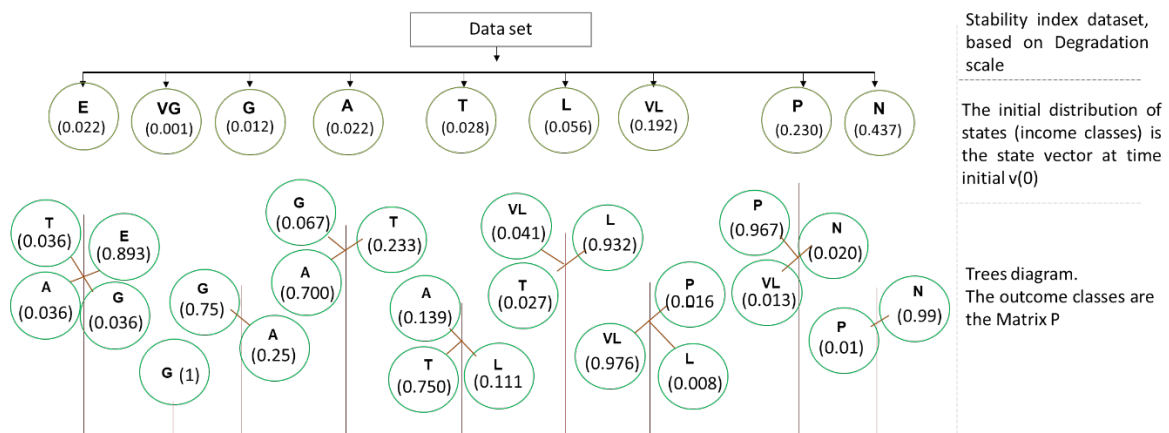


Fig. 3 - Generating the Matrix-P base on superheating steam temperatures

The transition diagram represents the system's degradation states and the probabilities of going from one state to another (figure 4).

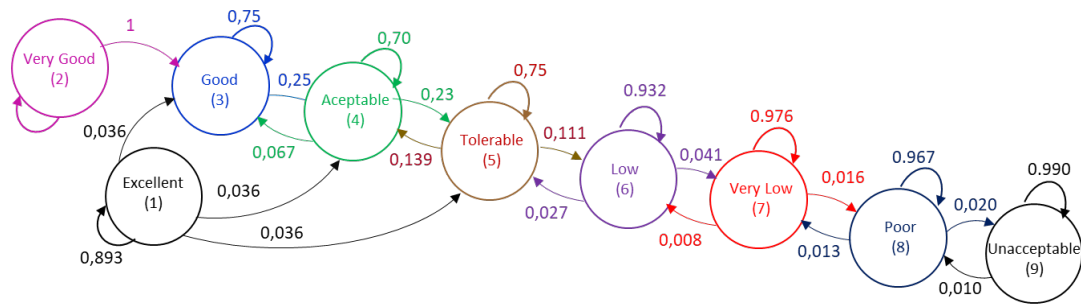
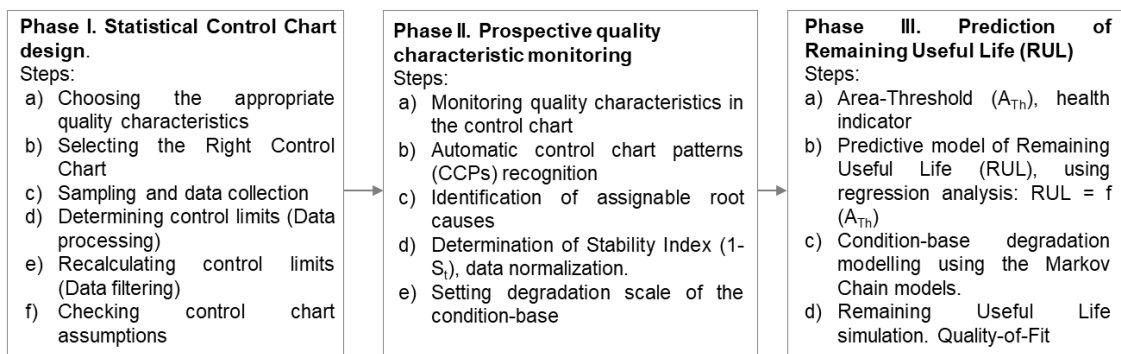


Fig. 4- Transition diagram based on Operational States and Tv

As shown in figure 4, there are several transition states, these are caused by potential special causes variation: little standardization and failures in the industrial network; mismatches and gradual deterioration of equipment, instruments, and accessories; worker fatigue and deposition of waste. ^(16,17)

The initial distribution of states (income class) can be written as the state vector at time initial $v(0)$ (figure 3), and the Matrix-P as illustrated in figure 4 (13)-(14).



Form figure 3, each tree in each time fraction gives its own prediction, so the final answer is the one obtained by combining the predictions (15).

$$(1 - S_t)_{(t)} = v_1(t) + 0.9 v_2(t) + 0.8 v_3(t) + 0.7 v_4(t) + 0.6 v_2(t) + 0.5 v_4(t) + 0.4 v_6(t) + 0.3 v_7(t) + 0.2 v_8(t) \quad (15)$$

The larger the scale of degradation, the greater the accuracy of the prediction.

Performance evaluation metrics

The validation was made by R-squared (R^2), mean absolute error (MAE), Root Mean Squared Error (RMSE), Average Relative Error (ARE), (16)-(8).

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^n Abs[y_i - y_i^*] \quad (16)$$

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^n [y_i - y_i^*]^2} \quad (17)$$

$$ARE = \frac{1}{n} \cdot \sum_{i=1}^n Abs\left[\frac{y_i - y_i^*}{y_i}\right] \quad (18)$$

where, y and y^* are observed and predicted respectively, n is the number of observations.

Results and discussion

Data were obtained from the SCADA system for 13 months, although three months were not included in the analysis because those months affected the assumptions of normality. The control chart X-RM was designed for the variables: boiler pressure (Pv), superheating steam temperature (Tv), and condenser pressure (Pv*). The control limits were: Pv = [13,22; 13,44] MPa, Tv = [519,21; 523,76] °C, and Pv* = [3,63; 5,47] MPa. These variables reached the following values assumed as a shutdown system: Pv = [0,10, 12,44] MPa, Tv = [191,1, 515,8] °C, Pv* = [1,52, 3,63) $\cup$ (5,47, 6,31] MPa.

Automatic control chart pattern recognition (CCPs) was performed using Nelson's Run rules. Then, the stability index ($1-St$) was calculated for the four cycles (figure 2). The area-threshold $A_{th}(n)$ belonging to Pv was [39, 223] u^2 , Tv [274, 796] u^2 , and Pv* [321, 965] u^2 . The initial remaining useful life $RUL(0)$ was modeled depending on the target area-threshold (19)-(20) (table 2).

$$RUL^*(0) = \sqrt{a + b \cdot A_{Th}^2} \quad (19)$$

$$RUL^*(0) = 99.3717 + \sum_{i=1}^3 [c \cdot A_{Th}]_i \quad (20)$$

Table 2- Model constants for the initial remaining useful life, RUL(0)

Variable	Constant (21)-(22)				Statistics ⁽¹⁾		
	a	b	c	r	R ²	R ² (d.g.)	DW
Tv	34 350.10	2.218 95	-0.572 853	0.9977	99.54	99.47	1.89
Pv*	11 056.10	1.504 12	0.298 033	0.9976	99.53	99.44	1.15
Pv	-	-	-0.681 695	-	99.37	98.74	2.06

⁽¹⁾ r: correlation coefficient. R²: R-Squared. R²: R-Squared adjusted by freedom degree. DW: Durbin-Watson

RUL based on superheating steam temperature (cycle IV)

The remaining useful life (RUL) was modelled based on superheating steam temperature for the following conditions: Matrix-P (21), state vector at time initial (22), parameters of the exponential waiting time in each state (23), small time (t) (step: 0.000 833 333 354), k = 60 (4) and target value in the interval A_{Th} = [431, 796] u². The distribution of income classes for the fourth cycle correspond to the average of the three previous cycles.

The chain (21) is irreducible and aperiodic since it is possibly going from any state to any other in a finite number of steps; and there is a self-transition, i.e., p₁₁>0. The state vector v(t) was evaluated by eq. (1). As a results, as the observations increase, the probability of the system being in states L to U increases, whereas the probability in states E to T decreases (23).

$$P = \begin{bmatrix} 0.818 & 0 & 0.091 & 0 & 0.091 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.727 & 0.273 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.077 & 0.692 & 0.231 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.156 & 0.750 & 0.094 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.030 & 0.940 & 0.030 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.027 & 0.933 & 0.040 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.017 & 0.956 & 0.028 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.015 & 0.985 \end{bmatrix} \quad (21)$$

$$v(0) = [0.016 \quad 0 \quad 0.015 \quad 0.036 \quad 0.045 \quad 0.093 \quad 0.104 \quad 0.247 \quad 0.444] \quad (22)$$

$$\lambda_i = [19.67 \quad 0 \quad 18.03 \quad 42.63 \quad 54.10 \quad 111.49 \quad 120.60 \quad 296.75 \quad 532.84] \quad (23)$$

In the stationary state $\pi(j)$, the higher the probability of the system being in states L and U; therefore, the stability index (1-S_t) tends to be lower, and the area-threshold (A_{Th}) to increase (23)-(24).

$$\begin{matrix} & E & VG & G & A & T & L & VL & P & U \\ v(1200) = & [0.0005 & 0 & 0.0447 & 0.0744 & 0.0910 & 0.1638 & 0.1936 & 0.2133 & 0.2188] \end{matrix} \quad (24)$$

$$\pi(j) = [0 \quad 0 \quad 0.0125 \quad 0.0444 \quad 0.0656 \quad 0.2062 \quad 0.1851 \quad 0.1909 \quad 0.2952] \quad (25)$$

The area-threshold $A_{Th}(t)$ was determined using the state vector $v(t)$ and eq. (15). The process was made from the target area-threshold $A^*_{Th}(n)$ and small time (t) until reaching $RUL^*(0)$. Stochastic Gradient Descent (SGD) Regressor was used to fit simple linear regression (figure 5). The quality of predictions was evaluated by comparing the expected and actual behavior of the area-threshold.

Based on superheated steam temperature (T_v), fourth cycle, and target value $A_{th}(n) = 796 \text{ u}^2$, the prediction resulted with absolute error (Ea) 54 u^2 . Furthermore, predicted *versus* actual plot achieved an intercept 41,206 (next to zero best), slope 0,812 (next to one best), and goodness-of-fit given by R^2 99.65 %, MAE 39.56 and RMSE 43.61. An ARE 0.080 was obtained for $\phi_{RUL} \geq 0,23$; however, the prediction was not satisfactory in the interval $\phi_{RUL} < 0,23$ (table 3).

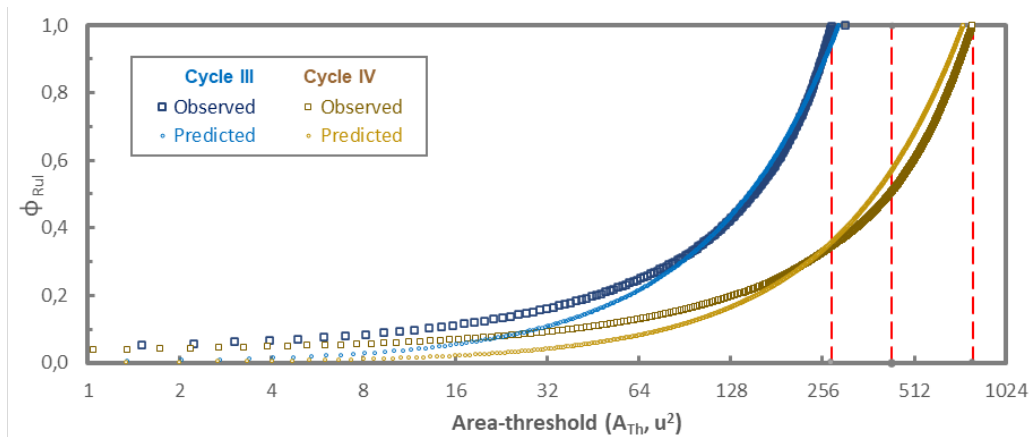


Fig. 5 – Fraction of remaining useful life (ϕ) *versus* area-threshold based on T_v

Table 3 - Quality of predictions

Variable	Cycle	A _{Th} (u ²)		Linear model (actual vs. expected)					$\phi_{RUL} \geq 0.23$ ARE	RUL Ea (h)
		Set	Ea ⁽¹⁾	a ⁽²⁾	b ⁽³⁾	R ²	MAE	RMSE		
T _v	III	271	33	10.614	0.956	99.30	9.94	8.89	0.033	8
	IV	796	54	41.206	0.812	99.65	39.56	43.61	0.080	4
P _v *	III	340	2	32.227	0.989	99.35	30.01	30.68	0.256	22
	IV	957	90	45.149	0.878	99.83	30.98	37.58	0.058	0.3

Condition-base: average previous cycles; ⁽¹⁾ Ea: absolute error; ⁽²⁾ a: intercept; ⁽³⁾ b: slope

The RUL prediction based on condenser pressure (P_v^*) also yielded satisfactory results; however, boiler pressure (P_v) was not effective, possibly because this is not a controlled variable in the automated system.

High-quality in the algorithm ejection is essential for the accuracy of RUL prediction. The proper technical condition and installation of the sensors, the stability in the

communications network, and the researchers' expertise in data analysis and process knowledge are some of the factors influencing. Furthermore, once the RUL is determined, effective actions are required before emergency shutdowns occur. This work is expected to contribute to implement condition-based maintenance strategy. Future research is planned to evaluate the algorithm's predictive performance in new operating cycles, and to compare predictions with different methods.

Conclusions

The remaining useful life (RUL) of a steam generator used in a thermoelectric power plant was modelled. The proposed approach is based on a real-time data acquisition system, data filtration, automatic control chart patterns recognition, data normalization by stability index, area-threshold calculation as health indicator, transition probability modelling between degradation states using Continuous-Time Markov Chain (CTMC) models, and performance evaluation.

The superheated steam temperature (T_v) was found to be a suitable RUL predictor; predicted *versus* actual plot achieved slope 0.81, intercept 41.20, R^2 99.64 %, and mean squared error 39.56. Future research will be made to evaluate the algorithm's predictive performance in new operating cycles and compare predictions with different methods.

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Declaration of competing interest

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Authorship contribution

Armando Rojas Vargas: conceptualization, methodology, investigation, software, writing - reviewing and editing.

Carmen Mulet Abreu: conceptualization, investigation, reviewing.

Oscar Bruzón Peña: conceptualization, investigation, reviewing.