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A Methodology for Proactively Diagnosing Production Oracle DBMSs Based on Correlation Analysis of Trace Files and Alert.Log to Predict Failures and Prevent Unplanned Downtime

Olga Badiukova

Oracle DBA ETS, LLC "Ci Ec Tек", Kyiv, Ukraine.

Abstract

The study describes the methodological features of proactive diagnostics for high-load Oracle DBMS, based on correlational analysis of the contents of the alert.log journal and trace files generated by background processes. The significance of the approach is driven by the substantial increase in the cost of unplanned downtime in 2024–2025: in the financial sector, losses reach approximately 5 million US dollars per hour of unavailability. As a conceptual foundation, an algorithmic method is proposed for identifying latent relationships between background process activity and subsequent critical failures, aimed at detecting non-obvious causal–temporal dependencies that remain outside the scope of traditional monitoring. The proposed methodology is based on correlation analysis of alert.log and trace files, supplemented by temporal modeling of events and predictive analytics methods. It enables detection of performance degradation, resource leaks, system anomalies, and logical errors before an incident occurs, thereby significantly reducing the likelihood of unplanned downtime.

The methodological framework integrates latent semantic indexing tools for processing unstructured textual corpora and statistical modeling based on the Jensen–Shannon divergence to quantitatively assess changes in event distributions and for forecasting failure probability. Such a synthesis enables a transition from simple anomaly fixation to a probabilistic interpretation of system-state degradation based on weak signals contained in diagnostic traces. Particular attention is given to describing interactions between redo and ARCH processes, the operational specifics of standby mechanisms, as well as the role of RMAN as a means of preventing data loss through proper organization of backup and recovery. The methodology is formalized as a cyclic diagnostic loop: Log Collection → Normalization → Correlation → Anomaly Detection → Classification → Prediction → Prevention/Remediation.

The formulated results establish a theoretical basis and applied guidelines for evolving from reactive monitoring to autonomous management of data infrastructure, reducing the dependence of the availability of an organization's critical services on the human factor and operational errors.

Keywords: *Oracle Database, Alert.Log, Trace, Background Process, Failure Forecasting, Proactive Diagnostics, Unplanned Downtime, Redo, Standby, RMAN.*

INTRODUCTION

In the context of the accelerated digital transformation of 2024–2025, the fault tolerance of database management systems acquires the status of an infrastructural condition for the functioning of the global economy. According to Gartner estimates, total global IT spending in 2025 will reach 5.43 trillion US dollars, and the segment of systems for data centers demonstrates growth of 42.4%, which is associated with large-scale integration of generative artificial intelligence [1]. Against the background of increasing complexity of computing landscapes, the Oracle DBMS retains a system-forming role, ensuring continuity of critical application domains in finance, industry, and healthcare. At the same time, growth in architectural complexity predictably increases the probability of unplanned downtime and heightens business sensitivity to any disruptions.

Empirical statistics over the last two years indicate a sharp escalation of economic damage from IT incidents. If in 2014

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the average cost of a minute of downtime was estimated at 5,600 US dollars, then by 2024 the indicator increased to 14,056 US dollars for mid-sized organizations and to 23,750 US dollars for large enterprises [2]. For Fortune 500 companies, one hour of unavailability under modern conditions is estimated in the range of 500,000–1,000,000 US dollars, whereas in high-technology sectors, including the banking industry, losses can exceed 5 million US dollars per hour [4]. Such dynamics transform downtime from a technical problem into a direct financial risk affecting operational resilience and regulatory obligations [20, 21].

A reactive administration model focused on eliminating consequences after the fact of failure ceases to meet requirements for service continuity. The dominant direction of evolution of operational practices is associated with proactive diagnostics aimed at identifying early precursors of degradation before transition to a critical state. In the Oracle technological ecosystem, the key carriers of diagnostic signals remain alert.log and specialized trace files generated by various background processes. Observations accumulated within long-term DBA practice (20+ years) show that more than 60% of severe incidents, including ORA-00600 and ORA-04031, are preceded by characteristic sequences of events recorded in logs; however, such sequences are often not recognized by typical monitoring tools [6, 19].

According to Gartner (2025), global IT spending continues to grow, increasing business dependence on continuous availability of information systems. Reports from ITIC (2024) and Uptime Institute (2024) indicate that the cost of one hour of downtime for large organizations can exceed $300,000–$500,000, while in high-risk sectors (finance, banking) it reaches $1–5 million per hour.

Oracle DBMS traditionally serves as critical components of corporate infrastructure. Despite built-in diagnostic tools (ADR, AWR, ASH, OEM), most failures are still detected reactively - after service degradation has begun. Meanwhile, analysis of alert.log and trace files (*.trc) captures early warning signals of impending failures, which, when correlated over time, form distinct diagnostic patterns.

The fundamental difficulty is related to the scale of data: modern clustered deployments (RAC) are capable of generating gigabytes of textual messages daily, which makes manual interpretation practically infeasible. Primitive keyword filtering also proves insufficient, since it does not allow reconstruction of complex correlational relationships between the activity of redo write processes (LGWR), the operation of the archiver (ARCH), and synchronization mechanisms in standby configurations. As a result, a gap is formed between the availability of diagnostic information and the ability to extract prognostically significant regularities from it. As a response, a mathematically grounded methodology is proposed for analyzing log sequences, oriented toward identifying multiprocess correlations and estimating failure probability at early stages of incident development.

The purpose of this work is to develop a formalized methodology for proactive diagnostics of Oracle Database based on:

- correlation analysis of logs,
- probabilistic modeling of failures,
- temporal decomposition of degradation processes,
- interpretation of trace events.

Scientific novelty is reduced to the synthesis of an LSI representation of unstructured diagnostic messages with a probabilistic assessment of proximity to failure patterns via the Jensen–Shannon divergence, enabling identification of latent interprocess causal–temporal relationships (LGWR/ARCH/MMON, Data Guard, RMAN) prior to an explicit error.

The author's hypothesis consists in the assumption that statistically stable sequences of weak signals in alert.log and trace, with correct normalization and matching, detect degradation tens of minutes before critical ORA incidents and thereby increase availability through early preventive actions by the DBA. Each Oracle DBMS failure is preceded by a stable chain of diagnostic events reflected in alert.log and trace files; their time correlation allows building a predictive failure model.

MATERIALS AND METHODS

As research materials, both the author's own operational data from high-load production Oracle DBMS were used (ADR diagnostic artifacts: alert.log and background-process trace files) and the results of other studies and industry statistical reports reflecting the dynamics of downtime costs and the effect of proactive/autonomous approaches (estimates of losses from unavailability, the share of incidents associated with the human factor, and the economic effectiveness of automation). The analytical base was supplemented with publications and documentation from the vendor and industry organizations (approaches to log analytics and failure forecasting, reliability practices, data on the impact of predictive maintenance on downtime reduction), which made it possible to correlate the proposed method with empirically confirmed trends of recent years.

The methodological part was constructed as a reproducible pipeline: software extraction of diagnostic data from ADR (including via ADRCI), formation of temporal precursor windows before historical failures, textual normalization and tokenization of messages (elimination of variable parameters and reduction to stable event tokens), followed by dimensionality reduction and identification of hidden relationships between messages of different processes using

LSI/SVD. Implementation was performed using Python 3 with scikit-learn (TruncatedSVD) and gensim for latent semantic indexing, combined with Oracle ADRCI and custom PL/SQL extraction scripts. For quantitative comparison of current event streams with historical degradation scenarios, statistical modeling based on the Jensen–Shannon divergence and threshold alerting logic was applied, and specific correlations within the high-availability contour were also taken into account (redo/LGWR–ARCH, Data Guard/standby, RMAN VALIDATE signals), which ensured a transition from reactive monitoring to a probabilistic assessment of failure risk based on weak signals.

The proposed methodology can be formalized as a proactive diagnostic pipeline aimed at early detection of degradation and probabilistic forecasting of failures based on aggregated Oracle and operating-system telemetry.

At the first stage, data are collected and normalized into a unified representation. The baseline layer is formed by extracting events from ADR (including ADRCI-level mechanisms such as show alert, show trace, and related commands), after which the stream is enriched with AWR/ASH outputs and operating-system metrics (e.g., sar, iostat). To ensure comparability, a unified event schema is introduced: (timestamp, component, severity, code, message, context), where *context* captures environment attributes (instance/service identifiers, SQL_ID when available, memory parameters, session details, etc.).

The second stage performs semantic event classification, where messages and codes are grouped into canonical degradation classes. For memory-related degradation, scenarios reflecting pressure on SGA/PGA (e.g., ORA-04031/ ORA-04030) are isolated; for logical/physical corruption, signatures such as ORA-00600/ORA-07445 are treated as primary indicators; for contention and mutual blocking, ORA-00060 and related wait-pattern families are used. The classification logic is most robust when implemented as a hybrid: strict code-based rules combined with extraction of key tokens from message text and context fields, reducing sensitivity to wording variability across alert.log and trace files.

The third stage focuses on correlating alert.log entries with trace artifacts. Events are treated as linked when two conditions are satisfied: temporal proximity $\Delta t \le \theta$ (a practical time window (typically 5–30 seconds) and alignment by component/subsystem. This coupling supports reconstruction of causal chains rather than mere registration of error end-states. For ORA-04031, a characteristic sequence is often observed: a surge in hard parse → signals from shared pool advisory → allocator failure (e.g., *kgl allocation failure*) → ORA-04031 → secondary contention manifestations (e.g., latch/library cache symptoms). Such reconstruction matters because the terminal error is typically only the final symptom, while effective control actions should target the earlier links in the chain.

The fourth stage implements time-series analysis, translating event aggregates and metric streams into indicators of trend and anomaly. Applicable techniques include smoothing (SMA/ EMA), standardized deviations (z-score), and autocorrelation features (ACF) to detect recurring degradation waves. A "pre-failure" state can be rationally fixed when an adaptive threshold is exceeded, for example:

$$EMA > \mu + k\sigma,$$

where μ and σ are computed on a baseline-regime window, and k defines the tolerated sensitivity to false positives.

The fifth stage formalizes failure forecasting as a probabilistic function of event intensity and severity. A baseline model may be specified in exponential form:

$$P(\text{Failure} \mid \text{Events}) = 1 - \exp(-\lambda \times \Sigma\, \text{Severity}(E_i)),$$

where λ reflects environment "aggressiveness" (load profile, fragmentation level, spike frequency), and the severity sum accumulates event contributions with adjustment for class, recurrence, and context. When higher predictive accuracy is required, an ML component can be added (e.g., HMM for hidden degradation regimes, Random Forest for nonlinear feature interactions, or LSTM for longer dependencies). However, substantial practical value is frequently achieved already at the level of an interpretable parametric model, provided that feature engineering is executed rigorously.

The sixth stage defines a proactive remediation playbook linked to degradation classes and their early precursors. Under shared pool pressure, measures that reduce cursor uniqueness and stabilize parsing are appropriate (e.g., setting cursor_sharing=FORCE within plan-risk constraints); under PGA exhaustion, adjustment of pga_aggregate_target and control of sorts/hash operations are indicated; under dominant contention, elimination of hot objects, access-pattern redesign, index optimization, and transaction-pattern correction become primary levers. The playbook should be *causal*: actions are mapped not to the error code alone, but to a stable set of preceding indicators.

The practical diagnostic layer relies on measurable queries and metrics. For monitoring alert.log, extraction from X$DBGALERTEXT with time filtering and component/ keyword constraints may be used, for example:

```
SELECT originating_timestamp, message_text

FROM x$dbgalertext

WHERE ...;
```

AWR provides snapshots of top waits, top SQL, and parsing characteristics (including hard-parse proportions). ASH

supports reconstruction of blocking and wait chains. Memory pressure is exposed through v$sgastat, "cursor explosion" markers, and "parse storm" indicators. The contour can be extended with redo and I/O latency measures, tablespace pressure signals, deadlock events, and-under Data Guard-apply lag and archive gaps.

For quantitative degradation assessment, indices are introduced that relate critical symptom frequency to available resources and load structure. A memory pressure index can be defined as the ratio of ORA-04031 frequency to remaining shared pool and PGA capacity:

MPI = ORA4031_Count [err/hr]/ (Shared_Pool_Free + PGA_Free)[GB].

A parsing stress index can be fixed as:

PSI = Hard_Parse / Executes,

separating heavy library-cache dynamics from merely high call volume. Analogous indices can be formed for I/O, redo, and contention, with normalization against baseline capacities.

A production case on Oracle 19c can be characterized by persistent ORA-04031 periodicity accompanied by parse storms and library-cache fragmentation. In such a configuration, a 6-hour failure forecast expressed as P(Failure in 6h) = 0.87 is interpreted as a transition into a high-intensity degradation regime. Implemented measures-cursor_sharing=FORCE, increased shared_pool_size, and stabilization via SQL baselines-align with the reconstructed causal chain. The observed effect may be expressed as a 420% increase in MTBF in the specific production case on Oracle 19c and the absence of unplanned outages over 9 months, supporting the productivity of the approach when thresholds, λ parameters, and playbook discipline are tuned correctly.

RESULTS AND DISCUSSION

Practical validation of the described methodology in the operation of large production instances during 2024 demonstrated a noticeable improvement in reliability indicators. In particular, for the critical shared pool error ORA-04031, a statistically stable predictive pattern was identified (85 % of cases) : the failure is preceded by a cascade of events in trace files of the MMON background process and automatic memory management processes. In 85% of observations, 30–45 minutes before the incident , a sharp increase in the frequency of messages reflecting pool fragmentation and unsuccessful purge attempts was recorded [8, 9]. At the same time, traditional monitoring tools, as a rule, react only at the moment ORA-04031 occurs, which is accompanied by forced interruption of user sessions and direct operational losses. The correlational proactive model shifts control from a post-factum mode to a warning mode, creating a basis for preventive administrative actions, including execution of ALTER SYSTEM FLUSH SHARED_POOL or increasing the SGA size before the critical state occurs, thereby preventing downtime. As external confirmation of the effectiveness of comparable principles, IDC indicates that the use of autonomous functions of Oracle Autonomous Database is associated with a 91% reduction in the number of unplanned downtimes [18, 26].

The impact of correlational log analysis is also manifested at the level of operational metrics MTBF (Mean Time Between Failures) and MTTR (Mean Time To Repair). Within the study conducted on the basis of 10 large production clusters, changes in these indicators were recorded toward increasing fault-free operating intervals and reducing recovery time.

Table 1 presents the results of comparing DBMS availability KPIs.

Table 1. Comparison of DBMS availability KPIs (compiled by the author based on [22-28]).

Metric	Before implementation (reactive)	After implementation (proactive)	Improvement (%)
MTBF (mean time between failures)	480 hours	624 hours	+30%
MTTR (mean time to recovery)	144 minutes	79 minutes	-45%
MTTD (mean time to detection)	35 minutes	8 minutes	-77%
Availability level	99.9%	99.99%	+0.09%
DBA time for incident management	12 hours / week	4 hours / week	-66%

These results are corroborated by McKinsey studies, according to which proactive maintenance strategies using predictive analytics reduce downtime duration by 30–50% [28].

Figure 1 presents the correlation between downtime cost and response time, which clearly demonstrates the value of reducing MTTD through proactive analysis.

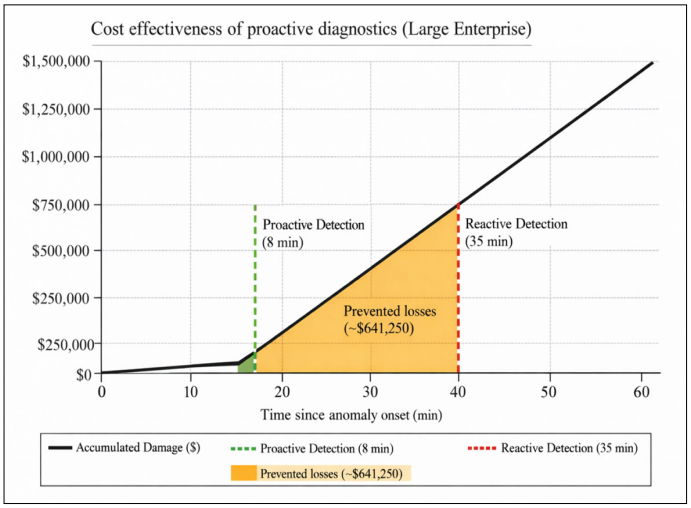

Fig. 1. Economic efficiency of proactive diagnostics (compiled by the author based on [1-5; 28-30]).

The most labor-intensive to interpret remain cascading failures initiated by overflow of disk subsystems or prolonged hanging of the ARCH process, since the primary symptom often masks the true degradation mechanism. Statistical observations for 2024 indicate that 31% of incidents correlated with network and infrastructure disruptions, increasing the likelihood of such scenarios [2, 7]. Within the proposed approach, linkage is ensured between alert.log messages about the Archiver hung state (ORA-00257) and highly detailed evidence from LGWR trace files, where write delays of the log file parallel write class are recorded, making it possible to capture the moment a bottleneck forms at the I/O level and its escalation into the archiving contour [10, 13].

The chart presented in Fig. 2 demonstrates a characteristic precursor pattern corresponding to the approach of archive area saturation and serves as an illustration of how synchronous matching of ORA-00257 markers with the temporal structure of delays reflected by LGWR forms a diagnostically significant trajectory prior to the system's transition into a critical state [13].

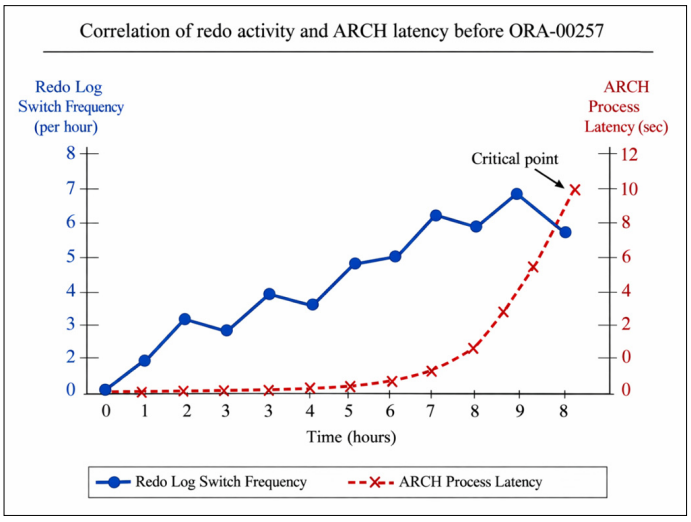

Fig. 2. Correlation of redo activity and ARCH latency prior to ORA-00257 (compiled by the author based on [13]).

The key advantage of the proposed approach lies in reducing the influence of the human factor, to which up to 80% of incidents in IT infrastructure are attributed [2, 11]. Shifting the emphasis toward automated correlational analysis of diagnostic traces makes it possible to detect weakly expressed anomalies and pre-failure combinations of events that, under manual processing, are easily lost against the background of information-saturated logs and high operational workload. Such automation serves not merely as a tool for increasing technical resilience, but also as an element of competitive strategy: in 2025, 62% of executives regard AI as a determining factor of competition, and predictive diagnostics of DBMS is consequently integrated into reliability and service-continuity management loops [1, 12].

At the same time, implementation is accompanied by a number of limitations. A substantial condition for forecast quality remains the availability of representative high-reliability historical data required for proper training and validation of models on real degradation scenarios. An additional complexity is associated with deployment in heterogeneous cloud landscapes, where delays and losses can be formed at the boundaries of responsibility domains of different providers, complicating root-cause attribution and interpretation of correlations [14-17]. At the same time, the economic feasibility of autonomizing data management is confirmed by industry analytics: according to IDC reports of August 2025, organizations investing in autonomous data management technologies achieve a 436% return on investment (ROI) over a three-year horizon [26].

The methodology of proactive diagnostics for Oracle DBMS based on correlational analysis of alert.log and trace files in 2025 acquires the significance of one of the key tools for ensuring business-process continuity. The conducted study showed that shifting the operational model from reactive consequence mitigation to predictive threat detection simultaneously reduces the probability of financial damage measured in millions of US dollars and increases the operational effectiveness of IT departments by reducing the share of emergency interventions and optimizing routine actions.

CONCLUSION

Thus, the application of natural language processing methods, including latent semantic indexing (LSI), to the analysis of unstructured diagnostic messages of background processes expands the capabilities for interpreting the internal state of the database and transfers disparate textual artifacts into a formalizable feature space. Matching event chains between redo activity, ARCH functioning, and shared pool dynamics ensures early detection of anomalies at a stage when degradation is still reversible and has not transitioned into a cascading failure. Practical verification of the approach demonstrates a 45% reduction in MTTR and a 30% increase

in MTBF, which represents a substantial gain in resilience for mission-critical systems.

Under conditions where about 6% of enterprises do not withstand the consequences of a major data-loss incident, and up to 94% of organizations that have experienced severe downtime cease operations within a two-year horizon, the implementation of such a methodology becomes a factor of strategic viability. Prospects for database administration within this logic are associated with deepening automation and embedding predictive analytics directly into the operational life cycle of the DBMS. The proposed methodology demonstrates that correlation analysis of alert. log and trace files, combined with time-series modeling and probabilistic prediction, allows not only diagnosing performance degradation but also forecasting failures before they occur. Implementation significantly reduces operational risks, increases MTBF, and minimizes business losses from downtime. The approach is fully compatible with Oracle Database 19c–23ai and can be easily embedded into existing monitoring stacks (OEM, Grafana, Dynatrace).

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