

Svitlana V. Popereshnyak

PhD in Physics and Mathematics, Associate Professor

National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute",

State University of Information and Communication Technologies, Kyiv, Ukraine

ORCID ID 0000-0002-0531-9809

spopereshnyak@gmail.com

METHOD FOR SEQUENTIALLY AGGREGATED ASSESSMENT OF STRUCTURAL CHANGES IN DATA STREAMS FOR DETECTING DEGRADATION OF TECHNICAL SYSTEMS

Abstract. This paper proposes a method for sequentially aggregated assessment of structural changes in data streams aimed at the early detection of technical system degradation. The relevance of the study is determined by the need to identify initial changes in technical condition that may be weak and unstable and may not be accompanied by the exceedance of established diagnostic thresholds. Current approaches to condition monitoring, anomaly detection, and degradation prediction are analyzed, revealing that the problem of interpretable aggregation of a sequence of local structural-probabilistic assessments while preserving information on the pattern of their evolution remains insufficiently investigated. The proposed method sequentially transforms local assessments of structural atypicality obtained from short data-stream fragments into a multicomponent aggregated representation. Five complementary components are introduced to characterize the dynamics of structural changes: level, trend, accumulation, duration, and variability. Their joint analysis makes it possible to distinguish isolated local deviations, directional growth of structural atypicality, and an established persistent degradation state. Rules for interpreting sequentially aggregated assessments are defined, and their responses to characteristic scenarios of condition change are investigated. The experimental simulation results demonstrate that an isolated deviation is primarily reflected by increased variability without substantial accumulation or duration, whereas degradation development is characterized by a pronounced positive trend followed by increases in the accumulation and duration components. It is shown that, once a persistent degradation state has been established, the trend may decrease while the level, accumulation, and duration components remain high, which substantiates the need for their joint interpretation. The practical applicability of the method is investigated using rolling-bearing vibration monitoring as a case study, based on the operating conditions and structure of the open XJTU-SY dataset. The simulation results confirm the possibility of detecting the directional development of structural changes before a persistent degradation state is established. The proposed method does not require the training of a complex parametric model on large datasets, provides an interpretable representation of the dynamics of the monitored process, and can be applied to streaming condition monitoring of technical systems as well as to the generation of additional features for diagnostic and prognostic tasks.

Keywords: data stream analysis, structural changes, sequentially aggregated assessment, time series analysis, technical system degradation, condition monitoring, condition prediction, machine learning

Поперешняк Світлана Володимирівна

К.ф.-м.н., доцент, доцент

Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського»,

Державний університет інформаційно-комунікаційних технологій,

Київ, Україна

ORCID ID 0000-0002-0531-9809

spopereshnyak@gmail.com

МЕТОД СЕКВЕНЦІЙНОГО АГРЕГОВАНОГО ОЦІНЮВАННЯ СТРУКТУРНИХ ЗМІН У ПОТОКАХ ДАНИХ ДЛЯ ВИЯВЛЕННЯ ДЕГРАДАЦІЇ ТЕХНІЧНИХ СИСТЕМ

Анотація. У статті запропоновано метод секвенційного агрегованого оцінювання структурних змін у потоках даних, орієнтований на раннє виявлення деградації технічних систем. Актуальність дослідження зумовлена необхідністю виявлення початкових змін технічного стану, які можуть мати слабкий і нестійкий характер та не супроводжуватися перевищенням установлених діагностичних порогів. Проаналізовано сучасні підходи до моніторингу технічного стану, виявлення аномалій і прогнозування деградації та визначено недостатню дослідженість задачі інтерпретованого агрегування послідовності локальних структурно-ймовірнісних оцінок зі збереженням інформації про характер їх зміни. Запропонований метод передбачає послідовне перетворення локальних оцінок структурної нетиповості коротких фрагментів потоку даних у багатокомпонентне агреговане представлення. Для характеристики динаміки структурних змін формуються п'ять взаємодоповнювальних компонентів: рівень, тренд, накопичення, тривалість і мінливість. Сукупність цих компонентів дає змогу розрізняти одиничні локальні відхилення, спрямоване наростання структурної нетиповості та сформований стійкий деградаційний стан. Визначено правила інтерпретації секвенційно агрегованих оцінок та досліджено їх реакцію на характерні сценарії зміни стану. Експериментально встановлено, що одиничне відхилення проявляється переважно збільшенням мінливості без значного накопичення і тривалості, тоді як розвиток деградації характеризується вираженим додатним трендом із подальшим зростанням компонентів накопичення та тривалості. Показано, що після формування стійкого деградаційного стану тренд може зменшуватися за одночасного збереження високих значень рівня, накопичення та тривалості, що обґрунтовує необхідність спільної інтерпретації компонентів. Практичну спрямованість методу досліджено на прикладі вібраційного моніторингу підшипникового вузла з використанням умов і структури відкритого набору даних XJTU-SY. Результати моделювання підтвердили можливість

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виявлення спрямованого розвитку структурних змін до формування стійкого деградаційного стану. Запропонований метод не потребує навчання складної параметричної моделі на великих вибірках, забезпечує інтерпретоване представлення динаміки контрольованого процесу та може використовуватися для потокового моніторингу технічних систем, а також для формування додаткових ознак у задачах діагностування та прогнозування.

Ключові слова: *аналіз потоків даних, структурні зміни, секвенційне агреговане оцінювання, аналіз часових рядів, деградація технічних систем, технічна діагностика, прогнозування технічного стану, машинне навчання.*

1. Introduction

Modern technical systems are characterized by a high degree of automation and are equipped with continuous monitoring facilities that generate data streams describing their operating parameters. Vibration, temperature, acoustic characteristics, current, voltage, pressure, and other measured parameters are used to assess equipment condition and detect faults in a timely manner. One of the key objectives of such monitoring is the early detection of degradation processes, since their identification before a system reaches a critical state enables maintenance planning, reduces the risk of unexpected failures, and improves equipment operational efficiency.

Degradation of a technical system usually develops gradually, while its initial manifestations may be weak and unstable and may not result in the controlled parameters exceeding predefined threshold values. Such manifestations may include changes in the frequency of local deviations, their clustering patterns, the duration of individual states, or the emergence of a directional trend. Therefore, the development of streaming data analysis methods capable of detecting not only an established critical state but also structural changes associated with its gradual development remains a relevant research problem.

2. Statement of the problem

A considerable proportion of technical monitoring systems rely on assessing current values of monitored parameters, calculating diagnostic indicators, or detecting predefined threshold exceedances. Such approaches are effective for identifying established deviations but may be insufficiently sensitive to early degradation when local changes remain within admissible limits.

For real-time analysis, a data stream can be represented as a sequence of short local fragments characterized by structural atypicality assessments. However, an elevated local assessment may result from noise, a random disturbance, an operating-mode change, or the onset of persistent degradation. Therefore, not only its magnitude but also its evolution over consecutive observation intervals is essential.

This creates the need for a method that transforms a sequence of local structural-probabilistic assessments into an aggregated representation of structural change dynamics. Such a representation should account for the deviation level, direction of change, accumulation, duration, and variability, enabling isolated fluctuations to be distinguished from developing and persistent degradation.

Vibration monitoring of rolling bearings represents a practically significant application of this problem. Bearing degradation may cause gradual structural changes in vibration signals before conventional diagnostic indicators reach critical values. Therefore, analysis of sequential local structural changes can provide additional information for early degradation detection.

3. Analysis of recent studies and publications

Condition monitoring of rotating machinery and early detection of degradation are important areas of modern diagnostics. Vibration signals are widely used for rolling-bearing monitoring because defects and wear are reflected in changes in their temporal and frequency characteristics. Time-domain vibration analysis techniques are reviewed in [1], while [2] considers bearing failure analysis and fault diagnosis. Methods combining vibration analysis with diagnostics and prognostics of bearing deterioration are presented in [3].

A separate research direction concerns the assessment of degradation dynamics. The study [4] systematizes *health indicators* for rotating machinery, emphasizing their sensitivity, monotonicity, and interpretability. Degradation monitoring under varying operating conditions is investigated in [5], whereas [6] addresses early fault prognosis based on vibration signals. These studies demonstrate the importance of assessing not only the current technical condition but also its evolution over time.

Recent approaches increasingly employ data-driven and neural-network models. Attention-based BiLSTM architectures are used for remaining useful life prediction [7], while combined deep learning models support bearing fault diagnosis under time-varying operating conditions [8]. Generative models for addressing limited and imbalanced diagnostic data are reviewed in [9]. At the same time, [10] identifies practical deployment, robustness, and remaining useful life prediction as continuing challenges in bearing health monitoring.

Another research direction focuses on the local structure of short binary sequences. The randomness of bit arrangements in local segments of a (0, 1)-sequence is investigated in [11], while [12] derives joint distributions of statistics of random binary sequences. These results provide a mathematical basis for probabilistic assessment of interrelated structural characteristics of short data fragments.

For early degradation detection, however, it is necessary to analyze not only individual local assessments but also their sequential evolution. An isolated increase may result from noise or an operating-mode change, whereas progressive growth, accumulation, and persistence may indicate degradation. The approaches in [11] and [12] characterize local sequence structure but do not aggregate the ordered trajectory of local assessments. Therefore, an

interpretable representation that preserves the direction, accumulation, persistence, and variability of structural changes over time remains insufficiently investigated.

Thus, **the problem** of sequentially aggregating local structural-probabilistic assessments in a data stream while preserving information on the order and pattern of their changes remains insufficiently investigated. There is a need for a method capable of simultaneously characterizing the level of structural deviation, its direction of change, accumulation, duration, and variability, thereby distinguishing random local fluctuations from persistent degradation development. Addressing this problem is particularly relevant to streaming vibration monitoring of rolling bearings, where early degradation-related changes may be weak and may not result in conventional diagnostic threshold exceedances.

4. Research objectives and tasks

The **aim of the study** is to develop a method for sequentially aggregated assessment of structural changes in data streams for the early detection of technical system degradation and to experimentally evaluate its properties using simulated degradation scenarios parameterized according to rolling-bearing vibration monitoring conditions.

To achieve this aim, the following **objectives** are defined:

1. to formalize the process of sequentially transforming local structural-probabilistic assessments of a data stream into a sequentially aggregated representation;
2. to develop procedures for constructing characteristics of the level, direction of change, accumulation, duration, and variability of local structural deviations;
3. to define rules for interpreting the set of sequentially aggregated assessments to distinguish random local deviations from persistent degradation development;
4. to experimentally investigate the response of the proposed method to different structural change scenarios;
5. to evaluate the applicability of the method to rolling-bearing degradation monitoring using simulation scenarios.

5. Research results

5.1. Method for Sequentially Aggregated Assessment of Structural Changes in Data Streams

The proposed method is intended to identify the evolution of structural changes in a data stream by sequentially analyzing short local fragments. Unlike individual-fragment assessment, it considers the ordering of local structural-probabilistic assessments and their evolution, thereby enabling isolated deviations to be distinguished from persistent or directional changes.

Let the observed process be represented by a data stream

$$X = (x_1, x_2, \dots, x_N), \quad (1)$$

which, after domain-specific preprocessing, is transformed into a discrete, in particular binary, sequence

$$\Gamma = (\gamma_1, \gamma_2, \dots, \gamma_N), \gamma_i \in \{0, 1\}. \quad (2)$$

Short fragments are generated using a sliding window of length n with step h :

$$\Gamma_n^{(r)} = (\gamma_{(r-1)h+1}, \dots, \gamma_{(r-1)h+n}), r = 1, \dots, R, \quad (3)$$

where $R = \lfloor \frac{N-n}{h} \rfloor + 1$.

When $h < n$, adjacent fragments overlap, which increases the temporal resolution of structural change tracking but also introduces dependence between neighboring local assessments. For each fragment $\Gamma_n^{(r)}$, a vector of structural statistics

$$\eta^{(r)} = (\eta_1^{(r)}, \eta_2^{(r)}, \dots, \eta_m^{(r)}) \quad (4)$$

is determined. Using the corresponding joint distributions, these statistics are transformed into a normalized local structural-probabilistic assessment $u_r \in [0, 1]$.

As a result, an ordered trajectory of local assessments is obtained: $U_R = (u_1, u_2, \dots, u_R)$.

To analyze its evolution, a sequential window of length L is introduced:

$$U_r^{(L)} = (u_{r-L+1}, \dots, u_r), r \geq L. \quad (5)$$

Thus, the method employs two levels of window-based representation: the local window n operates in the original data space, whereas the sequential window L operates in the space of local structural-probabilistic assessments.

For each $U_r^{(L)}$, five complementary characteristics are calculated.

The **current level** of structural atypicality is determined as

$$A_{lev,r} = \sum_{j=1}^L \omega_j u_{r-L+1}, \quad \omega_j \geq 0, \quad \sum_{j=1}^L \omega_j = 1. \quad (6)$$

The **direction of structural change** is characterized by the normalized linear trend

$$A_{tr,r} = \frac{\beta_r}{\beta_{max}}, \quad -1 \leq A_{tr,r} \leq 1, \quad (7)$$

$$\text{where } \beta_r = \frac{\sum_{j=1}^L x_j u_{r-L+1}}{\sum_{j=1}^L x_j^2}, \quad x_j = j - \frac{L+1}{2}.$$

Here, $A_{tr,r} > 0$ indicates increasing structural atypicality, $A_{tr,r} < 0$ indicates its decrease, and $A_{tr,r} \approx 0$ indicates the absence of a pronounced directional trend.

For an admissible local atypicality level c , the **accumulation component** is defined as

$$A_{acc,r} = \frac{1}{1-c} \sum_{j=1}^L \omega_j (u_{r-L+1} - c)_+, \quad (x)_+ = \max(0, x). \quad (8)$$

The **duration component** characterizes the persistence of the current uninterrupted sequence of threshold exceedances:

$$A_{dur,r} = \frac{l_r(c)}{L}, \quad (9)$$

where $l_r(c)$ is the number of consecutive values $u_i > c$ ending at the current position r , limited by the sequential window length L .

Finally, the **variability component** is determined as the normalized variance:

$$A_{var,r} = \frac{4}{L} \sum_{i=r-L+1}^r (u_i - \bar{u}_r)^2, \quad \bar{u}_r = \frac{1}{L} \sum_{i=r-L+1}^r u_i. \quad (10)$$

Consequently, the sequentially aggregated assessment is represented by the vector

$$A_r^{(L)} = (A_{lev,r}, A_{tr,r}, A_{acc,r}, A_{dur,r}, A_{var,r}). \quad (11)$$

Its components characterize complementary properties of structural change evolution: the current level, direction, accumulation, persistence, and variability, respectively. Their joint interpretation enables different patterns of structural dynamics to be distinguished.

The components of the vector correspond to five complementary characteristics of structural change evolution, as summarized in Table 1.

Table 1

Components of the sequentially aggregated assessment of structural changes		
Component	Notation	Interpretation
Level	$A_{lev,r}$	Current overall level of structural atypicality
Direction of change	$A_{tr,r}$	Direction and normalized rate of change in local assessments
Accumulation	$A_{acc,r}$	Accumulated magnitude of exceedances above the admissible level
Duration	$A_{dur,r}$	Persistence of the current uninterrupted run of exceedances
Variability	$A_{var,r}$	Stability or fluctuation intensity of local assessments

The composition of vector (11) is not arbitrary. Its components characterize different properties of the trajectory and cannot fully substitute for one another. A high level combined with low variability and a near-zero trend corresponds to a persistently high state. A positive trend indicates further growth of structural atypicality. High accumulation together with a large duration indicates the formation of a persistent deviation, whereas high variability combined with short duration is more typical of unstable or isolated changes.

The overall transformation implemented by the proposed method can be represented as

$$X \rightarrow \Gamma \rightarrow \Gamma_n^{(r)} \rightarrow \eta^{(r)} \rightarrow u_r \rightarrow U_r^{(L)} \rightarrow A_r^{(L)}. \quad (12)$$

The generalized structure of the method is shown in Fig. 1.

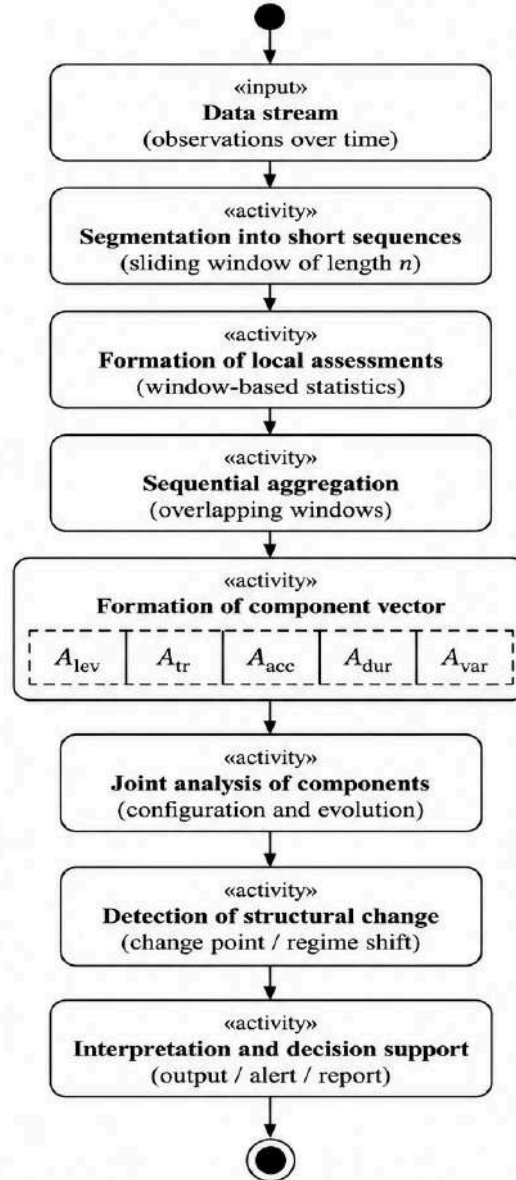


Fig. 1. Structural scheme of the method for sequentially aggregated assessment of structural changes in data streams

As shown in Fig. 1, n determines the scale of local structural analysis, h defines the resolution of the trajectory of local assessments, and L determines the interval over which their evolution is analyzed. Sequential application of these transformations produces an interpretable representation of structural change dynamics that can be used for early degradation detection and as input features for diagnostic and prognostic models.

5.2. Formation and Interpretation of Sequentially Aggregated Assessments

The sequentially aggregated assessment (11) characterizes both the current level of structural atypicality and the pattern of its evolution. For interpretation, component-specific thresholds

$$\tau_{lev}, \tau_{tr}, \tau_{acc}, \tau_{dur}, \tau_{var} \quad (13)$$

can be determined from a reference interval of normal operation, estimated empirically, or selected according to an acceptable false-alarm rate. These thresholds are application-dependent and are not treated as universal constants.

A stable state is characterized by low level, accumulation, and duration, with no pronounced trend. An isolated deviation primarily increases variability and may temporarily affect the level, but does not produce persistent accumulation or duration. In contrast, the onset of a structural change is indicated by a positive trend, $A_{tr,r} > \tau_{tr}$, followed by increasing accumulation and duration as the deviation persists. An established degradation state is characterized by $A_{lev,r} \geq \tau_{lev}$, $A_{acc,r} \geq \tau_{acc}$, $A_{dur,r} \geq \tau_{dur}$. At this stage, $A_{tr,r}$ may approach zero because the system can stabilize at an already elevated level of structural atypicality.

Therefore, the components should be interpreted jointly rather than independently. Their characteristic combinations are summarized in Table 2.

Table 2.

Characteristic combinations of sequentially aggregated assessment components

Type of structural dynamics	A_{lev}	A_{tr}	A_{acc}	A_{dur}	A_{var}
Stable state	low	≈ 0	low	low	low
Isolated local deviation	temporarily $\uparrow$	unstable	low	low	$\uparrow$
Onset of structural change	$\uparrow$	> 0	$\uparrow$	begins to $\uparrow$	moderate
Developing degradation	elevated	> 0	$\uparrow$	$\uparrow$	process-dependent
Persistent degradation state	high	≈ 0	high	high	low or moderate
Recovery	$\downarrow$	< 0	$\downarrow$	$\downarrow / 0$	transitional

The symbols $\uparrow$ and $\downarrow$ indicate increasing and decreasing tendencies rather than fixed numerical values.

The importance of preserving the order of local assessments can be demonstrated using two trajectories: $U^{(1)} = (0, 20, 0, 30, 0, 40, 0, 50, 0, 60)$, $U^{(2)} = (0, 60, 0, 50, 0, 40, 0, 30, 0, 20)$. Both have the same mean value, $\bar{u} = 0, 40$, and the same variance, but $A_{tr}^{(1)} > 0$, $A_{tr}^{(2)} < 0$.

Thus, the trend component preserves information on the direction of structural change that would be lost when using only the mean level or variability.

The duration component similarly distinguishes isolated from persistent deviations. For $U^{(3)} = (0, 75, 0, 20, 0, 75, 0, 20, 0, 75)$, $U^{(4)} = (0, 20, 0, 20, 0, 75, 0, 75, 0, 75)$, $c = 0, 60$, both trajectories contain three threshold exceedances, but $A_{dur}^{(3)} = \frac{1}{5}$, $A_{dur}^{(4)} = \frac{3}{5}$.

Hence, identical numbers of local deviations may correspond to fundamentally different structural dynamics depending on their ordering.

For streaming monitoring, degradation development can therefore be represented by a sequence of interpretative regimes

$$S_0 \rightarrow S_1 \rightarrow S_2 \rightarrow S_3, \quad (14)$$

where S_0 denotes a stable state, S_1 an isolated deviation, S_2 developing degradation, and S_3 a persistent degradation state. These regimes are determined by the joint behavior of the assessment components rather than by a single threshold condition.

The generalized interpretation scheme is shown in Fig. 2.

As shown in Fig. 2, the transition to S_1 is primarily associated with the emergence of a directional trend, whereas the transition to S_2 is characterized by accumulation and persistence of local deviations. In S_3 , the level, accumulation, and duration remain high, while the trend may decrease as the system stabilizes in the degraded state. Thus, degradation is interpreted as a sequence of structural regimes rather than a single threshold-crossing event, which provides a basis for its early detection.

5.3. Experimental Study Methodology

The experimental study of the proposed method was designed to evaluate its ability to distinguish characteristic regimes of structural dynamics and to identify the transition from isolated local deviations to the persistent development of a degradation process. Rather than classifying an individual data fragment, the analysis focuses on the joint behavior of the components of the sequentially aggregated assessment vector (11).

Four characteristic scenarios were considered: stable state S_0 ; isolated local deviation S_1 ; progressive increase in structural atypicality S_2 ; and persistent degradation state S_3 . This set of scenarios makes it possible to evaluate not only the response of the method to the presence of a deviation but also its ability to distinguish fundamentally different patterns of structural change evolution.

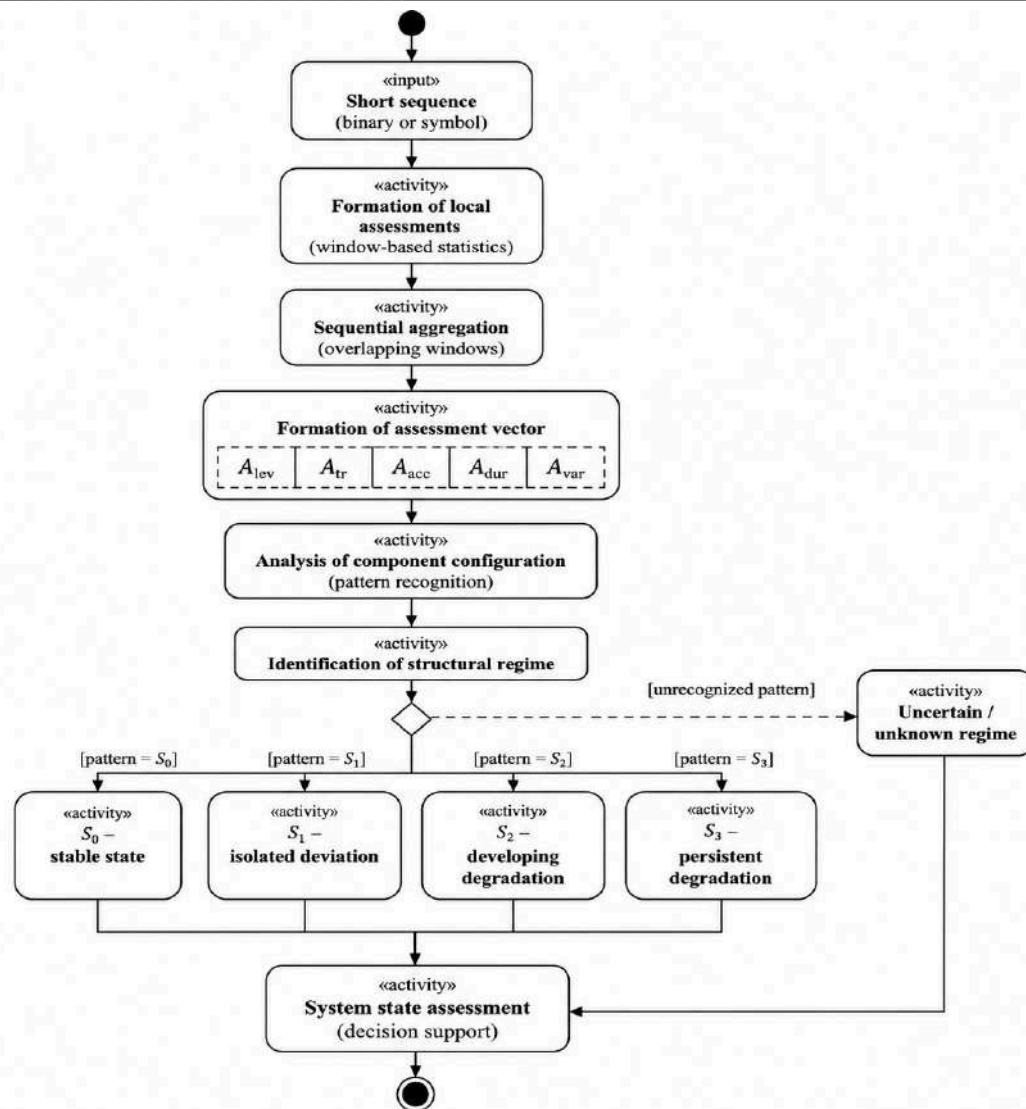


Fig. 2. Generalized scheme for interpreting the evolution of structural changes based on sequentially aggregated assessments

The experimental evaluation is based on the joint response of the five components of the assessment vector. The expected response patterns for the considered scenarios are summarized in Table 3.

Table 3.

Criteria for experimental identification of structural change patterns

Scenario	Pattern of local assessments	Expected response of the components
S_0 – stable state	Low values with minor fluctuations	Low A_{lev} , A_{acc} , A_{dur} , and A_{var} ; $A_{tr} \approx 0$
S_1 – isolated deviation	A single elevated value	Increase in A_{var} without substantial A_{acc} and A_{dur}
S_2 – developing degradation	Progressive increase in local assessments	Pronounced positive A_{tr} , followed by increasing A_{acc} and A_{dur}

Of particular importance is the comparison between scenarios S_1 – S_3 . An isolated deviation S_1 is expected to affect primarily the variability of the trajectory without producing a substantial duration component. For scenario S_2 , the main early indicator is a positive trend component reflecting a directional increase in structural atypicality. After transition to S_3 , the value of A_{tr} may decrease, while A_{lev} , A_{acc} , and A_{dur} remain high.

Accordingly, the experimental hypothesis is that the degradation pattern is determined not by the absolute value of an individual component but by the configuration of the sequentially aggregated assessment vector and the joint evolution of its components. In particular, the method should distinguish the following sequence of structural regimes (Fig. 3):

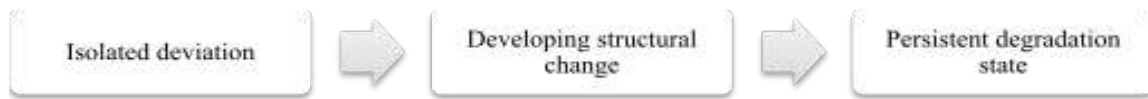


Fig. 3. Evolution of structural regimes in the degradation process

Bearing degradation monitoring was selected as the application domain because vibration data acquired over the complete bearing lifetime make it possible to observe the transition from normal operation to the development of a physical defect. The open XJTU-SY bearing dataset was used as the reference application framework. It contains run-to-failure data for 15 rolling bearings operated under three different conditions. Vibration signals were acquired in two orthogonal directions at a sampling frequency of 25.6 kHz; each record contains 32,768 samples acquired over 1.28 s, with consecutive measurements taken at 1-min intervals.

The subsequent simulation was parameterized according to the operating conditions of Bearing1_1, which was tested at a rotational speed of 2100 rpm under a radial load of 12 kN. Its run-to-failure trajectory consists of 123 consecutive measurements, and the final reported fault corresponds to an outer-race failure.

Thus, the experimental methodology provides a basis for separately evaluating the ability of the proposed method to identify isolated, directional, and persistent structural changes and for assessing whether changes in the configuration of $A_r^{(L)}$ can serve as indicators of degradation development. The specific simulation parameters and numerical results are presented in Section 5.4.

5.4. Simulation and Assessment of Characteristic Bearing Degradation Scenarios

To evaluate the applicability of the proposed method to technical condition monitoring, characteristic scenarios of rolling-bearing degradation were simulated. The experimental setup was parameterized according to the structure and operating conditions of the XJTU-SY Bearing Dataset, which contains accelerated run-to-failure tests of 15 rolling bearings. Vibration signals were acquired in the horizontal and vertical directions at a sampling frequency of 25.6 kHz. Each measurement contains 32,768 samples corresponding to a recording duration of 1.28 s, while the interval between consecutive measurements is 1 min.

The operating conditions of Bearing1_1 were used as a representative case. This bearing was operated at 2100 rpm under a radial load of 12 kN and was monitored through 123 consecutive vibration measurements over its run-to-failure lifetime. The final failure was associated with damage to the outer race.

To evaluate the properties of sequential aggregation independently of a particular vibration-signal preprocessing technique, four controlled trajectories of local structural-probabilistic assessments u_r were generated. They represent stable operation, an isolated local deviation, progressive development of structural atypicality, and a persistent degradation state.

The sequential analysis window length was set to $L = 10$, and the admissible level of local structural atypicality was defined as $c = 0.60$.

To ensure direct comparability between the scenarios, equal weights were used for the level and accumulation components: $\omega_j = L_1 = 0, 1$.

The four trajectories of local assessments were defined as follows:

$$U^{(1)} = (0, 18, 0, 22, 0, 20, 0, 19, 0, 21, 0, 23, 0, 20, 0, 22, 0, 19, 0, 21), \quad (15)$$

$$U^{(2)} = (0, 18, 0, 22, 0, 20, 0, 19, 0, 21, 0, 82, 0, 20, 0, 22, 0, 19, 0, 21), \quad (16)$$

$$U^{(3)} = (0, 20, 0, 25, 0, 31, 0, 38, 0, 46, 0, 54, 0, 62, 0, 70, 0, 78, 0, 86), \quad (17)$$

$$U^{(4)} = (0, 72, 0, 76, 0, 74, 0, 79, 0, 77, 0, 81, 0, 78, 0, 82, 0, 80, 0, 83). \quad (18)$$

Trajectory $U^{(1)}$ represents a stable technical condition with minor local fluctuations. Trajectory $U^{(2)}$ contains a single pronounced deviation against an otherwise stable background. Trajectory $U^{(3)}$ represents a progressive increase in structural atypicality, whereas $U^{(4)}$ corresponds to an established persistent degradation state.

For each trajectory, the five components of the sequentially aggregated assessment were calculated according to Eqs. (6) – (10). The resulting values are presented in Table 4.

Table 4.

Sequentially aggregated assessments for the simulated degradation scenarios

Scenario	A_{lev}	A_{tr}	A_{acc}	A_{dur}	A_{var}
S_0 – stable state	0,2050	0,0084	0,0000	0,0000	0,0009
S_1 – isolated deviation	0,2640	0,0320	0,0550	0,0000	0,1380
S_2 – developing degradation	0,5100	0,4960	0,1400	0,4000	0,1870
S_3 – persistent degradation	0,7820	0,0672	0,4550	1,0000	0,0045

The values reported in Table 4 were obtained by direct calculation from the trajectories defined in Eqs. (15) – (18) using the mathematical expressions of the proposed method. Therefore, they represent reproducible simulation results rather than expert-assigned scores.

The results demonstrate distinctly different responses of the assessment components to the considered structural dynamics. For the stable scenario S_0 , the overall level of structural atypicality remains low, $A_{lev} = 0,2050$, while the trend is close to zero, $A_{tr} = 0,0084$. No accumulation or persistent threshold exceedance is observed, and the variability is negligible, $A_{var} = 0,0009$.

Introducing a single local deviation in S_1 increases the level only to $A_{lev} = 0,2640$, while the accumulation remains low at $A_{acc} = 0,0550$. Moreover, $A_{dur} = 0$, because the deviation does not form a current uninterrupted sequence of threshold exceedances. The most pronounced response is observed for the variability component, which increases to $A_{var} = 0,1380$. Thus, an isolated deviation is represented primarily as local instability rather than as persistent degradation.

Scenario S_2 exhibits a substantially different pattern. The trend component reaches $A_{tr} = 0,4960$, which is the highest positive trend among the considered scenarios. At the same time, $A_{lev} = 0,5100$, $A_{acc} = 0,1400$, $A_{dur} = 0,4000$.

This combination is characteristic of a directional structural change: the overall level has not yet reached the value observed for persistent degradation, whereas the pronounced positive trend already indicates a systematic increase in structural atypicality. Thus, the transition toward degradation can be identified before the system reaches a persistently high level of structural deviation.

A particularly informative result is obtained by comparing S_2 and S_3 . Once the persistent degradation state is established, the trend component decreases from 0,4960 to 0,0672. At the same time, the level increases to 0,7820, accumulation to 0,4550, and the duration component reaches its maximum value, $A_{dur} = 1$.

This value indicates that all ten local assessments within the current sequential interval exceed the admissible level $c=0,60$. Simultaneously, A_{lev} decreases to 0,0045. This decrease should not be interpreted as recovery; rather, it indicates stabilization of structural atypicality at a persistently high level.

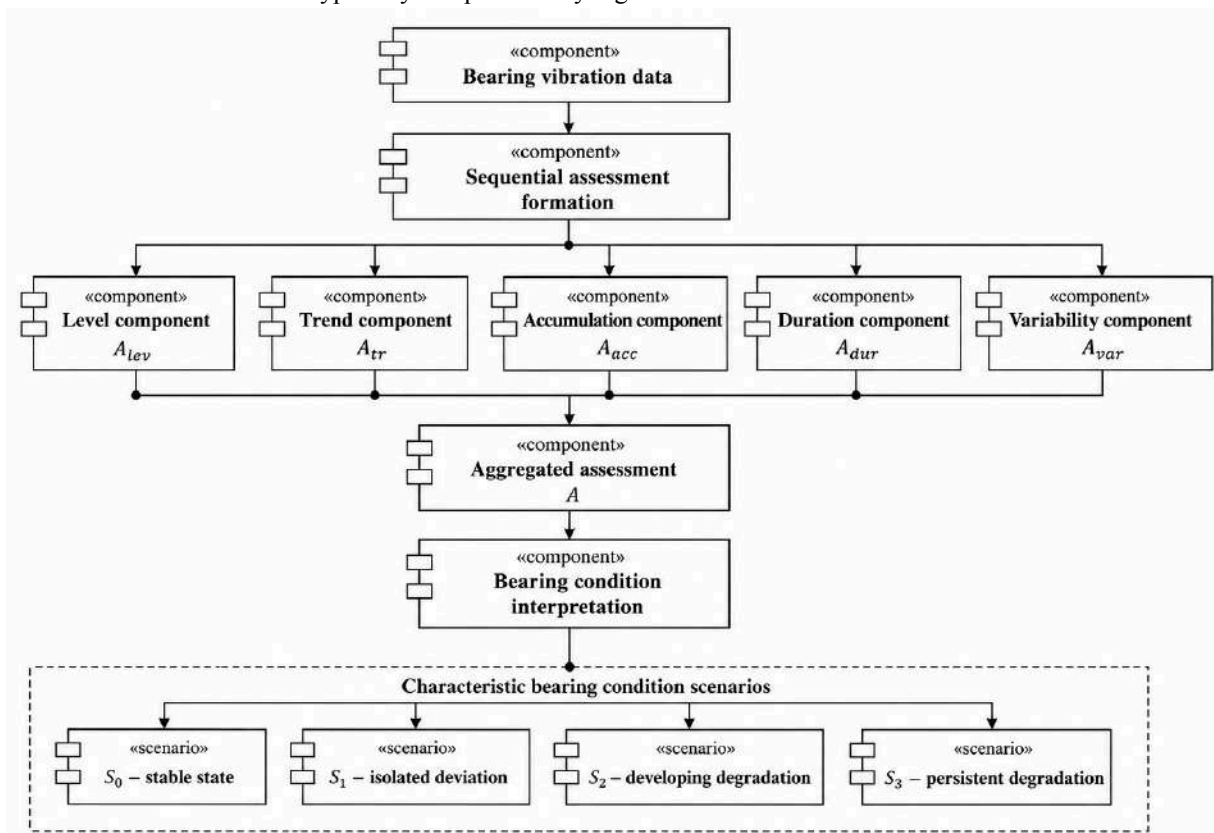


Fig. 4. Components of the sequentially aggregated assessment for characteristic bearing condition scenarios

For a visual comparison of the component responses, the results presented in Table 4 are illustrated in Fig. 4.

As shown in Fig. 4, no individual component is sufficient to characterize all stages of structural change. In particular, S_2 does not yet exhibit a high value of A_{lev} , but it is distinguished by the largest positive trend component.

Conversely, in S_3 , the trend decreases considerably, whereas the high values of level, accumulation, and duration clearly indicate an established persistent degradation state. The combined analysis of these components therefore provides more information about the degradation process than any individual indicator.

The simulation results demonstrate that the proposed method distinguishes four characteristic regimes of structural dynamics: stable operation, an isolated local deviation, progressive degradation development, and an established persistent degradation state. Importantly, the transition to S_2 is primarily reflected by an increase in the trend component before high values of the overall level, accumulation, and duration are reached. This finding supports the use of the proposed sequentially aggregated assessment not only for detecting an established deviation but also for the early identification of directional structural changes associated with degradation development.

6. Discussion of the Results

The obtained results confirm the feasibility of sequential aggregation for detecting structural changes in data streams. Unlike the assessment of individual fragments or the use of a single integral indicator, the proposed method jointly considers the level, trend, accumulation, duration, and variability components, thereby characterizing not only the presence of a structural deviation but also the pattern of its evolution.

The simulation results demonstrated the ability to distinguish between a stable state, an isolated local deviation, progressive degradation, and a persistent degradation state. In particular, the onset of degradation is characterized by an increase in the trend component before high values of the level, accumulation, and duration components are reached. Once a persistent degradation state has been established, the trend may decrease while the other components remain high. This confirms the importance of their joint interpretation and provides a basis for the early detection of structural changes.

An important advantage of the proposed method is the interpretability of the resulting assessments and the absence of a requirement to train a complex parametric model on large datasets. The method can be applied either as a standalone tool for streaming condition monitoring or as a means of generating additional features for machine learning, diagnostics, and prognostics.

The main limitation of the method is its dependence on the window parameters n , h , and L , the admissible level c , and the procedure used to generate local structural-probabilistic assessments. Further research should therefore focus on adaptive parameter selection and validation of the method using complete experimental run-to-failure trajectories of technical systems.

Thus, the proposed method enables a transition from detecting isolated local deviations to assessing the **dynamics of their evolution**, which is particularly important for the early detection of degradation in technical systems.

7. Conclusions and prospects for further research

A method for sequentially aggregated assessment of structural changes in data streams has been developed. The method combines local structural-probabilistic assessment of short sequences with the subsequent analysis of their ordered trajectory using five complementary components: level, trend, accumulation, duration, and variability.

The experimental results demonstrated that the proposed assessment distinguishes between stable operation, isolated local deviations, progressive structural changes, and persistent degradation. In particular, the trend component enables the identification of directional changes before a persistently high level of structural atypicality is established, whereas the accumulation and duration components characterize the subsequent development and persistence of degradation.

The proposed method provides an interpretable representation of degradation dynamics without requiring the training of complex parametric models on large datasets. Its simulation-based evaluation under rolling-bearing monitoring conditions demonstrated the potential for distinguishing different stages of degradation development and for supporting early detection of changes in technical system condition.

Further research will focus on adaptive selection of the method parameters, validation using complete run-to-failure trajectories, and integration of sequentially aggregated assessments into diagnostic and prognostic models for technical systems.

Declaration on artificial intelligence

During the preparation of this article, ChatGPT (OpenAI) was used for language and stylistic editing, refinement of selected formulations, and structuring of the manuscript. The artificial intelligence tool was not used to generate the source data, conduct experimental studies, perform calculations, or produce scientific results. The final content of the article, methodological provisions, analysis and interpretation of the results, and conclusions were formulated, verified, and approved by the authors.

Conflict of interest

The author declares that there is no conflict of interest and confirms that during the preparation of this work there were no commercial, financial, or other relationships that could be construed as influencing the results of the study or their interpretation. The work was performed in accordance with the principles of academic integrity, ethical standards for conducting scientific research, and editorial policy requirements for preventing conflicts of interest.

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