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Predictive Analytics in the Circular Economy as a Basis for New Approaches to Developing Effective Resource Management Strategies

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Abstract—*This article examines the key aspects of applying predictive analytics in the context of the circular economy (CE). It explores the evolution of resource management approaches and the transition to sustainable methods focused on minimizing waste and reusing resources. Special attention is given to the stages of implementing predictive analytics, including data collection, selection of forecasting methods, modeling, and integration into the resource management process. The study investigates the role of various forecasting methods, such as time series models, machine learning, and scenario modeling, in optimizing resource use and developing effective strategies for the transition to a CE.*

Keywords—*Predictive analytics, circular economy, resource management, sustainable development (SD), waste minimization, forecasting methods, machine learning.*

I. INTRODUCTION

Modern economies face multiple challenges related to the depletion of natural resources, environmental degradation, and increasing waste volumes. The traditional linear economic model, based on the «extract, produce, dispose» principle, is no longer capable of ensuring sustainable development (SD). In this context, the circular economy (CE) offers a concept directed at minimizing waste and maximizing resource use through reuse, recycling, and restoration. However, the successful transition to a CE requires the adoption of new data analysis approaches that can ensure high accuracy and predictability in resource management.

One such approach is predictive analytics, which leverages historical data and machine learning (ML) methods to forecast future events. This method can optimize resource use and enable the development of long-term management strategies based on scenario modeling. The theoretical study of predictive analytics in the context of the CE is becoming increasingly relevant, as it helps identify effective tools for addressing resource sustainability challenges.

The aim of this article is to explore the concept of predictive analytics and its application in the context of the CE. The research analyzes its role in creating new approaches to resource management and developing strategies that support the transition from a linear to a CE model.

II. MAIN PART. EVOLUTION OF RESOURCE MANAGEMENT APPROACHES IN THE CONTEXT OF SD

The history of resource management is a sequence of changes driven by both technological and social factors. Traditional approaches, directed at maximizing the extraction and use of resources, often overlooked the long-term environmental consequences. With the onset of the Industrial Revolution, the focus shifted to economic growth without consideration of its environmental impact. This led to waste accumulation, resource depletion, and climate change, ultimately creating the need for more sustainable management models.

In the mid-20th century, concepts of SD began to actively emerge, offering a new paradigm in resource management. The core idea was the necessity to consider environmental, economic, and social factors. The linear model, which was focused on production and disposal, began to be replaced by the CE. Circular approaches emphasize restoration, recycling, and waste reduction, which have led to a significant increase in their adoption among EU countries in recent years (fig. 1).

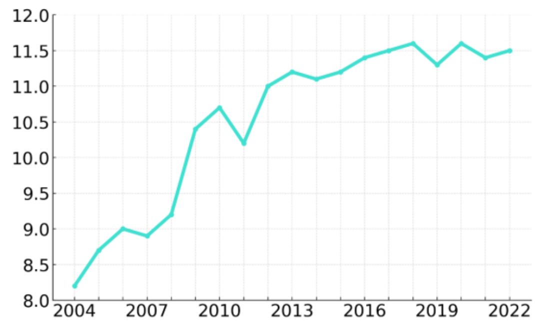

Fig. 1. Circular material use rate in the European Union (EU-27) from 2004 to 2022, % [1]

At this stage, forecasting methods became particularly important, allowing for better planning of resource use and reducing excessive consumption. With the development of digital technologies and analytical tools, resource management gained new momentum. Big Data, artificial intelligence (AI), and ML opened up opportunities for deep analytics, process optimization, and precise forecasting. A significant step in this development was the integration of digital technologies with the principles of the CE.

In the modern context, predictive analytics becomes the tool that bridges traditional approaches with digital innovations. It creates the foundation for long-term management strategies in the framework of the CE.

III. FEATURES AND STAGES OF USING PREDICTIVE ANALYTICS IN THE CE

Forecasting becomes one of the important tools in resource management within the CE, as it enables effective forecasting of resource needs, management of recycling processes, and waste minimization. Its implementation requires understanding specific characteristics and following structured stages to achieve maximum efficiency.

One of the key features of predictive analytics is its focus on long-term goals and its ability to process complex interrelationships inherent in circular systems. Unlike traditional linear economic models, where resources are used only once, the CE involves the repeated reintegration of resources into the economic cycle. This complicates the forecasting process, as it requires taking into account not only initial consumption but also recycling, distribution, and secondary use of materials.

Predictive analytics also relies on large datasets (Big Data), which contain information about product life cycles, supply chains, usage patterns and fluctuations, as well as environmental indicators [2]. This demands the use of advanced data processing methods such as ML, time series analysis, and scenario modeling. An important aspect is the integration of analytics into management systems, where the forecasting results must be easily interpretable and applicable for decision-making processes.

The CE presents additional difficulties for predictive analytics, such as the need to consider the impact of the secondary market, the unpredictability of consumer behavior, and the variability of environmental regulations. It also opens up opportunities to create adaptive management systems capable of responding effectively to external changes. The application of predictive analytics in the CE involves several sequential stages, each with its own tasks and specific features (table 1.)

TABLE I. Stages of predictive analytics implementation [3, 4].

Stage	Description	Methods/Tools
Data collection and processing	Involves collecting data from various sources, including production processes, supply chains, recycling and consumption data, and external data like market trends and environmental indicators.	Data cleaning tools, data transformation techniques, Big Data processing platforms.
Analysis and forecasting method selection	At this stage, the data is analyzed to identify the appropriate forecasting methods.	Time series models, ML, algorithms, statistical analysis tools.
Modeling and testing	The creation of a predictive algorithms includes building mathematical or statistical models that can accurately forecast future scenarios. Testing and validation are carried out to evaluate model accuracy and robustness.	Model testing and validation techniques, cross-validation, historical data comparison.
Interpretation and visualization of results	After model creation, it is important to interpret the results in a user-friendly format. Visualization tools are used to present the forecasts clearly.	Visualization (graphs, dashboards), Business intelligence tools.
Integration into resource management	Involves integrating the analytical system into operational processes. Forecasting results are used for planning procurement, recycling, logistics, and resource distribution.	Integration into resource management systems, supply chain and demand forecasting tools.

Predictive analytics provides powerful tools for addressing the complex challenges of the CE. Its capabilities, such as working with big data and adapting to the specifics of closed-loop systems, make it an indispensable component of sustainable resource management. The stages of analytics implementation secure its efficiency and adaptability to the needs of a specific organization. This forecasting forms the foundation for developing strategies that can facilitate the transition to a sustainable economic model.

IV. ANALYSIS OF FORECASTING METHODS IN RESOURCE ECONOMY

Forecasting is an important tool for analyzing current trends and developing resource management strategies. In the context of the CE, forecasting allows for consideration of the interconnection between production, consumption, and recycling, as well as the adaptation of economic models to new challenges. Different forecasting methods offer unique approaches to data analysis, depending on the set goals and characteristics of the data used.

The Time Series Method is based on analyzing sequences of data collected at regular time intervals. This method is used to study changes in resource use, such as energy demand or material production volumes, over time. Time series analysis enables the identification of trends, seasonal variations, and random deviations to predict future changes. ARIMA models and their extension, SARIMA, are applied for trend forecasting and accounting for seasonal factors [5]. Exponential smoothing is also used for short-term forecasts, where the relevance of recent data is important.

Supply and Demand Models provide tools for analyzing economic factors that influence resource utilization. These models allow for the evaluation of demand elasticity, measuring how changes in prices or resource availability affect their consumption. If resources become more expensive, the model can predict a reduction in their consumption or a search for alternatives. Using regression methods, such as linear or nonlinear models, interactions between supply, demand, and price factors can be analyzed.

Geostatistical Modeling is used to forecast the spatial distribution of natural resources, such as minerals, water, or agricultural land. This method relies on the analysis of geographic data and employs interpolation techniques, such as kriging or inverse distance weighting (IDW). Kriging enables the creation of accurate resource distribution maps based on a limited number of samples. These maps can be utilized to assess reserves and develop strategies for their efficient use. Geostatistical modeling is especially relevant in the CE, where spatial optimization of recycling and logistics processes plays a significant role.

Various ML algorithms offer a more flexible and adaptive approach to forecasting in resource economics [6]. Algorithms such as decision trees, random forests, and neural networks can analyze large datasets and uncover complex relationships between various variables. Decision trees assist in classifying data and predicting behavior based on multiple factors, such as resource type, region of consumption, or recycling levels. Neural networks are capable of forecasting long-term changes in resource demand, accounting for numerous factors that traditional methods might overlook. These methods are applied to analyze time series, assess product life cycles, and develop recycling strategies.

The effectiveness of such algorithms is demonstrated in a number of scientific papers. A 2024 study thoroughly examines the forecasting of municipal solid waste generation in the EU using an XGBoost model based on ML [7]. The model demonstrated high predictive accuracy, achieving an R^2 of 99% for training data and 75% for test data. This highlights its significant potential in optimizing waste management. However, the authors also note that despite model's accuracy, the XGBoost and SHAP may not account for unforeseen changes in future waste generation patterns.

In another study from 2024, various ML methods were applied, including regression models, classification algorithms (e.g., Support Vector Machines, Random Forest, XGBoost), and optimization algorithms, such as linear programming [8]. The study achieved 85% accuracy in forecasting waste generation trends, attributed to the integration of more diverse datasets, including socio-economic factors.

Scenario Forecasting enables the modeling of various development scenarios, particularly under high uncertainty. This method involves identifying key factors that may influence the future, such as changes in legislation or market conditions. Scenarios such as «best-case», «worst-case», and «most probable outcome» are created. For instance, scenario forecasting can be useful in assessing the risks of resource depletion or analyzing the potential consequences of introducing new recycling technologies.

Bayesian models utilize Bayes' theorem to update forecasts as new information becomes available. Unlike traditional statistical methods that rely on fixed assumptions, the Bayesian approach allows for the incorporation of uncertainty and the gradual refinement of predictions. For example, these models can be applied to assess the probability of success in recycling strategies or to identify risks associated with the use of certain resources.

Listed methods provide a diverse set of tools for analyzing and managing resources. Each model has its own strengths and limitations, allowing them to be tailored to specific tasks within the CE. Combining these approaches can increase forecast accuracy and support the development of effective resource management strategies.

V. CONCLUSION

The CE requires the implementation of integrated approaches that combine big data, digital technologies, and innovative analytical tools. Predictive analytics plays a vital role in advancing the CE through providing tools for accurate forecasting and optimizing resource use. In the context of limited natural resources and growing environmental constraints, forecasting methods such as time series, ML algorithms, geostatistical modeling, and scenario forecasting enable the consideration of complex interconnections between production, consumption, and material recycling. The flexibility of approaches like Bayesian models is particularly important, as they help adapt to changing conditions and uncertainties.

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