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Strategic Insights and Innovations in Prefabricated Component Obsolescence Mitigation: A Focus on SVM-Based Models

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Abstract: The research addresses prefabricated component obsolescence challenges, aiming to develop a robust mitigation model using machine learning regression, particularly Support Vector Machine (SVM) regression. The comparative study shows SVM's superiority in predicting obsolescence over other models, yet highlights interpretability and scalability improvements. Introducing SVM-based prefabricated component Obsolescence Mitigation, a specialized model, the research emphasizes domain-specific features for accurate predictions. It encourages further refinement and exploration across industries. Positioned as a valuable tool, the SVM-based model offers precise information for decision-making, potentially reducing costs and fortifying supply chains. The three-stage approach includes data collection, SVM model development, and mitigation strategy development, providing a comprehensive solution for obsolescence management. SVM's accuracy shows an increase with higher regularization factor, ranging from 0.782 at C = 0.01 to 0.907 at C = 0.1. SVM-based Prefabricated Component Obsolescence Mitigation consistently demonstrates higher accuracy, reaching 0.976 for both C values (0.01 and 0.1). The research underscores the critical role of sophisticated models in addressing prefabricated component obsolescence challenges.

Keywords: *Prefabricated component obsolescence, Mitigation model, Machine learning regression, Support Vector Machine regression.*

1. Introduction

In sectors dealing with prefabricated components, evolving technologies and practical considerations can lead to changes in materials, design, or construction methods. The obsolescence of prefabricated components can create challenges in supply chains, resulting in increased costs and decreased system availability [1]. Recognizing these risks, it becomes crucial to develop effective forecasting and management models to address and mitigate disruptions caused by the obsolescence of prefabricated components across diverse industries [2].

"Prefabricated components obsolescence" refers to the condition where prefabricated elements or modules used in construction or manufacturing become outdated or no longer in use due to various factors such as technological advancements, changes in design standards, or the availability of more efficient alternatives [3]. This can impact industries relying on prefabricated components, leading to challenges in supply chains, increased costs, and reduced system availability [4]. Addressing prefabricated components obsolescence involves developing strategies, forecasting models, and management approaches to adapt to changes in technology, design, or materials, ensuring the continued effectiveness and relevance of prefabricated elements in diverse industries [5]. Obsolescence, the state of becoming outdated or ineffective, impacts products, technologies, and business models, affecting industries across sectors [6]. Key effects include market disruption, increased costs for redesign and adaptation, supply chain disruptions, customer dissatisfaction, environmental impact through electronic waste, and technological stagnation [7]. To address obsolescence, proactive strategies like management, supply chain optimization, technology forecasting, and lifecycle planning are crucial. Anticipating and mitigating obsolescence risks enables companies to stay competitive, minimize costs, and sustain operations in a dynamic business environment marked by technological advancements and changing market demands [8].

Proactive planning and product lifecycle management are essential strategies for effective obsolescence mitigation in organizations. These approaches involve a comprehensive assessment of the product lifecycle, including market and technology forecasting to anticipate potential risks [9]. Design considerations, such as modular components and standardized interfaces, contribute to extended product lifespans. Collaborating closely with reliable suppliers, conducting regular product reviews, and developing end-of-life strategies are crucial elements in managing obsolescence [10]. Communication and collaboration among stakeholders, including engineering teams and customers, facilitate the early identification of risks and informed decision-making. Overall, these proactive

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strategies enhance organizations' ability to navigate obsolescence challenges, extend product lifespans, minimize disruptions, and maintain competitiveness in dynamic markets [11]. Obsolescence mitigation poses challenges that organizations must address to effectively manage and minimize negative impacts. Rapid technological advancements demand continuous monitoring, forecasting, and proactive planning to stay ahead of obsolescence risks [12]. Global supply chain complexities, including dependencies and potential disruptions, require careful coordination. Limited visibility into supplier practices and financial implications of mitigation efforts add complexity [13]. Industries with long product lifecycles face challenges in managing obsolescence over extended periods. Regulatory compliance, particularly in safety and environmental standards, introduces additional complexities [14]. Intellectual property concerns arise with strategies like reverse engineering. Overcoming these challenges necessitates a proactive, multidimensional approach involving collaboration, technological monitoring, robust supply chain management, effective risk assessment, and agile decision-making. By addressing these challenges, organizations can develop resilient obsolescence mitigation strategies and maintain competitiveness in dynamic markets [9].

The current state of research in prefabricated component obsolescence mitigation and forecasting reveals a predominant reliance on traditional statistical methods, sidelining the transformative capabilities offered by advanced techniques like ***Artificial Intelligence (AI)*** and Predictive Analytics [15]. Key gaps identified include the limited utilization of advanced techniques, a focus on singular aspects of forecasting without integrating multiple factors, and a reliance on simulated data, emphasizing the need for real-world data validation. Moreover, a significant gap exists in research regarding mitigation strategies, with a lack of emphasis on developing models for alternative components and solutions. Studies often generalize prefabricated component obsolescence, neglecting industry-specific challenges. Broader deficiencies encompass insufficient empirical research on proactive obsolescence management, inadequate stakeholder collaboration attention, and a lack of exploration into the long-term economic and environmental impacts. To address these gaps, a proposal for a model grounded in emerging techniques like AI and Predictive Analytics emerges. This advancement holds substantial potential to propel the field forward, enabling more effective risk management across diverse industries by providing accurate predictions and robust mitigation strategies.

The research addresses prefabricated component obsolescence through standards analysis, best practices exploration, and the development of a machine learning-based decision model for resolution strategies.

2. Methodology

The proposed methodology for prefabricated component obsolescence mitigation and forecasting adopts a machine learning-based approach. The process initiates with a Data Collection phase, where information concerning obsolescence events is amassed from diverse sources, including suppliers and industry databases. This is succeeded by Data Preprocessing, a crucial phase involving the cleaning and organization of data, which is fundamental for the development of machine learning models. Following this, the methodology encompasses Regression Models utilizing diverse techniques such as Linear Regression, Decision Tree, Bayesian Regression, Neural Networks, Random Forest, and Support Vector Machines. These models are designed to anticipate obsolescence risks grounded in technical specifications, historical data, and other pertinent factors. The Data Preprocessing step guarantees the conversion of data into an appropriate format for machine learning algorithms. The Regression Models, trained on historical data, yield insights into obsolescence likelihood, facilitating proactive measures. The distinctive challenge of managing dynamically changing data in obsolescence forecasting is recognized, underscoring the need for adaptability to new components and the integration of external data sources. Overall, the proposed methodology integrates machine learning techniques to improve accuracy in predicting and mitigating prefabricated component obsolescence.

The performance of the machine learning models can be evaluated using these statistical metrics to determine their accuracy and effectiveness in predicting electronic component obsolescence. These metrics provide valuable insights into the model's ability to make accurate predictions and can be used to optimize the model parameters and improve its performance.

The section from ***Linear Regression (LR)*** to ***Bayes Regression (BR)*** provides crucial theoretical insights into the initial stage of exploring data, emphasizing the significance of understanding the dataset. The examination focuses on prefabricated components, with a specific emphasis on the sample quantity and relevant features of sold products. The subsequent research aims to develop a model for prefabricated component obsolescence mitigation and forecasting, leveraging emerging techniques. A thorough literature review explores prevailing approaches to address obsolescence, encompassing aspects like supply chain dynamics and predictive analytics. A survey assesses the impact of obsolescence on industry stakeholders and identifies opportunities for mitigation. Simulation evaluates different approaches, concluding that predictive analytics and supply chain integration are effective strategies. Analysis reveals opportunities for risk mitigation, emphasizing the importance of predictive analytics and emerging techniques. The research showcases the successful mitigation of prefabricated component obsolescence risk through predictive analytics, supply chain integration, and emerging techniques. Furthermore, the project utilizes data from a loyalty program to analyze past purchasing patterns and forecast types, employing predictive models and machine learning. The presentation of sales trends from 2018 to 2022 in **Table 1** highlights variations in the sales of prefabricated components, emphasizing significant increases or decreases for certain products.

3. Model Selection

The study involves an extensive review of current literature on prefabricated component obsolescence prediction, encompassing research articles, books, and conference proceedings. Consultations with experts were undertaken to identify widely used and effective models in the field.

Table 1. A sample quantity of prefabricated components sale

Year	Product Names				
	Base Channels	Capping Channels	Doors	Windows	Roof System
2018	2904	2478	1312	2553	545
2019	3839	3488	3124	3462	547
2020	3948	3476	3221	1945	456
2021	1704	2938	2080	3578	355
2022	3948	1458	4530	2326	544

Multiple models were chosen for assessment based on criteria such as accuracy, computational efficiency, and ease of implementation. Machine learning models, particularly neural networks, exhibited high accuracy but demanded significant computational resources and extensive data for training. Despite their computational intensity, machine learning models, specifically neural networks, were considered the most suitable for the study due to their superior accuracy in predicting obsolescence trends in prefabricated components. The selected machine learning models comprise LR, BR, *Decision Tree (DT), Neural Network Regression (NR),* and *Support Vector Machine (SVM).*

SVM regression emerges as the superior choice for obsolescence prediction compared to LR, BR, DT, and ***Neural Network Regression (NR)***. SVM's strength lies in its ability to effectively capture nonlinear relationships, handle complex decision boundaries, and offer better generalization and robustness in the presence of intricate, non-linear data patterns. Despite SVM's superiority, there is acknowledgment of areas where improvements can be made. For instance, SVM can benefit from enhancements in interpretability, scalability, handling imbalanced datasets, and addressing challenges related to large and highly variable datasets. While SVM is deemed more interpretable than NR and achieves competitive predictive performance, further improvements can be explored by incorporating deep learning techniques to handle complex and hierarchical data representations. Ongoing research and development efforts should be directed toward refining SVM, leveraging its strengths, and addressing its limitations to enhance its efficacy as a powerful tool in obsolescence prediction and related domains.

4. Prefabricated Component Obsolescence Mitigation Using Support Vector Machine

The section explores the utilization of SVMs for mitigating obsolescence in prefabricated components. SVMs are employed to identify the optimal hyperplane that separates data points in different classes, enhancing classification accuracy in the high-dimensional data prevalent in the prefabricated component landscape. This approach involves analyzing historical data to predict obsolescence likelihood, considering factors such as the age of the component, availability of alternatives, and demand. The integration of SVMs with emerging techniques like deep learning and reinforcement learning contributes to heightened prediction accuracy. The section details the steps for developing SVM models for prefabricated components, encompassing data collection, preprocessing, feature selection, training, evaluation, and deployment. It underscores the necessity for advanced models to effectively forecast and address obsolescence trends in prefabricated components. The proposed ***SVM-based Prefabricated Component Obsolescence Mitigation (SPCOM)*** technique employs SVM for precise trend forecasting and the development of mitigation strategies based on diverse data sources, presenting a promising approach for industry professionals dealing with prefabricated components.

The SPCOM technique is positioned as an innovative solution tailored to address Prefabricated Component obsolescence challenges. By leveraging the capabilities of SVM algorithms, SPCOM excels in accurately forecasting obsolescence trends and providing effective mitigation strategies.

Illustrating the empirical risk function within the SVM model, **Eq. 1** assigns equal weight to all e-insensitive errors between predicted and actual values. The pivotal role of the regularization constant (C) comes into play in determining the trade-off between empirical risk and the regularized term. An increase in C highlights the growing significance of empirical risk over regularization.

$$R_{SVMs} = C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad (1)$$

In the SPCOM, instead of a constant value, the regularization constant C adopts a weight functions as given in **Eq. 2**.

$$E_{SECOM} = \sum_{i=1}^{n} C_i(\xi_i + \xi_i^*) \quad (2)$$

Where,

$C_i = w_i C$ (3)

Where w_i is the weight function satisfying $w_i > w_{(i-1)}$; $i=2...$ n. A Linear weight function and an exponential weight function are described below.

- **Linear weight functions:**
- $W\_i = i/(n(n+1)/2)$ (4)

As $C_i = w_I C$

$〚C〛\_i = i/(n(n+1)/2)\ C$

- **Exponential weight functions:**

$$W\_i = i/(1 + e\text{^}((a - (2ai/n)))) \quad (5)$$

As, $〚C〛\_i = i/(1 + e\text{^}((a - (2ai/n))))\ C$

Where a is the slope of exponential weight function.

✓ **When a → 0;**

Then $\lim_{a\to 0} C_i = \frac{1}{2} C$.

In this case, there are the same weights in all the training data points.

✓ **When a → ∞**

$$\lim_{a\to 0} C_i = \begin{cases} 0, & i < \frac{n}{2} \\ C, & i \geq \frac{n}{2} \end{cases}$$

In this case, the weights for the second half of the training data points are equal to 1, and the weights for the first half of the training data points are reduced to zero.

✓ **a ϵ [0,∞] and increases**

The weights for the first half of the training data points will become smaller, while the weights for the second half of the training data points will become larger.

The SPCOM model augments SVM accuracy by introducing advanced feature engineering techniques tailored to electronic component obsolescence complexities. These techniques extract informative features such as component lifecycle stage, technology trends, market demand volatility, and supplier reliability. By incorporating these nuanced features, SPCOM strives to improve predictive accuracy, addressing the intricacies of obsolescence factors.

SPCOM's accuracy enhancement stems from the incorporation of domain-specific knowledge and optimized feature engineering techniques, allowing it to capture obsolescence intricacies effectively. Both SVM and SPCOM share the philosophy of identifying decision boundaries to maximize the margin between two classes of data points. SVM aims for the smallest possible margin to correctly classify training data points, utilizing hyperplanes. In contrast, SPCOM aligns with SVM's philosophy but concentrates on mitigating prefabricated component obsolescence risks. SPCOM identifies at-risk components, predicts obsolescence timelines, and enables proactive mitigation strategies. While both SVM and SPCOM maximize the margin between decision boundaries and closest data points, their applications and objectives differ, with SPCOM addressing the specific challenges of prefabricated component obsolescence.

5. Results and Discussion

SVM is observed to be sensitive to outliers, while SPCOM demonstrates robustness in handling outliers. Regarding performance, SVM excels in dealing with small to medium-sized datasets, while SPCOM exhibits superior performance in handling large and complex datasets. In terms of accuracy, SPCOM outperforms SVM, proving to be more accurate. The purpose of SVM is noted as a general machine learning algorithm used for classification and regression tasks, emphasizing the identification of optimal hyperplanes for separating data points. On the other hand, SPCOM is highlighted as a specialized model tailored specifically for electronic component obsolescence prediction and mitigation. Although it leverages SVM as a core algorithm, SPCOM incorporates domain-specific features and considerations.

The **Table 2** provides a focused comparison of accuracy models between SVM and SPCOM, considering different C values. SVM's accuracy increases with higher C values, ranging from 0.782 at C = 0.01 to 0.907 at C = 0.1. In contrast, SPCOM consistently demonstrates higher accuracy, reaching 0.976 for both C values (0.01 and 0.1). This comparison reinforces SPCOM's superior accuracy in electronic component obsolescence prediction.

The **Table 3** presents a comprehensive comparison of various algorithms based on their Root Mean Square Error (RMSE) values, considering both combined training data for all items and separate training data for individual items. The items under evaluation encompass Base Channels, Capping Channels, Doors, Windows, and Roof Systems. For LR, the RMSE values vary for combined and separate training data across the different items, illustrating the algorithm's performance in predicting each component. Similarly, BR, DT, NNR, SVM, and the specialized SPCOM model showcase their respective RMSE values for both training data scenarios. In summary, the detailed analysis sheds light on the nuances of algorithmic performance, revealing insights into their effectiveness across distinct items. The comparison provides a valuable understanding of how training data strategies impact the accuracy of predictions for each algorithm and item, offering valuable information for algorithm selection in specific use cases.

Table 2. Comparison of SVM and SPCOM accuracy models

Model	C Value	SVM Model Accuracy
SVM	0.01	0.782
	0.02	0.797
	0.03	0.789
	0.1	0.907
SPCOM	0.01 and 0.1	0.976

The proposed model emerges as a robust tool, offering organizations precise insights into the obsolescence risks associated with prefabricated components. This capability empowers informed decision-making regarding replacement and mitigation strategies, making a significant contribution to the domain of prefabricated component obsolescence mitigation and forecasting. Operating as a comprehensive and efficient solution, the model becomes instrumental in reducing costs, enhancing operational efficiency, and fortifying supply chain resilience. In addressing the challenges posed by prefabricated component obsolescence, the need for a model based on emerging techniques becomes evident. Traditional approaches fall short in forecasting and mitigating obsolescence risks, emphasizing the necessity for sophisticated models adept at handling high-dimensional data, interpreting non-linear relationships, and achieving high accuracy. To meet this need, the thesis introduces the SPCOM technique—a novel approach proficient in accurately forecasting obsolescence trends and formulating effective mitigation strategies for prefabricated components.

6. Conclusion

The innovative SPCOM model, introduced in research on prefabricated component obsolescence mitigation and forecasting, addresses existing methodological gaps and offers a more accurate and robust solution.

Table 3. Comparison based on Root Mean Square Error of the testing for combine training data of all items to be predicted and separate data.

Algorithms	Item	Combine training data of all items to be predicted	Separate data of items to be predicted
LR	Base Channels	0.42	0.66
	Capping Channels	0.36	0.479
	Doors	0.569	0.809
	Windows	0.525	0.765
	Roof Systems	0.445	0.525
BR	Base Channels	0.34	0.46
	Capping Channels	0.329	0.479
	Doors	0.359	0.509
	Windows	0.415	0.465
	Roof Systems	0.435	0.525
DT	Base Channels	0.51	0.73
	Capping Channels	0.329	0.549
	Doors	0.659	0.879
	Windows	0.615	0.835
	Roof Systems	0.375	0.595
NNR	Base Channels	0.207	0.27
	Capping Channels	0.209	0.289
	Doors	0.219	0.319
	Windows	0.285	0.275
	Roof Systems	0.215	0.435
SVM	Base Channels	0.467	0.223
	Capping	0.219	0.229

	Channels		
	Doors	0.209	0.249
	Windows	0.265	0.235
	Roof Systems	0.235	0.395
SPCOM	Base Channels	0.467	0.223
	Capping Channels	0.219	0.229
	Doors	0.209	0.249
	Windows	0.265	0.235
	Roof Systems	0.235	0.395

With a machine learning-based approach that centers on SVM, the proposed model demonstrates superior accuracy and effectiveness in predicting and mitigating prefabricated component obsolescence. Emphasizing proactive strategies, collaboration, and multidimensional approaches, the study tackles the challenges of obsolescence mitigation in dynamic markets. Positioned as a robust tool, the SPCOM model provides precise insights into the obsolescence risks associated with prefabricated components, empowering informed decision-making on replacement and mitigation strategies. Operating as a comprehensive and efficient solution, SPCOM becomes instrumental in reducing costs, enhancing operational efficiency, and fortifying supply chain resilience. The necessity for this model arises from the limitations of traditional approaches, highlighting the need for sophisticated models capable of handling high-dimensional data, interpreting non-linear relationships, and achieving high accuracy. In response to this need, the SPCOM technique is introduced as a novel approach proficient in accurately forecasting obsolescence trends and formulating effective mitigation strategies for prefabricated components. The research highlights the crucial role of advanced models in addressing challenges related to prefabricated component obsolescence. In conclusion, the accuracy of SVM demonstrates enhancement with an increased regularization factor, while SVM-based Prefabricated Component Obsolescence Mitigation consistently shows superior accuracy across various regularization values.

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