# Disassembly Waste Generation

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Disassembly waste generation forecasting is the foundation for determining disassembly waste treatment and process formulation and is also an important prerequisite for optimizing waste management. The prediction of disassembly waste generation is a complex process which is affected by potential time, environment, and economy characteristic variables. Uncertainty features, such as disassembly amount, disassembly component status, and workshop scheduling, play an important role in predicting the fluctuation of disassembly waste generation. We therefore focus on revealing the trend of waste generation in disassembly remanufacturing that faces significant influences of technology and economic changes to achieve circular industry sustainable development.

Keywords: disassembly ; DG-HMM ; waste forecasting ; digital twinning ; optimization ; real-time interaction

## 1. Introduction

With the shortening of product life cycle and the acceleration of product upgrade, the rapid growth of obsolete products will put tremendous pressure on the ecological environment and human health [1][2]. The development of environmental awareness and the circular economy has forced manufacturers to increasingly consider the importance of environment protection in the production process [3]. Effective treatment of disassembly waste has become an important factor in the industrial circular economy and sustainable industrial development [4]. Disassembly waste is the useless solid, semi-solid and oil–water mixture produced in dismantling activities, including rust and nonferrous metals (cadmium, chromium, mercury, etc.), batteries, plastics, and various working fluids (lubricants, engine oil, etc.) [5]. Random dumping or improper disposal of disassembly waste can seriously endanger human health and even cause damage to the ecological environment. The prediction of disassembly waste generation is a complex process, which is affected by many factors, including rapid product upgrades, new technological innovations, machine usage conditions, component damage, and storage time. These influential factors in waste generation and their uncertainties are difficult to quantify [6]. Therefore, how to predict the generation of dismantling waste in an uncertain environment has become full of challenges. On this basis, in order to promote the sustainable development of resources, the ecosystem, and the environment [7][8], it is of great significance to study disassembly waste in the industrial system.

The existing approaches for waste generation forecasting are classified into four main categories: traditional statistical models [9][10], the gray and fuzzy models [11], simulation models [12], and nonprobabilistic statistical learning models [13]. In terms of traditional statistical models, Karpušenkaitė [14], Box [15], Giannouli [16], Chen [17], Althaf [18], and others have studied the time series prediction of uni-variate models involving environmental applications. Denafas [19] applied the municipal waste composition data to a time series prediction model, which can quantitatively estimate seasonally changing waste generation. Unlike deterministic models, stochastic models and probabilistic model-driven statistical methods have been widely used to predict waste generation under uncertain conditions [20][21], for example, by Peeters [22], Karpušenkaitė [23], Abdoli [24], and Kannangara [25]. However, the uncertainties about input data and predicted recovery potential are often overlooked. Gray and fuzzy theories can solve the problem of uncertainty [26], and a reliable model output can be obtained even with poor data. Chauhan [27] integrated interpretive structure modeling, a fuzzy analytic hierarchy process, and fuzzy technology to predict medical waste with order preference. Noori [28] combined a wavelet transform fuzzy system and a wavelet transform artificial neural network to predict solid waste generation. At the same time, with the increasing requirements for green sustainable development and cleaner production management technology [29][30], in terms of the current research situation, Tsai [31], Roubík [32], and Ahamed [33] have conducted extensive research on waste resource reuse, environmental climate change, and waste system management. Bai [34] presented an overview of the current solid waste management situation in Singapore and provided a brief discussion of the future challenges.

## 2. A Real-Time Dynamic Probability Model

We proposes a real-time dynamic probability model to predict the amount of disassembly waste generation under uncertainty. We integrate digital twinning, Gaussian mixture, and a hidden Markov model for dynamic prediction of disassembly waste generation. The prediction results show that, in terms of MAE, MSE, $R^2$ and $\bar{R}^2$, the performance of the DG-HMM method is better than that of HMM, ARIMA, ES, ANN and SVM. Based on the MSE skill score, the accuracy of the point prediction obtained by DG-HMM is verified. The unified PIT diagram proves the reliability of DG-HMM. The training results of the example data set show that DG-HMM can effectively solve the problem of predicting disassembly waste generation. Through the model, the prediction will be able to eliminate the uncertainty in disassembly waste generation yield, which allows for more efficient disassembly planning decision making. The DG-HMM model expands the application scope and depth of the traditional input–output method to a certain extent. However, the proposed model is a uniform hidden Markov model, and the waste generation process of the production system is a complex giant system with a huge amount of nonuniform data. Future research on prediction can use virtual simulations and verified methods such as regression analysis, neural networks, or machine learning [35].

With the promotion and application of digital technology, digital management of industrial production and big data simulation will be the future trend [36]. The implementation of clean production and green economy development strategy on technological upgrading will have a significant impact on waste management. Furthermore, the dynamic prediction model here can provide a useful reference for relevant personnel to predict the generation of disassembly waste. Therefore, combining these findings of DG-HMM with real-time disassembly waste generation situations, three policy suggestions are provided on future disassembly management for green remanufacturing. Firstly, enterprises should strengthen the norms and standards for disassembly waste. The forecast trend of the proposed model can provide references for workshop scheduling, process improvement and product life cycle management. Secondly, the government should increase subsidies and policies for disassembly waste disposal. The government’s policy support can promote enterprise to introduce advanced technology and equipment, so as to better improve the management of disassembly waste. Finally, digitizing will be the trend of disassembly waste dynamic prediction and intelligent management in the future. Meanwhile, the real-time data storage of the detection system will provide timely and effective guarantee for disassembly waste prediction.

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