TECNOLOGÍA QUÍMICA
UNIVERSIDAD DE ORIENTE
Vol.46 (2026)
ISSN: 2224-6185

Control Chart X-Rm and Area-Threshold for the Remaining Useful Life at Thermoelectric Power Plant

Carta de Control X-Rm y Área-Límite para la Vida Útil Restante en una Planta Termoeléctrica

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ABSTRACT

The statistical process control charts are an important diagnostic technique indicative of operational deviations to enhance the quality of automated systems and products. The purpose of this work was to design the control chart (X-Rm) for monitoring the superheating steam temperatures in a thermoelectric power plant. The automatic control chart patterns recognition was performed using decision rules and test zones, from which the stability index and the area-threshold for the remaining useful life were calculated. The chart consisted of 2163 normal data, center line 521,73 °C, lower control limit 519,31 °C, and upper control limit 523,76 °C. Shift-trend presented the highest relative frequency due to the possible general causes: poor standardization, changes in work procedures, and failures in the industrial network. The area-threshold was 581-1193 u^2 for WECO rules. This work is expected to contribute to implement condition-based maintenance strategy.

Keywords: control chart; predictive maintenance; remaining useful life.

RESUMEN

Las cartas de control estadístico de procesos son una importante técnica diagnóstica indicativa de desviaciones operacionales para mejorar la calidad de los sistemas automatizados y productos. El propósito de este trabajo fue diseñar la carta de control X-Rm para el monitoreo de la temperatura del vapor sobrecalentado en una planta termoeléctrica. El reconocimiento automatizado de los patrones se realizó mediante reglas de decisiones y zonas, a partir del cual se calculó el índice de estabilidad y el área-límite para la vida útil restante. La carta consistió en 2163 datos normales, línea central 521,73 ºC, límite de control inferior 519,31 ºC, y límite superior 523,76 ºC. El patrón cambio de nivel presentó la mayor frecuencia relativa debido a las posibles causas generales: poca estandarización, cambio en los procedimientos de trabajo, y fallas en la red industrial. El área-límite fue 581-1193 u^2 para las reglas WECO. Se espera que este trabajo contribuya a la implementación de la estrategia de mantenimiento basada en condiciones.

Palabras clave: carta de control; mantenimiento predictivo; vida útil restante.

Recibido: 20/08/2025

Aceptado: 04/12/2025

Introduction

The statistical process control (SPC) charts are an on-line process-monitoring technique widely used for quality management of automated systems and products. Its major objective is to quickly detect the occurrence of assignable causes of variation such as machine failure, change in standards, and inadequate training. A process that is operating in the presence of assignable causes is said to be an out-of-control process, so that investigation and corrective actions are required to find and minimize the root cause for this behavior. Consequently, the variability will be reduced, and the stability process will be improved.[1, 2, 3, 4]

Methods for looking for the most common sequences, or nonrandom patterns, are applied to control charts to detect out-of-control conditions and identify the root causes that may produce such patterns. The control chart patterns (CCPs) can be classified in single abnormal patterns or concurrent patterns, which can be combined with two or more single patterns.[5, 6, 7] CCPs recognition use methods such as decision rules and test zones. Shewhart rule (1924), Wester Electric Co. rules (WECO) (1956), Nelson´s test (1984) and AIAG rules (2005) are widely used.[8, 9, 10, 11, 12]

In the recent years, the abnormal patterns are identified via soft computing methods. These mainly consists of two parts: Learning module and Recognition module. During the learning module, statistical features and shape features are extracted through raw data.[5, 6, 7, 13, 14, 15] On the other hand, technologies from Industry 4.0 are incorporated for the recognition module. Machine learning (ML) algorithms that include artificial neural networks (ANNs), support vector machines (SVM) and decision trees (DT) are used. In addition, fuzzy inference system (FIS), and hybrid methods are evaluated. At the same time, genetic algorithm (GA), particle swarm optimization (PSO), fireworks algorithm (FWA) and grid search are chosen to optimize parameters and improve recognition efficiency.[6, 7, 13, 14, 15, 16]

From above, the accurate recognition of abnormal patterns makes the control chart an important diagnostic technique indicative of operational deviations, to enhance the quality of automated systems, processes, and products.

Advancements diagnostic technologies led to the Predictive Maintenance (PdM) strategy. PdM is a technology used to predict the failure of a machine component so that schedule maintenance can be performed just in time to prevent failure and production downtime. Condition-based maintenance (CBM) is an efficient method for PdM. This technique utilizes sensors directly integrated into the specific machinery that collect a wide variety of real-time measurements, including vibration analysis, acoustic emission, electrical signature analysis, thermography, tribology, flow rates, temperature, and pressure. A component's degradation state is evaluated based on deviations from normal running conditions.[17, 18, 19, 20, 21]

Remaining useful life (RUL) is a prognostic technique. This is defined as the length of time a machine can operate before tool replacement or repair. To estimate RUL, data-driven method is used, this involve diagnosing the health of a machine and predicting potential issues.[19, 20, 21, 22, 23, 24]

Thus, by combining the statistical process control and Industry 4.0 technologies - sensors, data acquisition systems, big-data collection, and data-driven algorithm - to monitor equipment performance in real time, remaining useful life can be satisfactory evaluated.[20, 21, 22, 23, 24]

The purpose of this work was to design Individuals and moving range (X-MR) chart for monitoring the superheating steam temperatures in a thermoelectric power plant. Variation patterns on the control chart and the possible assignable causes were identified using decision rules and test zones. Finally, the area-threshold for the remaining useful life was evaluated.

Materials and methods

The research was carried out using the following steps.[25]

Phase I. Statistical Control Chart design.

a) Choose the appropriate metrics

Quality characteristics were chosen based on Rankine cycle analysis, these are the boiler pressure (Pv), the superheating steam temperatures before the fourth reheat stage (Tv-SH#4), and the condenser pressure (Pv*).[25]

b) Select the control chart

Individuals and moving range (X-MR) chart was selected because the quality characteristics are continuous; and an automated inspection and measurement technology is used.[2, 4]

c) Sampling and data collection

Data were obtained every two hours for eight months of operations using Supervisory Control and Data Acquisition (SCADA) System, at a Cuban thermoelectric power plant. The sample size was 2163 individual points, using Z=1.96, two-sided test, 95% confidence level, assuming a standard deviation $\sigma(x)$ = 0,759 3, and error e = 0, 032.[25]

d) Determination of control limits or Data processing.

Control limits of an individuals and moving range (X-MR) chart were determined from the average, mean range and standard deviation. The boiler pressure (Pv) was selected as the guiding variable.[1, 2, 3, 4, 25]

e) Recalculation of control limits or Data filtering

Measurement points beyond the control limits were removed from the data set after analyzing the possible assignable causes. The elimination and recalculation process were repeated while one or more points exceeded the new limits.

f) Checking control chart assumptions

Assumption of normality was checked using StatGraphic Centurion v.19.0, by graphical and numerical methods. The standardized Skewness statistic and the log likelihood statistic were also evaluated for the comparison of alternative distributions.

Phase II. Prospective quality characteristic monitoring

g) Quality characteristic monitoring and recognizing control chart patterns

The points beyond the control limits, abnormal patterns within the limits, and special causes of variation were analyzed (table 1).

Table 1- Non-random patterns and their description

Rules			WECO	Nelson run	AIAG
No.	**Pattern**	**Description**			
R-1	Beyond Limits	One or more points beyond the control limits	x	x	x
R-2	Shift-trend	9 or more consecutive points on one side (above or below) of the Central Line	X (8)	X (9)	x (7)
R-3	Trend	6 or more consecutive points trending up or trending down		x	x
R-4	Over-control	14 consecutive points alternating up and down (cyclic pattern)		x	
R-5	Large shift	2 out of 3 consecutive points in Zone A (or F) or beyond	x	x	
R-6	Small shift	4 out of 5 consecutive points in Zone B (or E) or beyond	x	x	
R-7	Stratification	15 consecutive points in Zone C (and D), either above or below LC		x	
R-8	Mixture	8 consecutive points on both sides of LC with no points in Zone C		x	

Source: Montgomery (2009); Trip (2010), Noskievičová (2013), Zhao (2017), Mu (2021), García (2022)

A software application was performed for the automatic CCPs recognition, both simple and concurrent. This application consisted of a decision tree (DT), tendency and dispersion statisticians, and shape features such as: mean value, standard deviation, determination coefficient of the least-square line, slope and sign, common difference, and average of three successive mensuration.

g) Identification of root assignable cause

When an unnatural pattern is identified on the control chart, it indicates that the process is out-of-control. Therefore, it is necessary to identify the potential root cause linked to the pattern and developing corrective actions to improve the process.[2, 4, 12] In this work, the relative frequency distribution for the simple pattern, and conditional probability for concurrent patterns were determined (1). [1]

$$P(A \mid B) = \frac{P(A \cap B)}{P(B)} \quad (1)$$

h) Stability index or data normalization

The stability index ($1-S_t$) is expected to tend to one at each instant, which means that the variation due to special - causes is minimal (2).[2]

$$(1 - S_t) = 1 - \frac{SP_{Rul}}{TP} \quad (2)$$

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.

From table 1, R-1, R-5, and R-6 patterns contribute $SP_{RUL} = 1$; however, the remaining patterns contribute from the last point onward, for example, the trend (R-3) consists of six or more points, so it contributes $SP_{RUL} = SP - 5$. When ($1-S_t$) is less than 95%, it becomes impossible to address all the special signals. In these cases, it is better to analyze the main patterns in the chart, generate conjectures about their causes, and proceed to corroborate those conjectures.[2]

i) Area-Threshold for Remaining Useful Life. Health Indicator

The area-threshold (A_{RUL}) between the functions f(t)=1 and f($1-S_t$) was determined using the definite integral method. Subsequently, using the area contributed by each significant process variable, the area-threshold for remaining useful life (RUL) was obtained.

Results and discussion

Superheating steam temperatures (Tv-SH#4) were obtained every two hours for eight months from the SCADA real-time database. Two months were excluded from the data set because these affected the normality assumptions. The control chart was finally designed with 2163 measurements, mean range (R̄m) 0.86 ºC, standard deviation 0.76 ºC, mean value (μ) 521,73 ºC, lower control limit (LCL, -3σ) 519.31 ºC, and upper control limit (UCL, +3σ) 523,76 ºC (figure 1).

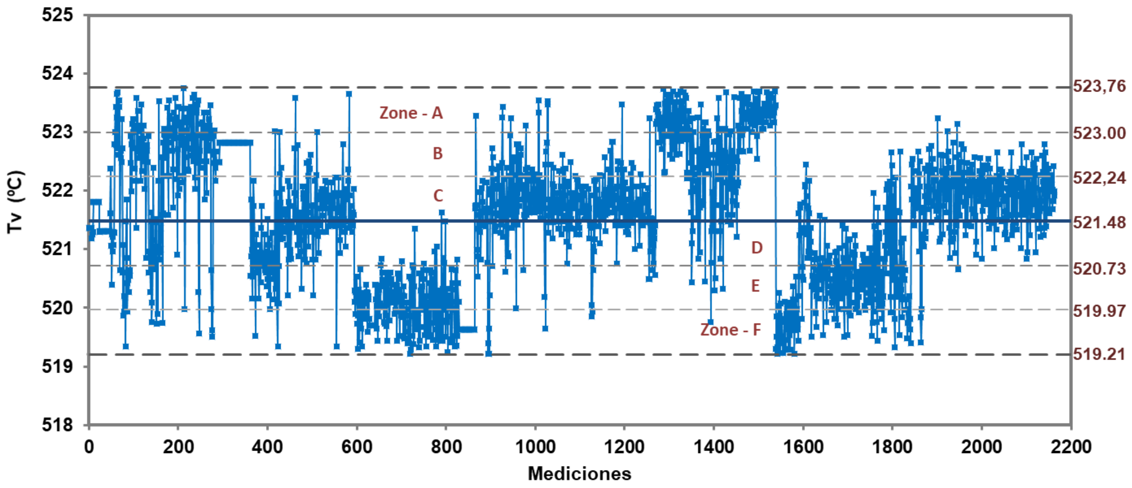

Fig. 1 - Statistical control chart of superheating steam temperatures (Tv-SH#4, °C). 2163 individual points. Sampling every two hours

In addition, the temperature was distributed above the central line (CL) for 52,9 % of measurements and below CL 47,1 %, within Zone-A 10.5 %, Zone-B 16,8 %, Zone-C 25,6 %, Zone-D 22,2 %, Zone-E 15,3 %, and Zone-F 9.6 %. According to design parameters, Tv is 525 °C at 13,70 MPa.

Variation patterns were determined on the control chart such as downward and upward shift (R-2), upward and downward trend (R-3), large shift (R-5), small shift (R-6), and stratification (R-7) (figure 2). The unnatural pattern shift-trend (R-2) had the highest number of special points, with a relative frequency of 88,94 %, due to possible general causes: poor standardization, changes in work procedures, and failures in the industrial network (table 2).[2, 4, 12]

Concurrent patterns reached 5.9 % conditional probability, due to combinations of Nelson's run rules: shift-trend, large shift, small shift, and stratification (table 3). The stability index (1-S_t) in the Phase I was 59,8 %, indicating an out-of-control statistic process.

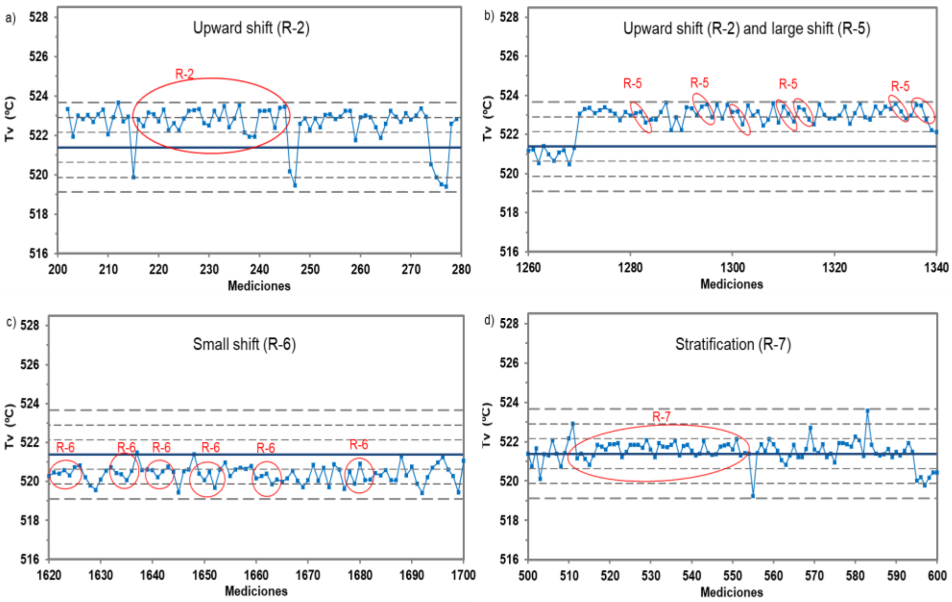

Fig. 2 – Variation patterns on the control chart of superheating steam temperatures

Table 2- Phase I. Unnatural pattern Tv-SH4 (relative frequency, %)

Rules	R-2 Shift-trend		R-3 Trend		R-5 Large shift		R-6 Small shift		R-7 Stratification
	Av[(a)]	Bw[(b)]	Up[(c)]	Dw[(d)]	Av	Bw	Av	Bw	Zone C - E
SP_{RUL}[(e)]	44.05	44.90	1.61	0.76	0.66	0.47	0.95	0.38	6.33

[(a)]Av: Above Central Line; [(b)]Bw: Bellow Central Line; [(c)] Up: Upward; [(d)] Dw: Downward; [(e)] SP: Special Points

Table 3- Phase I. Combination of patterns Tv-SH4 (conditional probability, %)

Combination		Large shift $(R\text{-}5)_{Bw}$	Small shift $(R\text{-}6)_{Bw}$	Stratification (R-7)
Shift-trend	$(R\text{-}2)_{Av}$	1.54	-	0.75
	$(R\text{-}2)_{Bw}$	1.10	1.19	0.68

[(a)]Av: Above Central Line; [(b)]Bw: Bellow central Line; [(c)] Up: Upward; [(d)] Dw: Downward; [(f)] SP: Special Points

Checking assumptions of normality

Normality was check using StatGraphic Centurion v.19.0. Density trace and frequency histogram show a shape like a Gaussian bell curve with moderate asymmetry (figure 3a, b). The data were arranged on the trend line in the symmetry graph, but points negatively skewed between 0.8-2.4 can be seen (figure 3c). Though, the points were located on the curve cumulative distribution for the standard normal curve (figure 3d).

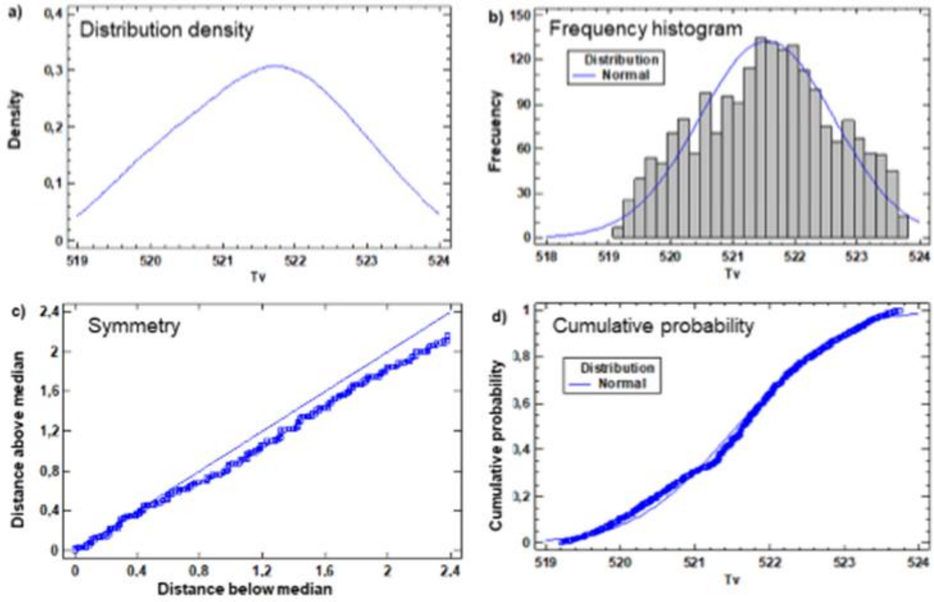

Fig. 3 – Normality check for the superheating steam temperatures (Tv-SH#4)

The temperature was modeled by normal distribution with 95% confidence according to Kolmogorov-Smirnov. However, modified Kolmogorov-Smirnov D, Cramer-Von Mises W^2, and Anderson-Darling A^2 tests were not satisfactory (p-value < 0.01). This could be due to non-random variation within the limits on the control chart. Therefore, the sample size must be increased.

In addition, standardized Skewness statistic obtained a value of -1,615 3 in the expected range [-2; 2]. According to the log likelihood statistic, the best fitting distribution is the normal distribution. Then, the assumptions of normality were accepted with the above exceptions.

Quality characteristic monitoring

X-Rm chart was applied for monitoring Tv-SH#4 for 1166 h consecutive. Individual points were distributed above the central line (CL) 79,4 % of measurements and below LC 20,6 %, within Zone-A 3,9 %, Zone-B 33,8 %, Zone-C 43,9 %, Zone-D 13,4 %, Zone-E 3,4 %, and Zone-F 1,7 % (figure 4).

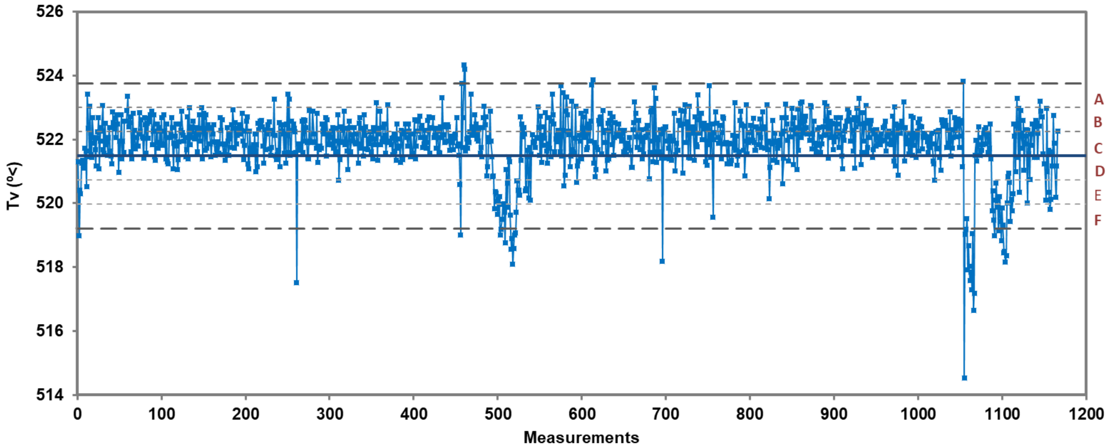

Fig. 4 - Superheating steam temperatures (Tv-SH#4, °C), sampling every one hour

The points beyond the control limits (R-1) reached 8,5 % relative frequency, and the shift-trend pattern (R-2) 77.9 %, due to poor standardization and set-up changes. The stability index resulted 66,3 % (table 4).

Table 4- Phase II. Unnatural pattern Tv-SH4 (relative frequency, %)

Rules	R-1 Beyond Limits		R-2 Shift-trend		R-3 Trend		R-5 Large shift		R-6 Small shift		R-7 Stratification
	Av[a] +3σ	Bw[b] +3σ	Av LC[c]	Bw LC	Up[d]	Dw[e]	Av LC	Bw LC	Av LC	Bw LC	Zone C-D
SP_{RUL}[f]	1.3	7.2	77.4	0.5	4.6	3.1	0.8	0.3	3.6	-	1.3

[a]Av: Above; [b]Bw: Bellow; [c] CL: Central Line; [d] Up: Upward; [e] Dw: Downward; [f] SP: Special Points

Area-Threshold for the Remaining Useful Life

The stability index (1-S_t) was calculated for four stages of continuous operation. The operating variables and control limits were boiler pressure Pv = [13,22, 13,44] MPa [25], superheating steam temperatures Tv = [519,21, 523,76) °C, and condenser pressure Pv* = [3,63, 5,47] MPa. These variables reached the following values assumed as a shut-down system: Pv = [0,10, 12,44] MPa, Tv = [191,1, 515,8] ºC, Pv* = [1,52, 3,63) ∪ (5,47, 6,31] MPa (figure 5).

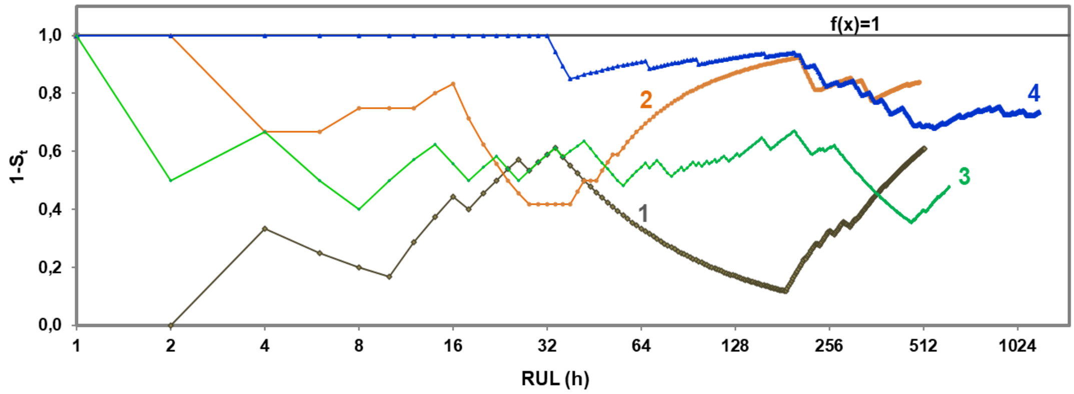

Fig. 5 – Stability index (1-S_t) for Tv-SH#4 (°C) *versus* Remaining Useful Life (RUL)

In figure 5, the stability index (1-S_t) fluctuated with ups and downs. It shows periods of decline (1-S_t) < 0,95, characteristic of an unstable process due to special causes of variation, followed by periods of rise with a predominance of normal points (NP). The area-threshold (permissible value) for the Remaining Useful Life (RUL) was determined between the functions f(t)=1 and f(1-S_t). It ranged from 581 to 1193 u², with a standard deviation of 285 u² relative to the WECO standards (figure 6).

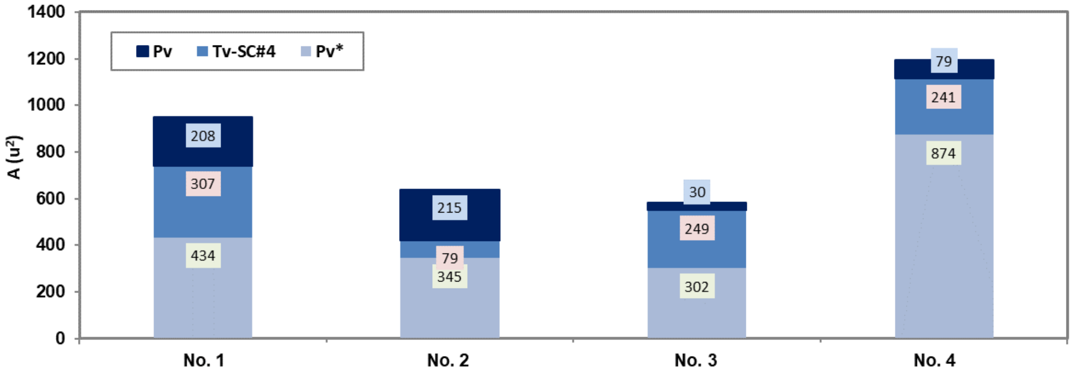

Fig. 6 - Area-Threshold (A_{RUL}) for the Remaining Useful Life (RUL), WECO rules

It should be noted that scheduling maintenance cycles in electrical grid is a complex activity due to the close coordination required by different stakeholders. This is influenced not only by the quality and durability of the equipment components, maintenance effectiveness, environmental conditions, and costs; but decision-makers also consider balancing system availability and potential failures [26, 27]. A summary of the area thresholds for the WECO rules, the Nelson run, and the AIAG is presented in table 5.

Table 5- Area-Threshold for the Remaining Useful Life (RUL)

Rules	Pattern	$(A_{RUL})_{mean}$	$(A_{RUL})_{min}$	$(A_{RUL})_{max}$	$\sigma_{(x)}$
WECO	4	840	581	1193	285
Nelson's run	8	979	634	1996	593
AIAG	3	886	605	1289	308

It was suggested that superheating steam temperatures control limits be implemented, and appropriate corrective measures be taken to increase the stability index in operations. This project continues with the goal of analyzing new variables, extending the evaluation period, and predicting Remaining Useful Life. It is expected to contribute to the implementation of a condition-based maintenance strategy, aimed at achieving proper utilization of installed thermal capacity.

Conclusions

Individuals and moving range (X-MR) chart was designed to monitor superheating steam temperatures with 2163 individual points, central line (CL) 521,73 ºC, lower control limit (LCL) 519,31 ºC, and upper control limit (UCL) 523,76 ºC.

Abnormal patterns were determined, with the shift-trend having the highest relative frequency due to possible general causes: poor standardization, changes in work procedures, and failures in the industrial network. Concurrent patterns, a combination of two single patterns, reached a 5,9 % conditional probability.

The area-threshold for remaining useful life was evaluated using decision rules and test zones, representing a range 581 to 1193 u^2 and standard deviation 285 u^2 for WECO rules.

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Declaration of competing interest

The authors declare that there are not conflicts of interest.

Authorship contribution

Armando Rojas Vargas: conceptualization, methodology, investigation, software, Writing - Reviewing and Editing.

Margarita Penedo Medina: conceptualization, investigation, writing – reviewing.