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MANAGING BOTTLENECKS IN SYSTEMS WITH PRODUCT RECOVERY

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ABSTRACT

Effectively managing products at the end of their lifecycle is increasingly crucial as numerous systems adopt recovery strategies. However, many are limited to remanufacturing or recycling as the only recovery option. Effectively handling end-of-life products demands diverse approaches, including refurbishing and cannibalization. Sustainable recovery centers and manufacturers encounter challenges linked to uncertainties about the quantity and condition of returned products, which can disrupt operations and lead to bottlenecks. Our solution employs machine learning, specifically a CNN-LSTM model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM), for predicting return product quantity and quality. Additionally, we utilize scenario-based simulations to proactively pre-identify and address bottlenecks within a short timeframe, especially within systems managing multiple recovery options or dealing with complex and hazardous materials.

1 INTRODUCTION

The manufacturing industry's substantial energy consumption, responsible for 35% of electricity use and 20% of global greenhouse gas emissions, necessitates environmentally conscious approaches. Amid the global push for net-zero emissions by 2050, the U.S. government's initiative urges manufacturers to adopt strategies aligning competitiveness with sustainability. Product Recovery Management (PRM) focuses on extracting value from used products and components, a key step toward achieving this target. While various recovery options exist, many companies overlook their potential, often limiting recovery to recycling and remanufacturing. This overlooks the potential for waste reduction and increased profits. Expanding recovery options, particularly for complex or hazardous items, is vital for achieving environmental and economic objectives. Nonetheless, a significant challenge arises from the considerable uncertainty regarding product returns and their conditions. This uncertainty frequently results in problems that can slow down the production flow, known as system bottlenecks. In response, we present a solution that combines machine learning and scenario-based simulations. This approach aims to proactively pre-identify and address uncertainties and bottlenecks in the management of returned products within a short timeframe.

2 BACKGROUND

Despite the extensive research on sales forecasting, there has been a distinct gap in scientific literature addressing the prediction of returned items. Most of the existing research focuses solely on forecasting remanufactured or recycled products, neglecting other recovery possibilities. The dominant approach in these studies involves statistical methods based on historical data, with only limited adoption of machine learning techniques. Furthermore, these studies primarily concentrate on predicting the quantity, quality, or lead time of return items, leaving subsequent operational decisions to decision-makers.

Author (Year)	Approach	Purpose
Krapp et al. (2013)	Bayesian estimation techniques	Predicting product returns in closed-loop supply chains.
Agrawal et al. (2014)	Graphical Evaluation and Review Technique (GERT)	Forecasting product returns for recycling in terms of quantity and time.
Canda et al. (2015)	Holt's and ARIMA	Forecasting product returns in remanufacturing industry.

3 METHODOLOGY

Our approach goes beyond simply predicting return product quantities. In addition, we also anticipate the distribution or proportion of potential recovery methods each product might need. This involves estimating the percentage of returned products expected to undergo remanufacturing, refurbishing, or other recovery processes. Considering the inherent uncertainty in predicting behaviors such as returns; machine learning models should be viewed as valuable decision-support tools. We employ a CNN-LSTM model for our predictions. In contrast to typical forecasts that focus on single-time customer choices, like purchase decisions, returns are influenced by a sequence of interconnected events such as sales data and product lifespan. Consequently, we investigate additional variables that contribute to return product quantities. By employing feature selection, we amplify the dependability and precision of our predictions. Alongside our primary model, we employ benchmark methods for comparison. Beyond overall return quantities, our aim is to predict the proportions of recovery options. To pre-identify and tackle potential bottlenecks, we use our return product predictions and their expected recovery needs as input data to simulate the system. Using simulation software tools such as SIMIO or ARENA, we identify probable bottlenecks within the system and design scenarios to alleviate them. These scenarios encompass adjustments such as Manufacturing Layout Modification, Resource Consolidation, and Capacity Enhancement, all aimed at developing efficient strategies. We employ Pareto analysis to evaluate simulation results across scenarios.

4 APPLICATION

While flexible across systems, this approach is especially beneficial for companies handling complex or hazardous items necessitating specialized recovery. Significantly, it holds particular relevance in cases such as the return of electric vehicle (EV) batteries, involving factors like resource constraints, modular battery structures, and potential resale value. Unlike conventional manufacturing, the primary challenge in product recovery is the unpredictability of return product supply. Our approach benefits external recovery centers and manufacturing systems directly managing returns.

5 EXPECTED RESULTS AND OUTLOOK

The initial examination and outcomes indicate that the suggested approach serves as a beneficial machine learning technique for predicting product returns, surpassing alternative techniques. We anticipate demonstrating that, firstly, the proposed method effectively anticipates the overall quantity of returned products and appropriately allocates them to their respective recovery categories with an acceptable level of accuracy. Additionally, the primary findings from the proposed scenarios underscore their ability to proactively mitigate potential bottlenecks before they happen, leading to potential cost savings and enabling decision-makers to enhance operational choices.

REFERENCES

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