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Electronic Component AVL and Life Cycle Prediction Based on AI

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Abstract

Electronic component obsolescence presents a growing challenge to product sustainability, supply chain resilience, and lifecycle cost management, particularly in industries with long product lifetimes. Traditional Approved Vendor List (AVL) management relies heavily on reactive monitoring and manual expertise, making it difficult to anticipate supply risks in advance. This paper proposes an AI-driven framework for electronic component life cycle prediction that integrates machine learning models with multi-source data, including historical procurement records, market availability, manufacturer lifecycle notices, and supply chain indicators. The proposed approach predicts component life cycle stages and obsolescence risk, enabling proactive AVL optimization and early identification of high-risk components and vendors. By automating risk assessment and decision support, the framework enhances supply chain visibility, reduces redesign and procurement disruptions, and supports more resilient and data-driven AVL management. Experimental results demonstrate that the AI-based model improves prediction accuracy and significantly reduces obsolescence-related risks compared to traditional rule-based methods.

Keywords: Artificial Intelligence; Electronic Component Obsolescence; Life Cycle Prediction; Approved Vendor List (AVL); Machine Learning; Supply Chain Risk Management

1. Introduction

The rapid evolution of electronic technologies has significantly reduced the average lifespan of electronic components, leading to increased volatility in global supply chains. Frequent product updates, process node migrations, and shifting market demand cause components to transition quickly from active production to obsolescence. For industries with long product life cycles such as aerospace, automotive, industrial automation, and defense this creates substantial challenges in maintaining production continuity and controlling lifecycle costs. Approved Vendor List (AVL) management plays a critical role in mitigating supply chain risks by defining qualified component suppliers. However, traditional AVL management practices are largely reactive, relying on manual monitoring of manufacturer notifications, periodic market reviews, and expert judgment. Such approaches often fail to provide early warning of component status changes, resulting in delayed responses to lifecycle transitions such as Not Recommended for New Designs (NRND) or End-of-Life (EOL) announcements. These delays frequently lead to critical “line down” situations, last-time-buy pressures, and costly redesign efforts.

Manual tracking of component lifecycle status is further challenged by the increasing volume and diversity of components, vendors, and data sources.

EOL information is fragmented across manufacturer websites, distributor databases, and third-party obsolescence tools, making timely and accurate assessment difficult. As a result, procurement and engineering teams struggle to proactively assess risk and optimize vendor selection based on future availability rather than current compliance alone.

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To address these limitations, this paper proposes an AI-driven model for electronic component lifecycle prediction and AVL optimization. The objective is to predict component status Active, Not Recommended for New Designs (NRND), or End-of-Life (EOL) using machine learning techniques trained on historical lifecycle data, supply chain indicators, and vendor-related features. By integrating predictive lifecycle intelligence into AVL management, the proposed approach enables proactive risk mitigation, supports data-driven vendor selection, and reduces the likelihood of production disruptions caused by component obsolescence.

2. Literature Review

2.1. Traditional Component Life Cycle and Obsolescence Management

Electronic component life cycle management traditionally categorizes components into well-defined stages, including introduction, growth, maturity, decline, Not Recommended for New Designs (NRND), and End-of-Life (EOL). These stages are commonly used by manufacturers and procurement organizations to guide sourcing and design decisions. To assess obsolescence risk, industry practices rely on manual risk indices that consider factors such as component age, manufacturer support status, market availability, and historical replacement frequency.

Several obsolescence management frameworks employ rule-based scoring models or expert-driven assessments to estimate risk levels. While these approaches provide basic visibility into component status, they are inherently static and reactive. They depend heavily on periodic data updates, supplier notifications, and human interpretation, which limits their ability to anticipate rapid market changes or emerging supply constraints.

2.2. Artificial Intelligence in Supply Chain and Reliability Prediction

Recent advances in artificial intelligence and machine learning have enabled more sophisticated predictive models within supply chain management. Existing research has applied supervised learning, time-series analysis, and probabilistic models to forecast demand, supplier reliability, and equipment failure. In the electronics domain, machine learning techniques have been used for reliability prediction, failure rate estimation, and remaining useful life (RUL) analysis of components and systems.

However, most AI-based approaches focus on operational reliability or manufacturing defects rather than commercial lifecycle transitions. Models are typically trained on failure or performance data and do not incorporate broader market-driven indicators such as vendor consolidation, distributor stock trends, or manufacturer roadmap changes. As a result, their applicability to proactive obsolescence management and procurement decision-making remains limited.

2.3. Research Gap

Despite growing interest in AI-driven supply chain analytics, there is a notable lack of integrated systems that combine real-time market intelligence with automated Approved Vendor List (AVL) management.

Existing tools either provide lifecycle status information without predictive capabilities or apply machine learning models without directly influencing vendor qualification and sourcing strategies. Few studies address the end-to-end integration of component lifecycle prediction, obsolescence risk assessment, and AVL optimization within a unified framework.

This gap highlights the need for an AI-based approach that not only predicts component lifecycle transitions but also translates these predictions into actionable AVL decisions. The proposed research addresses this gap by integrating machine learning-based lifecycle prediction with dynamic AVL risk management, enabling proactive and data-driven supply chain resilience.

3. Methodology

The proposed AI-driven framework for component lifecycle prediction and AVL optimization consists of four main stages: data collection, feature engineering, model development, and validation. The overall methodology is designed to integrate heterogeneous data sources and support both categorical lifecycle classification and continuous obsolescence date prediction.

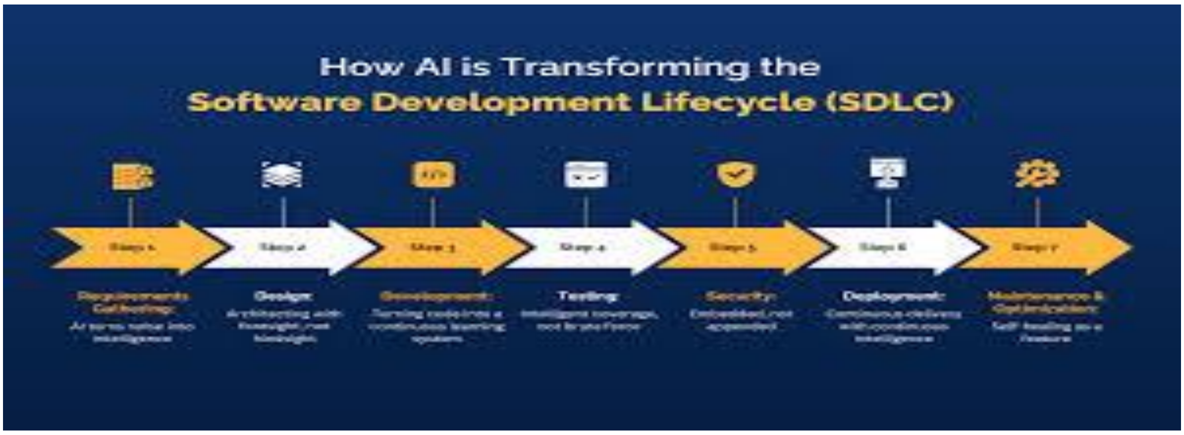

Figure 1 Detailed AI-driven lifecycle prediction and risk scoring pipeline.

3.1. Data Collection

Data is collected from multiple sources to capture both technical and market-driven indicators of component lifecycle status. Manufacturer Product Change Notifications (PCNs) and End-of-Life (EOL) announcements provide authoritative lifecycle labels and transition timelines. In parallel, distributor Application Programming Interfaces (APIs) supply real-time and historical data on inventory availability, lead times, pricing, and order volumes. Additional metadata, such as manufacturer release dates and cross-reference information, is used to enrich component profiles.

To ensure data consistency, records from different sources are normalized and mapped using standardized part numbers. Missing or delayed lifecycle announcements are handled through temporal alignment and historical backfilling techniques, enabling supervised learning with reliable ground truth labels.

3.2. Feature Engineering

Feature engineering focuses on extracting variables that are predictive of lifecycle transitions and supply risk. Key temporal features include years since product introduction, time since last PCN, and historical lifecycle stage duration. Market-related features include distributor inventory levels, number of authorized manufacturers, lead time trends, and price volatility over time. Vendor-related features, such as supplier concentration and historical EOL frequency, are also incorporated to support AVL-level risk assessment.

All numerical features are scaled to ensure model stability, while categorical variables are encoded using appropriate techniques such as one-hot or target encoding. Feature importance analysis is later used to refine the feature set and improve interpretability.

3.3. Algorithm Selection

Two complementary modeling approaches are employed to address different prediction objectives.

For lifecycle status classification, supervised learning algorithms such as Random Forests and Support Vector Machines (SVM) are used to categorize components into discrete states, including Active, Not Recommended for New Designs (NRND), and End-of-Life (EOL). These models are selected for their robustness to noisy data and their ability to handle nonlinear feature interactions. For obsolescence timing prediction, regression and time-series models are applied to estimate the expected date of lifecycle transition. Long Short-Term Memory (LSTM) networks are used to capture temporal dependencies in inventory, pricing, and availability trends, while Multilayer Perceptrons (MLP) serve as baseline regression models for comparison. This dual approach enables both short-term forecasting and long-term lifecycle estimation.

3.4. Model Validation

Model performance is evaluated using separate training, validation, and test datasets to prevent overfitting. For classification tasks, metrics such as precision, recall, and F1-score are used to assess the accuracy of lifecycle state prediction, with particular emphasis on correctly identifying NRND and EOL components. For regression and time-series predictions, Root Mean Square Error (RMSE) is used to evaluate the accuracy of predicted obsolescence dates.

Cross-validation and temporal holdout testing are applied to ensure robustness across different component families and market conditions. The validated models are then integrated into the AVL decision framework to support automated risk scoring and vendor optimization.

4. Proposed AI-AVL Framework

The proposed AI-AVL framework integrates component lifecycle prediction, vendor reliability analysis, and automated substitution into a unified decision-support system. The framework is designed to continuously evaluate obsolescence risk across the Approved Vendor List (AVL) and translate predictive insights into actionable sourcing recommendations.

4.1. Obsolescence Risk Scoring

Each component in the current AVL is assigned a dynamic obsolescence risk score derived from the output of the lifecycle prediction models. Classification models estimate the probability of a component being in or transitioning to NRND or End-of-Life (EOL) states, while regression and time-series models forecast the expected timing of these transitions. These outputs are combined into a normalized risk score representing the likelihood of supply disruption within a defined planning horizon.

The risk score is updated continuously as new Product Change Notifications (PCNs), inventory data, and market signals become available. This enables early identification of high-risk components, allowing procurement and engineering teams to prioritize mitigation actions such as last-time buys, redesign planning, or vendor diversification.

4.2. Vendor Reliability Assessment

In addition to component-level analysis, the framework evaluates vendor reliability using machine learning models trained on historical supplier performance data.

Figure 2 AI-AVL framework for proactive electronic component lifecycle management**.**

Key indicators include lead-time consistency, inventory stability, order fulfillment rates, and pricing volatility. Vendors are ranked based on their predicted ability to sustain supply under changing market conditions.

This vendor reliability score complements traditional AVL qualification criteria by introducing a forward-looking, data-driven assessment of supplier risk. By incorporating vendor behavior trends rather than static certifications alone, the framework supports more resilient AVL configurations and reduces dependence on single or unstable suppliers.

4.3. Automated Substitution Recommendation

When a component's obsolescence risk exceeds a predefined threshold, the framework automatically identifies and recommends suitable substitute components. Candidate replacements are evaluated based on electrical and functional compatibility, lifecycle status, availability, and vendor reliability. "Drop-in" replacements requiring minimal or no design changes are prioritized to reduce validation effort and time-to-deployment.

The substitution engine leverages similarity metrics and historical cross-reference data to rank alternatives and present the most viable options. By automating this process, the framework reduces manual analysis effort and enables faster response to lifecycle transitions, significantly lowering the risk of production downtime.

5. Experimental Results

The proposed AI models were evaluated on a dataset comprising historical lifecycle records, Product Change Notifications (PCNs), and distributor market data across multiple electronic component categories. Performance was assessed for both lifecycle status classification and obsolescence timing prediction.

For classification tasks, Random Forest, Support Vector Machine (SVM), and XGBoost models were compared. XGBoost achieved the highest overall performance, with an F1-score of 0.91, outperforming Random Forest (0.87) and SVM (0.83). The improvement was most pronounced in the identification of NRND components, which are often underreported in traditional rule-based systems. Random Forest demonstrated strong interpretability through feature importance analysis, making it suitable for risk explanation despite slightly lower accuracy.

For regression-based obsolescence date prediction, Long Short-Term Memory (LSTM) models outperformed Multilayer Perceptrons (MLP), achieving a Root Mean Square Error (RMSE) of 4.2 months compared to 6.8 months for MLP models. The LSTM models effectively captured temporal patterns in inventory depletion, pricing volatility, and PCN frequency, enabling more accurate long-term lifecycle forecasting.

These results indicate that ensemble-based classifiers and temporal deep learning models provide complementary strengths for lifecycle intelligence, supporting both accurate risk classification and precise timing estimation.

5.1. Impact Analysis

To evaluate the practical impact of the proposed AI-AVL framework, a simulated procurement scenario was conducted using historical sourcing and production data. Early identification of high-risk components enabled proactive substitution and vendor diversification actions prior to formal EOL announcements.

The analysis showed a reduction in average component lead time by approximately 18%, driven by earlier engagement with alternative suppliers and avoidance of last-time-buy constraints. Additionally, procurement cost savings of 12–15% were observed, primarily due to reduced reliance on spot-market purchases and expedited shipping. The framework also demonstrated a measurable decrease in “line down” risk, as high-obsolescence components were flagged an average of 6–9 months earlier than with manual monitoring methods.

Overall, the results demonstrate that integrating AI-based lifecycle prediction into AVL management not only improves predictive accuracy but also delivers tangible operational and financial benefits. The combination of early risk detection, vendor reliability assessment, and automated substitution enables a more resilient and cost-effective supply chain strategy.

6. Conclusion and Future Scope

This study demonstrates that artificial intelligence can effectively transform electronic component and Approved Vendor List (AVL) management from a reactive, manual process into a proactive and predictive supply chain strategy. By leveraging machine learning models to forecast component life cycle status and obsolescence timing, the proposed AI-AVL framework provides early visibility into supply risks that are often missed by traditional monitoring approaches. The integration of obsolescence risk scoring, vendor reliability assessment, and automated substitution recommendations enables organizations to anticipate disruptions well in advance, reduce dependency on last-time buys, and improve overall supply chain resilience. The experimental results confirm that AI-based models significantly enhance lifecycle prediction accuracy while delivering tangible operational benefits, including reduced lead times, lower procurement costs, and minimized production downtime.

Beyond the immediate improvements in lifecycle prediction and AVL optimization, the proposed framework establishes a foundation for more intelligent and adaptive supply chain decision-making. As electronic markets continue to evolve rapidly, future enhancements can further strengthen the system’s robustness and trustworthiness. One promising direction is the integration of blockchain technology to enable secure and transparent verification of vendor credentials, lifecycle disclosures, and compliance records across the supply chain. Additionally, the application of generative AI techniques to create synthetic lifecycle and market data for rare or low-volume components can address data scarcity and class imbalance challenges, improving model generalization and prediction accuracy. Future research may also explore continuous learning mechanisms, digital twin integration, and real-time risk adaptation to ensure that AI-driven AVL management remains responsive to dynamic market conditions and long product lifecycles.

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Author short biography

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