Heliyon 10 (2024) e38609

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Empowering the circular economy practices: Lifecycle assessment and machine learning-driven residual value prediction in IoT-enabled microwave oven

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ARTICLE INFO

Keywords:
IoT-enabled Circular Economy
Machine Learning
Lifecycle Assessment
Predictive Maintenance
Pseudo Code

ABSTRACT

In an era of resource scarcity and environmental concerns, integrating Internet of Things (IoT) technology into the circular economy (CE), particularly for household appliances like microwaves, is crucial. The lack of systematic assessment of their post-use residual values often reduces utilization and shortens lifespans. Inadequate disposal and management contribute to electronic waste and environmental pollution. Addressing these challenges is vital for efficient appliance management within resource constraints, ensuring meaningful contributions to sustainable resource management. Thus, this study addresses these concerns by integrating IoT technology into microwave ovens, enabling real-time monitoring of key parameters such as voltage, current, door closures, and motor/blade rotations. Data from integrated sensors enables performance analysis and trend tracking, offering potential for advancing CE practices and sustainable product management. Subsequently, utilizing the insights stored from IoT data analysis and tailored surveys, a predictive maintenance model is developed, aiming to predict the life cycles of microwave oven components and categorize them within the CE principles, including reuse, repair, remanufacturing, and cascade. Finally, to mitigate the challenges of lower effective utilization and shortened operating lifespans observed in household appliances, this research employs machine learning models such as Random Forest, Gradient Boosting, and Decision Tree to accurately predict the residual values of IoT-enabled microwaves. Notably, Random Forest demonstrates superior accuracy compared to the other models. Therefore, these technological advancements allow household appliances to be utilized more effectively, thereby enhancing resource utilization.

1. Introduction

According to the “UNEP IRP Global Material Flows Database”, from the year 2000–2024, the average Domestic Material Consumption (DMC) derived from non-renewable sources (such as Fossil Fuels, Metal Ores, Non-metallic Minerals, Products from Fossil fuels, and products from Metals) has nearly doubled across the globe, with skyrocketing from approximately 106 million metric tonnes in the year 2000 to over 214 million metric tonnes in the year 2024—a staggering 103% increase. The most significant growth occurred in the last decade, between the years 2011 and 2024: DMC surged by 28% soaring from almost 166 to 215 million metric tonnes. This

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https://doi.org/10.1016/j.heliyon.2024.e38609
Received 12 June 2024; Received in revised form 25 September 2024; Accepted 26 September 2024
Available online 27 September 2024

pronounced upward trend reflects the unprecedented pressures exerted on natural resources as countries incessantly push the boundaries of material consumption to substantiate their development trajectories. In response to these exigent challenges, a transformative approach known as the circular economy has gained substantial prominence in recent years, promoting sustainable resource management and environmental conservation. In contrast to the traditional linear "take-make-dispose" model, a CE seeks to eliminate waste and extend the lifespan of materials, thereby curtailing the depletion of finite resources, minimizing adverse environmental impacts, and fostering economic resilience [1]. According to Aguilar-Hernandez et al.[2], achieving ambitious CE goals by 2050 could potentially result in a 55.3% reduction in CO_2 emissions as cited in [3]. Additionally, a global shift from primary to secondary materials might decrease the use of primary materials by 27% for metals and 8% for nonmetallic minerals [4]. The CE approach has the potential to significantly mitigate pollution in the air, land, and water, while also benefiting human health [4]. Moreover, this transition could spur job creation and enhance GDP, leading to a "win–win–win" scenario across the economic, social, and environmental spheres [2]].

The transition from the existing linear "cradle-to-grave" model of production and consumption to the CE framework not only reduces waste generation and environmental burdens but also introduces opportunities for innovation, job creation, and economic resilience [5]. By 2040, adopting a CE approach could curtail global greenhouse gas emissions by 25%, generate up to 700,000 jobs, and lead to annual savings of $200 billion [6,7]. These predictions underscore the transformative potential of the circular economic model, encompassing substantial environmental and financial benefits. Notably, among the key global players, the G20 nations—-which together accounted for 95.03% of global GDP and 65.32% of the world's population in 2021—are pivotal in driving this. Recent research conducted by [7] emphasized the significance of these countries' roles, as their efficiency in adopting CE practices directly influences the progress toward multiple SDGs, like affordable energy (SDG 7), decent work (SDG 8), responsible consumption (SDG 12), clean water (SDG 6), and life on land (SDG 15). Their findings suggested that investing in research and development of resource-efficient technologies is crucial for achieving sustainable development goals, albeit with variable progress observed among different nations.

Life cycle analysis (LCA) has solidified its position as a fundamental methodology in the CE framework in recent years, providing a comprehensive evaluation of environmental impacts associated with products and processes throughout their entire lifecycle [8]. This approach provides critical insights that inform decision-making and sustainability assessments [9–11]. Notwithstanding its significance, traditional LCA methodologies often confront obstacles related to data availability, timeliness, and granularity, which can hamper their effectiveness in guiding CE strategies and initiatives [12].

However, the integration of digital technologies has revolutionized the approach to overcoming these challenges in conventional life cycle analysis (LCA), and most importantly, it has the potential to become a cornerstone methodology for the practical implementation of the CE concept. Technologies can be exemplified by Internet of Things (IoT) sensors, blockchain, artificial intelligence (AI), and advanced analytics, which enable real-time monitoring, comprehensive data aggregation, and sophisticated predictive modeling. These advancements are transforming how organizations utilize resources, design products, and assess their sustainability performances, thereby offering novel and effective solutions for augmenting CE strategies [13–15].

Despite the swelling recognition of digitalization's potential to hasten the transition towards a CE, explic-itly in augmenting life cycle analysis methodologies, a considerable research gap persists in comprehensively understanding the specific roles, practical applications, and implications of digital technologies in this domain. This gap leaves critical questions about the operationalization of CE concepts in real life, how to utilize them practically, and the socioeconomic impacts of these technologies, which are largely unexplored.

While numerous studies have been conducted to elucidate the principles and frameworks of digital technologies within the context of the CE, the practical implementations of these concepts are concerningly meagered in the literature. Although recent studies have emerged, highlighting the practical implementations of CE, such as in smart home applications, and applications in products such as coffee machines and washing machines(as detailed in the literature review), there is still a noticeable absence of research on how digital technologies can optimize energy use and consumption in everyday household appliances. Therefore, this research aims to bridge this gap by leveraging a focused examination of IoT-enabled CE models in the context of household appliances, notably microwave ovens, which have become ubiquitous in modern kitchens, serving as a prime example of home electric appliances, that are essential to daily life.

Unlike other studies that may provide broader themes of IoT and CE without concentrating on specific practical implementation in real life, this research will delve into a specialized interpretation and practical application of IoT in microwave ovens. This targeted methodology allows for an in-depth examination of how digital technologies can facilitate sustainable practices in everyday household kitchen items, thereby contributing to the larger domain of CE strategies.

As reported by Statista [16], in 2024 the global microwave oven market is projected to generate approximately $9.62 billion in revenue, accompanied by an anticipated Compound Annual Growth Rate (CAGR) of 4.20% from 2024 to 2029. The U.S. is poised to lead the market, with an expected $1.998 billion in revenue, and a forecasted market volume of circa 87.2 million units by 2029, highlighting the importance of microwave ovens in households worldwide [16]. Therefore, this research seeks to contribute by being a pioneer for the integration of IoT technologies within the CE framework on household appliances, focusing on microwave ovens. Advancing this field holds significant potential for the development of innovative business models that not only adhere to CE principles but also empower companies to generate value while promoting sustainability [17,18]. This approach represents a substantial business opportunity, with prospective economic benefits projected to reach €1.8 trillion by 2030 within the European region alone [19,20].

Thus, the specific objectives of this study are as follows.

- Investigate the optimization of resource utilization through the integration of IoT technology into microwave ovens, thereby enabling accurate real-time monitoring and analysis of resource consumption patterns.

- Develop a comprehensive parts classification model aimed at maximizing the post-initial usage lifespan of microwave ovens, thereby contributing to sustainability efforts within the CE framework.
- Evaluate the actual market value or residual worth of microwave ovens post-initial usage, leveraging IoT-enabled data collection to inform pricing strategies and enhance decision-making processes.

The rest of this article is organized as follows: Section 2 reviews the relevant literature on the integration of IoT technology in predictive maintenance and price optimization within the framework of the CE. Section 3 illustrates how the research will be conducted including the strategy and construction of the model. Section 4 will primarily concentrate on the process of data gathering and analysis, with specific emphasis on the interpretation of findings and engaging in comprehensive debates. Section 5 discusses the managerial insights obtained through result analysis. Finally, Section 6 will provide the inferred conclusions from the results of the research, followed by an examination of potential future areas of investigation. The study will be bolstered by an extensive compilation of references.

2. Literature review

Despite knowing the benefits of the CE, its practical application remains relatively rare in industries. Therefore, motivated by the principles of the CE, this research takes pioneering steps in its application to household appliances. Though several studies have already explored into CE applications in appliances such as washing machines [21] and espresso coffee machines [22], the integration of IoT in the context of microwave ovens remains uncharted territory.

This research is highly relevant within the context of the global transition towards a CE model. The European Parliament underscores the significance of adopting a CE approach in the final stages of a product's life cycle, emphasizing resource preservation and reuse, with potential economic benefits projected to reach 4.5 trillion by 2030 [23]. In alignment with this global trend, the Netherlands has initiated a CE strategy aimed at achieving 100% circularity by 2050 and 50% by 2030, with a particular focus on key sectors such as plastics, biomass and food, construction, manufacturing, and consumer goods. The government's commitment to this transition is evidenced by the allocation of €300 million annually to a climate-related fund, expected to generate €7.3 billion in revenue and create approximately 540,000 new jobs [24].

The CE concept, initially proposed by Winans and Kendall in the 1990s, aimed to reconcile economic growth with limited natural resources through material flow recycling. Over time, this paradigm has gained momentum as a promising approach to achieving sustainable development, although some argue that its efficacy warrants further scrutiny [25,26]. The proliferation of microchips and electronic components in everyday life has led to a surge in electronic waste (e-waste) globally, posing significant environmental and public health risks. In response, initiatives such as Bangladesh's National 3 R Strategy (Reduce, Reuse and Recycle) and regulatory efforts seek to optimize e-waste management and achieve Sustainable Development Goals (SDGs) (CERM Report; NIES Workshop). However, challenges persist, including the lack of transparency in product life cycle information and consumer trust issues, hindering the transition to a CE [27,28].

Recent research has underscored the pivotal role of digital technologies, such as the IoT, in driving CE practices forward. Bressanelli et al. [27] conducted a comprehensive study on CE strategies and digital technologies, where the authors highlighted the potential of IoT-driven innovations to revolutionize various industries, including home appliances. Cavalieri et al. [29] claimed that their bibliometric analysis sheds light on the digitization of the CE and its intersections with IoT and additive manufacturing, underscoring the transformative potential of these technologies. IoT-enabled Smart Home Systems (SHS) and appliances offer new avenues for energy management and efficiency, aligning with CE principles [30,31]. Furthermore, DSS powered by IoT hold promise for optimizing energy usage and facilitating intelligent decision-making in various domains [32]. Moreover, Ferreira et al. [33] demonstrated the integration of IoT and predictive maintenance technologies while Krupitzer et al. [34]offered innovative solutions for appliance maintenance and resource optimization. These advancements pave the way for sustainable practices and CE transitions in diverse sectors.

In line with the demonstrated potential for energy optimization in industrial settings, as shown in an energy audit conducted in a food production facility in Jordan, which identified substantial opportunities for reducing energy consumption by 18% and CO_2 emissions by 772.82 tons annually, resulting in monthly savings of 14,205.85 Jordanian Dinar (JD) through boiler system optimization and equipment replacement [35]. Similarly, integrating IoT technologies in household appliances like microwave ovens could revolutionize energy management. reduce waste, and contribute to significant environmental benefits. By harnessing real-time data analytics and predictive maintenance, IoT-enabled microwave ovens are endowed with the capabilities for significantly enhanced energy efficiency, diminished waste generation, and numerous environmental benefits within the broader framework of a CE.

The emerging field of circular business models emphasizes the importance of minimizing resource consumption, extending product lifecycles, and maximizing value extraction to drive CE adoption (Ellen MacArthur Foundation). comprehensive review of CE and sustainability aligned business model innovation techniques further enriches our understanding of practical strategies for CE implementation [36]. Recent studies project substantial economic benefits associated with CE adoption, including increased GDP and material cost reductions (Ellen MacArthur Foundation). Industry 4.0, characterized by the convergence of digital technologies, plays a crucial role in realizing CE objectives by enabling enhanced automation, communication, and resource extraction [37]. Overall, the integration of IoT, digital technologies, and CE principles offers promising pathways towards sustainable development and resource optimization on a global scale.

Despite recognizing the benefits of the CE, its practical application in industries remains limited. Motivated by CE principles, this research pioneers the application of CE to household appliances, focusing on the uncharted integration of IoT in microwave ovens.

While CE applications in washing machines and espresso coffee machines have been explored, the integration of IoT within microwave ovens remains unexplored. The relevance of this research aligns with the global transition towards CE models, with significant economic and environmental benefits highlighted by entities such as the European Parliament and national strategies like those of the Netherlands. However, the proliferation of electronic waste poses challenges that CE can address. Digital technologies, especially IoT, are pivotal in advancing CE practices, offering new avenues for energy management, efficiency, and sustainable development in home appliances. Research underscores the transformative potential of IoT-driven innovations in CE, with smart home systems and predictive maintenance technologies enhancing appliance maintenance and resource optimization. The convergence of CE principles and Industry 4.0 technologies, including IoT, presents promising pathways for sustainable development and resource optimization globally.

3. Research Methodology

Section 3 outlines a comprehensive methodology in three stages. Section 3.1 details the integration of IoT sensors into microwave ovens and their respective functions. Section 3.2 provides a comprehensive overview of the data acquired by implementing IoT sensors, the intended purpose of this data collection, and real-time user interaction. Section 3.3 introduces a predictive maintenance model that assimilates insights from 16 microwave oven experts and 2 oven manufacturers, acquired through a simulation based survey. The predictive model's two parts are further discussed in depth. In section 3.3.1 the classification of sensor data to categorize microwaves within CE cycles like Reuse, Repair, Remanufacture, and Cascade is delineated. Section 3.3.2 describes the process of gathering the data for residual value assessment of the IoT-enabled microwave oven. Finally, Section 3.3.3 outlines the procedure for utilization of machine learning models to predict and evaluate the appliance's value. The detailed methodology of this study is depicted in Fig. 1,and Section 3.4 presents research findings in a pseudo code representation.

3.1. IoT sensors installation in microwave oven

The integration of IoT sensors aims to capture essential data to implement CE principles in microwave oven operation. This includes monitoring electrical current consumption to provide insights into energy efficiency and usage patterns, identifying potential problems through irregular current use, and evaluating voltage levels to assess power supply stability and its impact on oven performance. Additionally, tracking door closure counts offers valuable information on user interactions and appliance usage, helping to determine the oven's longevity and wear. Measuring blade rotation frequency further reveals user engagement and usage duration, particularly important for models with rotating trays. This following phase details the integration of IoT sensors into the microwave oven to collect real-time data on current consumption, voltage levels, door closure count, and blade rotations, each serving a specific role in supporting CE applications.

a) **Voltage sensors:** AC voltage sensors measure and monitor the amplitude of alternating current voltage within a system. Their operational mechanisms vary by sensor type; some utilize a voltage divider circuit with resistors to determine output voltage based on circuit resistance.

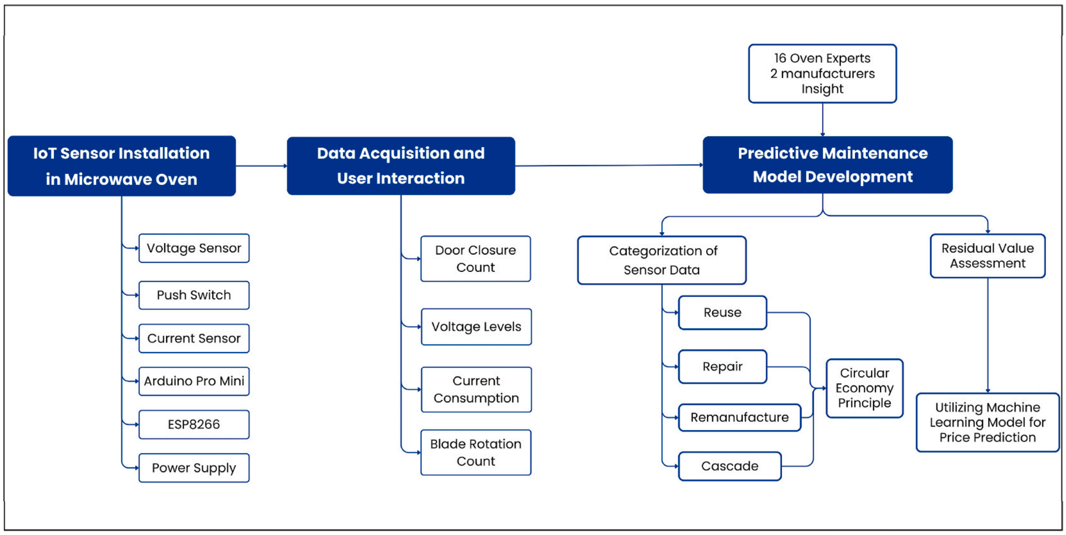


Fig. 1. Research methodology for IoT-enabled microwave oven.

b) **Current sensors:** Current sensors, such as current transformers (CT) and Hall-effect sensors, measure energy consumption by detecting current flow through a wire. These sensors sense both alternating (AC) and direct current (DC), providing outputs proportional to the induced magnetic field.
c) **Push Switch:** A push switch is integrated into the microwave oven to analyze user interaction and usage patterns by tracking door closures. This data is crucial for understanding user behavior, informing product design, maintenance strategies, and CE practices.
d) **Arduino Pro Mini:** The Arduino Pro Mini microcontroller acts as the central processing unit, coordinating data collection, analysis, and communication among integrated sensors. It is essential for creating a unified system that ensures seamless coordination and efficient data processing.
e) **ESP8266:** The ESP8266 module, serving as the primary communication interface, enables real-time transmission of sensor data from the microwave oven to external devices or storage systems. This connectivity is crucial for remote monitoring and preventive maintenance.
f) **Power Supply:** A dedicated power supply unit is crucial for providing a stable and reliable power source to integrated sensors and components. This ensures the continuous operation of IoT sensors and the uninterrupted collection of critical data.

3.2. Data acquisition and user interaction

The primary aim of deploying IoT sensors was to collect data from the IoT-enabled microwave oven as this data was crucial in determining the actual condition of the oven. By having this data, the overall condition of the oven can be determined and the residual value of the oven can also be predicted. The microwave oven's performance and user interaction could be comprehensively examined by observing the following parameters.

i. **Current Consumption:** The purpose was to meticulously observe the current consumption of the microwave oven to assess its energy efficiency and operational patterns. Any irregularities or high current usage for normal operations could indicate underlying potential issues with the oven. More specifically, the maximum current consumption was observed, as it served as a key metric in determining the residual value and categorizing sensor data of the appliance effectively.
ii. **Voltage Levels:** A brief conception of the voltage levels allows a more precise assessment of voltage stability and the power supply at the operational time of the oven as voltage variations can impact the oven's performance. The maximum voltage deviation from the standard voltage for household electricity would primarily be considered in the residual value determination and sensor data categorization.
iii. **Door Closure Count:** Counting the number of door closures of the oven could provide valuable insights into oven utilization patterns and usage duration. This data would hold significance in assessing the appliance's durability, longevity and determining the wear and tear it has gone through by supporting the principle of CE.
iv. **Blade Rotations Count:** As microwave ovens utilize rotating blades driven by a motor, calculating the number of rotations would offer insights into user interactions and the usage duration of the appliance. Furthermore, this parameter was particularly valuable for evaluating motor health conditions, longevity, and usage patterns over time. This approach enabled informed decisions to be made about appliance longevity and maintenance strategies within the CE framework.

Fig. 2 depicts a configuration in which the Arduino Pro Mini interfaces with both the voltage and current sensors, enabling the Arduino Pro Mini to receive data from these sensors. Furthermore, two limits are employed to track the total count of door closures and blade rotations throughout the lifespan of the microwave oven. Subsequently, these four sets of data are then transmitted to the Arduino.

Following this, the ESP8266 module is linked to the Arduino, facilitating the seamless transfer of this data to the ESP8266. The data

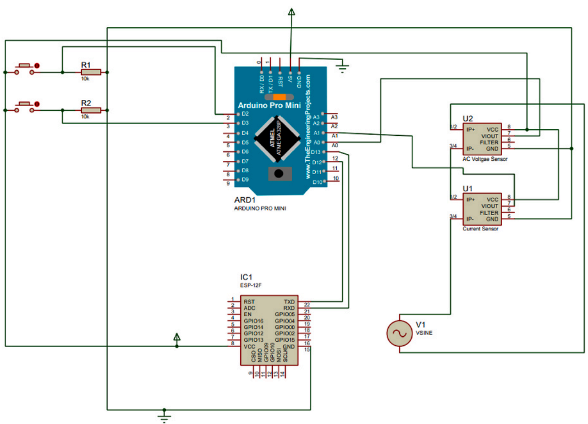


Fig. 2. Circuit Diagram of IoT enabled microwave oven.

may be readily accessible over a Wi-Fi connection, either by using a Google Sheet or by utilizing a mobile application. For that reason, data was stored in both the cloud based system and the mobile app interface. Therefore, data was stored in a Google sheet, and real-time data could be observed in a mobile app interface to gain insight into the microwave oven's current condition for the user.

3.3. Predictive maintenance model development

In order to illustrate the feasibility and practical implementation of IoT sensor data analysis within the framework of CE, a simulation based survey was conducted utilizing synthetic data. Due to the unavailability of real-life IoT-based sensor data for microwave ovens, a synthetic dataset consisting of ninety data points was generated. This dataset was meticulously designed to simulate realistic sensor readings and usage patterns of microwave ovens. This survey's primary objective was to validate our approach's effectiveness in a practical environment and explore its potential applications within the context of a CE. Our purpose was to demonstrate the tangible benefits of IoT sensors for practical uses and CE concepts by physically integrating them into a microwave oven. Following the simulation of the data points, We conducted a survey to predict prices across various microwave oven models, examining the intricate relationship between key technical characteristics and pricing. Data were gathered from a diverse group of oven maintenance specialists and manufacturers, focusing on key factors like voltage (V), current (A), blade rotations, and door closures, with price as the dependent variable. In Dhaka, we reached out to 18 individuals, including 16 oven experts and 2 manufacturers, whose responses are pivotal for decision-making throughout the microwave oven's life cycle within the CE framework and for assessing its resale value based on its current health status. These 90 data points were equally distributed among these 18 expertise people and their experience in this field was also listed below.

Our analysis revealed that the majority of respondents, 72%, possessed over 5 years of experience in the field, as shown in Fig. 3. Detailed instructions were provided to experts prior to survey commencement to ensure consistency in their assessments. Experts evaluated the microwave oven's resale value based on its initial health condition, and in a subsequent survey, respondents selected the microwave oven's life cycle range for predictive maintenance. Parameters such as voltage capacitor fluctuations, current consumption, blade rotation, and door enclosure were considered to determine the microwave oven's lifespan.

By having their insights, we developed a model named "Predictive Maintenance Model" which consisted of two parts.

3.3.1. Categorization of sensor data

Following the effective integration and data gaining by IoT sensors, the next crucial phase in this research is the categorization of these sensor data. The categorizing process plays a fundamental role in assessing the present state of individual microwave ovens, hence facilitating the efficient implementation of CE concepts. The data sets that have been gathered contain a wide array of metrics, including current consumption, voltage levels, the overall count of door closes, and the total number of blade rotations. Following the integration and data acquisition by IoT sensors, the next crucial phase is the categorization of this sensor data. This process is fundamental in assessing the current state of individual microwave ovens, thereby facilitating the efficient implementation of CE principles. The collected data encompasses metrics such as current consumption, voltage levels, door closure count, and blade rotations. These metrics are systematically used to classify microwave ovens into four categories based on their condition, each corresponding to a specific CE function. This categorization is essential for informed decision-making regarding the fate of individual ovens, offering manufacturers, service providers, and consumers insights for optimal management strategies, including reuse, repair, remanufacturing, or cascading. This process underscores the core principles of the CE: sustainability, resource preservation, and waste reduction in microwave oven management. However, the optimal management strategies are described as follows.

a) **Reuse** Microwave ovens in this category show minimal wear and are fully functional, promoting reuse without extensive refurbishment. This aligns with sustainability principles, extending their lifespan and conserving resources [38].
b) **Repair** In the repair category, microwave ovens need minor fixes, addressing simple malfunctions or aesthetic flaws. This encourages efficient repairs, reducing waste, extending product lifespan, and promoting sustainability [39].

Fig. 3. Work experience of survey participants.

c) **Remanufacture** Remanufacturing involves comprehensive refurbishment procedures, including disassembly, component inspection, and potential performance enhancements, to revive microwave appliances. This classification underscores the rejuvenation of appliances, aligning with CE principles by ensuring resource efficiency and sustainable product lifecycles [40]. Remanufactured ovens retain their functional value, minimizing waste and diminishing the necessity for new production.
d) **Cascade** Cascade classification involves grouping microwave ovens and their components no longer yielding substantial financial returns to the manufacturer, yet retaining value for secondary markets or recycling initiatives [41]. Prioritizing component repurposing over device longevity, this classification promotes resource and material efficiency, advocating for optimal component utilization to enhance circularity and minimize waste.

This predictive maintenance model of categorizing IoT sensor data has been developed to integrate the expertise of oven experts and manufacturers to analyze the technical attributes of microwave ovens in the context of CE. By defining each level of parts classification, it was quite evident for the experts to give their opinions on which parts range should get which level of categorization, facilitating effective categorization based on factors such as CE principles, appliance condition, repair needs, and remanufacturing feasibility. Subsequently, they gave their opinions and based on their expert opinions, the IoT sensor data points of microwave ovens were categorized according to this classification. Furthermore, it will also improve user interaction and resource utilization by knowing the actual condition of the oven.

3.3.2. Residual value assessment

In this methodology, we attempted to generate a model that would provide a monetary value for the oven. By leveraging our synthetic data, we asked our experts for their expert opinions to give their expert opinions based on these data points. The synthetic data in this case would each represent a hypothetical microwave oven scenario, together with the estimated monetary worth of each scenario derived from expert opinions on IoT sensor data. Based on our experts' opinions, we developed a machine learning model utilizing these ninety synthetic data points, which can predict any microwave oven's residual value based on its IoT sensor data.

The primary aim of the survey is to predict microwave oven prices, with the price variable exhibiting significant variation. Prices ranged from 2000 to 9500 BDT, reflecting the dynamic nature of microwave oven pricing, which is intricately linked to their technical specifications. By integrating these methodologies within the CE framework, the research aims to enhance resource utilization and waste reduction strategies in microwave oven management. As a result, this dataset not only facilitates predictive modeling but also sheds light on the intricate relationship between technical attributes and pricing dynamics.

3.3.3. Utilizing machine learning models for predicting microwave oven prices

In this methodology, a model is developed that can predict the prices of IoT-enabled devices. The steps of the modeling process are as follows.

i) **Data Preparation:** In the initial phase of this methodology, meticulous attention is given to data preparation. Integrated IoT sensors provide essential information such as current consumption, voltage measurements, door closures, and blade rotations, which are then organized into a structured dataset. This consolidation ensures the suitability of the data for training machine learning models and involves crucial preprocessing steps to maintain dataset integrity. Within the data preparation stage of the machine learning process, particular focus is placed on key features pivotal to the predictive model's accuracy and efficacy. These features include:

- **Maximum Voltage Fluctuations in Microwave Oven:** This parameter denotes the highest magnitude of voltage fluctuation observed in the microwave oven while in operation, assuming a standard voltage supply of 230V. Voltage fluctuations can offer valuable insights into the power consumption patterns of appliances and their ability to adapt to changes in electrical conditions.
- **Maximum Current Consumed in the Oven:** The characteristic measures the highest amount of electrical current that is utilized by the microwave oven during its operation. The provided information is valuable as it pertains to the energy consumption patterns of the appliance, which are crucial for assessing its overall performance and efficiency.
- **Total Count of Door Closures:** The quantification of the frequency with which the oven door has been closed is of utmost importance in comprehending user interactions and usage patterns. This data point facilitates the classification of microwave ovens into distinct CE cycles, including Reuse, Repair, Remanufacture, or Cascade.
- **Total Count of Blade Rotations:** This feature is responsible for recording the overall number of blade rotations that occur within the microwave oven. This analysis offers valuable insights into the mechanical components of the appliance, enabling a comprehensive assessment of its current condition and potential for remanufacturing.

The selection of these data points was conducted meticulously, considering their relevance to our research objectives, especially within the framework of predicting microwave oven prices within the CE context. The aim of this study is to enhance the accuracy of categorizing microwave ovens and providing precise pricing recommendations by incorporating these characteristics into our machine learning model.

ii) **Data Splitting** The dataset is divided into a training set and a testing set. The training set is used to teach the machine learning model to recognize patterns, while the testing set evaluates the model's effectiveness on new data.
iii) **Selection of Model** Three machine learning algorithms—Random Forest, Decision Tree, and Gradient Boosting—are chosen for their effectiveness in handling regression tasks and complex datasets.

iv) **Model Training** The selected models are trained using the training dataset to learn patterns and relationships that influence microwave oven pricing. This process helps the models make accurate predictions based on input sensor data.
v) **Model Evaluation** The trained models are assessed using the testing dataset and metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to measure prediction accuracy.
vi) **Model Comparison** The performance of the Random Forest, Decision Tree, and Gradient Boosting models is compared based on evaluation metrics to identify the model with the lowest prediction error and highest accuracy.
vii) **Model Selection** The model with the best prediction accuracy is selected for deployment. This model will be integrated into IoT-enabled microwave ovens to predict pricing based on real-time sensor data.
viii) **Deployment of the Model** The chosen model is implemented in IoT-enabled microwave ovens to forecast pricing accurately, supporting CE principles by extending product lifespan and reducing waste.
ix) **Continuous monitoring and improvement** The models are continuously monitored and updated to maintain accuracy over time, adapting to changing conditions. This ongoing process is essential for the sustainable and economically efficient operation of IoT-enabled microwave ovens.

3.4. Pseudo code for IoT-enabled microwave oven

The pseudo code below depicts a clear, structured framework of the logic and processes involved in monitoring and assessing IoT-enabled microwave ovens. It serves a crucial role in facilitating the transparency and effectiveness of the workflow.

IoT database for Microwave Oven:

$$O_{\mathrm{ID}} = \{O_1, O_2, O_3, \ldots, O_n\} \tag{1}$$

In equation (1), where O_{ID} represents the IoT database for multiple microwave ovens.

Extract Features from IoT Database (Input Variables):

$$O_i = \left\{V_{\mathbf{max}}^{(i)}, I_{\mathbf{max}}^{(i)}, R_{\mathbf{total}}^{(i)}, D_{\mathbf{total}}, M_{\mathbf{total}}^{(i)}\right\} \tag{2}$$

In equation (2), where O denotes the data for the ith microwave and $\left\{V_{\mathrm{max}}^{(i)}, I_{\mathrm{max}}^{(i)}, R_{\mathrm{total}}^{(i)}, D_{\mathrm{total}}\right\}$ are the processed IoT data for voltage fluctuation, current consumption, motor, and door closure count respectively.

Fig. 4, as part of the data acquisition and user interaction methodology for IoT-enabled microwave ovens systemically records and analyzes four fundamental parameters: voltage fluctuations, current consumption, blade rotations, and door closures count. It establishes a benchmark for each parameter and iterates through the data to update maximum or total values. Voltage and current measurements are examined to identify maximum fluctuation and consumption levels, while rotation and door activity data are consolidated to determine total counts. These metrics are crucial for understanding the appliance's operational behavior and form the basis for predictive maintenance and lifecycle management strategies within a CE framework, thereby promoting extended product lifespans and reduced waste generation.

In Fig. 5, the predictive maintenance model proposed in this research integrates a CE framework to optimize the lifecycle management and uses machine learning techniques to determine the residual value of IoT-enabled microwave ovens. Sensor data, including voltage, current, rotation, and door closure, are categorized based on predefined thresholds, which are set from the survey conducted by oven maintenance experts in this field, to determine the maintenance strategy—whether to reuse, repair, remanufacture, or cascade the appliances. Additionally, a machine learning model is trained on historical sensor data to predict the residual value (in terms of Taka (BDT)) of each microwave oven based on its actual usage, providing valuable insights for manufacturers and policymakers on sustainable practices and informed decision-making. This dual approach offers both the optimal performance of appliances and the effective management of their end-of-life stages.

4. Result analysis

This chapter consists of analyzing the collected data using the method described in Research Methodology. Section 4.1 demonstrates the implementation of IoT sensors in a microwave oven. Section 4.2 discusses real-time monitoring and integration of data management. Section 4.3 shows the implementation of the predictive maintenance model. Section 4.3.1 focuses on the implementation of the categorization of IoT sensor data in a microwave oven. Finally, Section 4.3.2 provides the integration of Machine Learning Models for residual Value assessment, while Section 4.3.3 shows the validation of data by K-Fold cross-validation for Random

Voltage Fluctuations	Current Consumption	Blade Rotations	Door Closures
▪ Initialize $V_{max} = 0$ ▪ For each V_i in Voltage Data: – **If** $\lvert V_i - 230\rvert > V_{max}$, **then** $V_{max} = \lvert V_i - 230\rvert$ ▪ Store $\mathbf{V_{max}}$ as the maximum voltage fluctuation.	▪ Initialize $I_{max} = 0$ ▪ For each I_i in Current Data: – **If** $I_i > I_{max}$, **then** $I_{max} = I_i$ ▪ Store $\mathbf{I_{max}}$ as the maximum current consumption.	▪ Initialize $R_{total} = 0$ ▪ For each R_i in Rotation Data: – $R_{total} = R_{total} + R_i$ ▪ Store $\mathbf{R_{total}}$ as the total blade rotations.	▪ Initialize $D_{total} = 0$ ▪ For each D_i in Door Data: – $D_{total} = D_{total} + D_i$ ▪ Store $\mathbf{D_{total}}$ as the total door closures.

Fig. 4. Pseudo code for data acquisition and user interaction.

Categorize Sensor Data based on Circular Economy Model (Output Variable)	Residual Value Assessment for Each Oven (Output Variable)
▪ Threshold Values are determined from the survey from expertise in this field ▪ For each sensor (V_{max}, R_{total}, D_{total}): **If** Sensor Value <= Reuse_Threshold, Print "**Reuse**" **Else If** Sensor Value <= Repair_Threshold, Print "**Repair**" **Else If** Sensor Value <= Remanufacture_Threshold, Print "**Remanufacture**" **Else**, Print "**Cascade**"	▪ Train Machine Learning Model: - $\mathbf{X_{train}}$ = {V_{max}, I_{max}, R_{total}, D_{total} } - $\mathbf{Y_{train}}$ = {Residual Values} - Train Model: $\mathbf{M_{model}}$ = TrainModel(X_{train}, Y_{train}) • Predict and Evaluate: - $\mathbf{Y_{pred}}$ = M_{model}(X_{new}) - $\mathbf{E_{perf}}$ = Evaluate(M_{model}, X_{test}, Y_{test})

Fig. 5. Pseudo code for predictive maintenance model.

Forest. Lastly, Section 4.4 demonstrates how our proposed model prevails over the traditional mainstream microwave ovens in terms of functionality and efficiency. All data are presented numerically for better comprehension. The flowchart of result analysis is shown in Fig. 6.

4.1. *Implementation of IoT sensors in microwave oven*

The implementation process began with the seamless integration of IoT sensors into the microwave oven. Fig. 7 depicts the selected microwave oven model used in our prototype. By incorporating IoT sensors, we've laid a robust foundation for future innovations. Fig. 8 displays the microwave oven after the installation of IoT sensors, demonstrating the successful integration of this technology. This marks the start of a transformative journey towards improved functionality and efficiency in microwave oven operations.

In this Fig. 8, the setup of sensors including current and voltage sensors, along with a limit switch inside the microwave oven, determines essential values. These sensors allow for the collection of real-time data on voltage, current consumption, door closures, and blade rotations. This data will be conveniently accessible via a mobile app and Google Sheets, facilitating thorough monitoring and analysis.

4.2. *Real-time monitoring and data management integration*

In the mobile app interface as shown in Fig. 9, users can access real-time data. This interface provides immediate insights into voltage, current, total door closures, and motor/blade rotation count, allowing users to monitor these parameters dynamically. This capability not only enhances user engagement but also enables informed decision-making regarding microwave oven usage, promoting efficiency and sustainability.

Similarly, the integrated IoT sensors generate real-time data stored systematically in a Google Sheet as reported Table 1, ensuring organized records of crucial parameters. Data logging occurs at regular intervals, resulting in a time-series dataset that documents the oven's performance and usage trends. This compiled information holds significant potential for future research, particularly in advancing CE practices. By leveraging this data, sustainable product lifecycle management, especially in microwave oven contexts, can be further developed, contributing significantly to resource conservation and waste reduction objectives. Thus, this data repository serves as a valuable resource for prospective inquiries in sustainable appliance management.

4.3. *Implementing predictive maintenance model*

The implementation of the predictive maintenance model is described in Section 4.3.1 and 4.3.2.

4.3.1. *Assessing and predicting microwave oven health*

The initial phase of the report meticulously outlined the survey's primary objective: to thoroughly assess the current state of

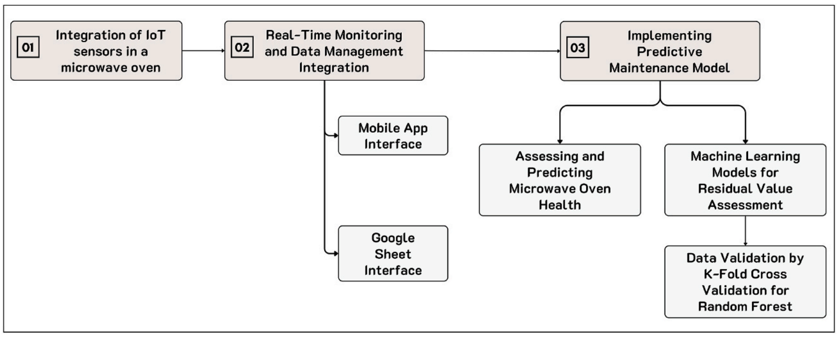


Fig. 6. Result analysis flowchart.

Fig. 7. IoT enabled Microwave oven.

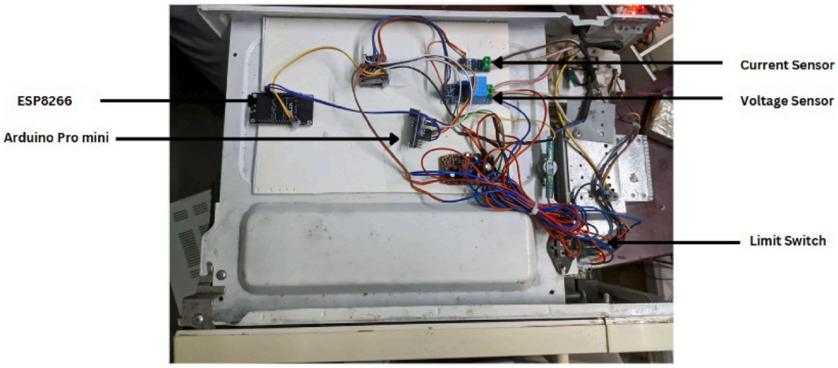


Fig. 8. IoT sensors implementation in Microwave oven.

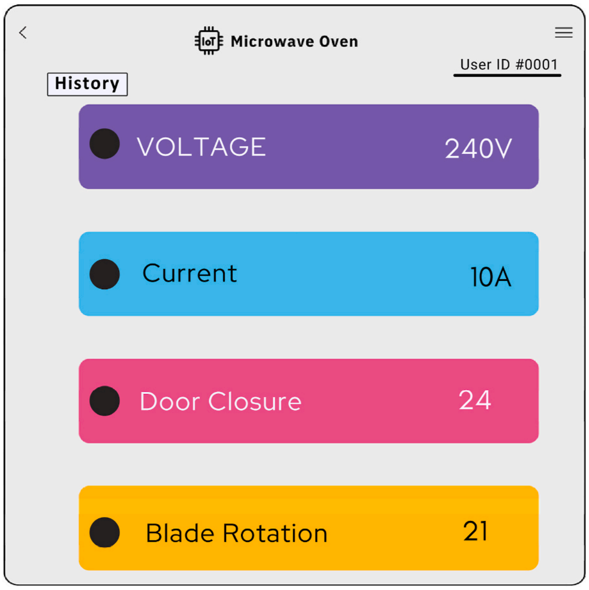


Fig. 9. Mobile App Interface of IoT enabled Microwave oven.

microwave ovens, ensuring both reliability and safety for consumers. Subsequently, a distinct aim emerged in the subsequent survey: to define the parameters for predictive maintenance. This phase involved distributing questionnaires to 18 participants, aiming to unravel key components such as reusability, repairability, remanufacturing feasibility, and potential cascade scenarios. The survey meticulously addressed critical elements including voltage capacitors, blade rotation mechanisms, and door enclosure dynamics, all pivotal in preserving appliance longevity and performance efficiency. This section is dedicated to develop a comprehensive parts

Table 1
Data sorted in Google sheet.

DATE	TIME	Voltage	Amps	Door Value	Motor Value
12-Sep-23	4:12:50 a.m.	222.00	0.00	17.00	14.00
12-Sep-23	4:12:53 a.m.	229.00	2.52	17.00	14.00
12-Sep-23	4:12:57 a.m.	230.00	9.02	17.00	14.00
12-Sep-23	4:13:01 a.m.	230.00	9.16	17.00	15.00
12-Sep-23	4:13:05 a.m.	230.00	4.50	17.00	15.00
12-Sep-23	4:13:09 a.m.	230.00	2.27	17.00	15.00
12-Sep-23	4:13:12 a.m.	230.00	4.87	17.00	16.00
12-Sep-23	4:13:16 a.m.	230.00	4.39	17.00	16.00
12-Sep-23	4:13:20 a.m.	230.00	4.71	17.00	16.00
12-Sep-23	4:13:24 a.m.	230.00	4.90	17.00	16.00
12-Sep-23	4:13:28 a.m.	230.00	2.37	17.00	17.00
12-Sep-23	4:13:31 a.m.	230.00	0.00	17.00	17.00

classification model aimed at maximizing the post-initial usage lifespan of microwave ovens, thereby contributing to sustainability efforts within the CE framework.

i) **Voltage Capacitor:** This study aimed to predict the voltage capacitor's life cycle and categorize it within the CE, focusing on maximum voltage fluctuations during microwave oven operation. Collaboration with experts and manufacturers was initiated due to limited availability of IoT-enabled microwaves, resulting in various CE categorizations.

Fig. 10 illustrates expert opinions obtained, revealing a significant 61 % consensus favoring Category I, denoting direct reuse of voltage capacitors with fluctuations ranging from 10 to 60. Fluctuations between 60 and 80 may require repair, while the 80 to 100 range necessitates remanufacturing. Beyond 100, parts are unsuitable for the parent organization, requiring regeneration in other companies, termed cascading. Although expert opinions for other categories were collected, they constituted a minority of responses.

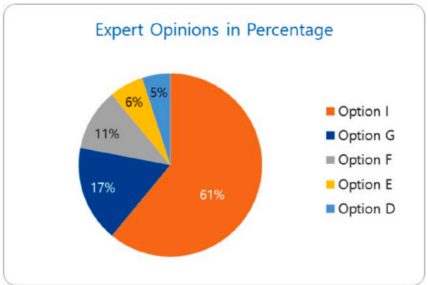
ii) **Rotational Blade:** In our investigation centered on the IoT-enabled CE, we evaluated the condition of microwave oven synchronous motors by assessing their rotational blade counts. Participants were asked to select suitable predictive maintenance actions from provided ranges of blade rotations, encompassing reuse, repair, remanufacturing, and cascade.

Prior to the survey, participants were given detailed procedural instructions. Analysis of expert opinions, presented in Fig. 11, revealed a substantial 67% majority favoring Category G. This category indicates that the synchronous motor can be directly used if blade rotation falls within the range of 100–190,000. Rotational ranges of 190,000 to 270,000 may require repair for reuse, while remanufacturing is necessary for ranges of 270,000 to 350,000 rotations. Beyond 350,000 rotations, the motor is considered unsuitable for use within the parent company and requires repurposing through cascading. Minor responses were recorded for alternative categories in the chart.

iii) **Door:** Participants were informed that the data analysis aimed to evaluate the overall health of microwave oven doors. The maximum limit for door enclosures was set at 22,000. The lifespan of doors depends on the type of maintenance conducted, ranging from reuse to remanufacturing.

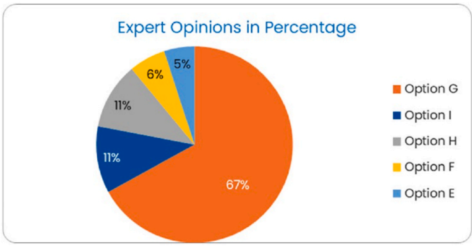
Fig. 12 depicts that Category F, preferred by 56% of experts, suggests direct usage for door enclosure ranges of 10–14,000. Maintenance is required for ranges of 14,000 to 18,000, while remanufacturing is needed for ranges of 18,000 to 21,000 enclosures. Beyond 21,000 uses, doors are deemed unsuitable for continued use within the parent company, requiring repurposing through cascading. Minor responses in the chart exhibit similar trends.

Table 2 provides a comprehensive list of microwave oven components that can be effectively monitored and assessed using IoT



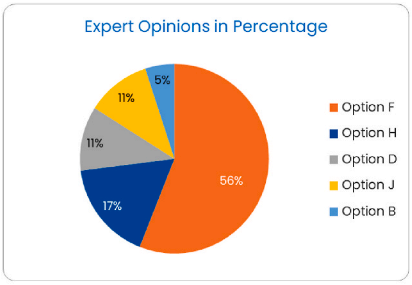
Survey Options for Expert Opinions				
Option	Reuse	Repair	Remanufacture	Cascade
I	10-60	61-80	81-100	>100
G	10-50	51-80	81-100	>100
F	10-40	41-70	71-100	>100
E	10-40	41-70	71-90	>90
D	10-40	41-60	61-80	>80

Fig. 10. Voltage capacitor lifespan survey response.



Survey Options for Expert Opinions				
Option	Reuse	Repair	Remanufacture	Cascade
G	100-190,000	190,000-270,00	270,000-350,000	>350,000
I	100-220,000	220,000-300,000	300,000-350,000	>350,000
H	100-200,000	200,000-290,000	290,000-350,000	>350,000
F	100-180,000	180,000-260,000	260,000-350,000	>350,000
E	100-170,000	170,000-250,000	250,000-350,000	>350,000

Fig. 11. Synchronous motor lifespan survey response.



Survey options for expert opinions				
Option	Reuse	Repair	Remanufacture	Cascade
F	30-14,000	14,000-18,000	18,000-21,000	>21,000
H	30-15,000	15,000-18,000	18,000-21,000	>21,000
D	30-13,000	13,000-17,000	17,000-21,000	>21,000
J	30-16,000	16,000-18,000	18,000-21,000	>21,000
B	30-11,000	11,000-16,000	16,000-20,000	>20,000

Fig. 12. Door lifespan survey response.

Table 2
Summary Table of Parts Classification in IoT enabled Microwave oven.

Parts	Reuse	Repair	Remanufacture	Cascade
Voltage Capacitor	10–60	60–80	80–100	>100
Motor	100–190000	190000–270000	270000–350000	>350000
Door	10–14000	14000–18000	18000–21000	>21000

sensors. It also presents the outcomes of our survey, delineating the reuse, repair, remanufacture, and cascade possibilities for each component. In addition, the corresponding values associated with these lifecycle stages are comprehensively summarized in the table for reference and analysis. Following the implication of the categorization of the sensor data mode was applied, the data was shown as follows.

This Table 3 demonstrates how the data will be categorized by utilizing this model. Therefore, any user can assess the actual oven condition and make the right decision for improving the performance of the microwave oven.

4.3.2. Machine learning models for residual value assessment

Three distinct machine learning predictive models, namely Random Forest, Gradient Boosting, and Decision Tree were utilized for precise pricing predictions after extensive training on feature data collected through a customized survey. Their performance was evaluated using essential metrics like MAPE and RMSE, with the model exhibiting the lowest error on the test dataset chosen for future predictions. To bolster the models' strength and reliability, K-Fold cross-validation was employed. This involved dividing the data into five folds, one serving as the test set with 18 data points and the remaining four as the training set with 72 data points. The systematic

Table 3
Implied categorization of parts classification in IoT enabled microwave oven.

Voltage	Motor	Door	Voltage_Categorized	Motor_Categorized	Door_Categorized
63.81	94,706	9143	Repair	Reuse	Reuse
64.11	101,852	9684	Repair	Reuse	Reuse
100.86	319,256	18,164	Cascade	Remanufacture	Remanufacture
101.10	321,367	18,551	Cascade	Remanufacture	Remanufacture
10.67	333	66	Reuse	Reuse	Reuse
11.26	770	262	Reuse	Reuse	Reuse
14.69	830	360	Reuse	Reuse	Reuse
60.26	91,958	8951	Repair	Reuse	Reuse
64.07	98,933	9444	Repair	Reuse	Reuse
99.65	316,458	17,936	Remanufacture	Remanufacture	Repair
63.82	98,553	9252	Repair	Reuse	Reuse

rotation of test and training sets ensured each data point was tested exactly once, and the process was replicated for five times, facilitating a comprehensive assessment of model performance across different data subsets, thereby enhancing overall dependability and resilience. To compute both the RMSE and MAPE for each iteration, the RMSE and MAPE values were initially determined for the test set of the respective fold. Subsequently, these values obtained from each iteration were aggregated by summing them and dividing the sum by the total number of iterations, which in this particular case was five, resulting in the mean RMSE and MAPE, respectively.

The comparison presented in Table 4 elucidates the performance metrics, namely MAPE and RMSE, associated with three distinct machine learning models. These values were determined through rigorous evaluation of the test dataset. Among the examined models, the Random Forest model showcased the most favorable performance, boasting a notably low MAPE of 2.35% and an RMSE of 173.33. Conversely, the Decision Tree algorithm displayed a slightly higher MAPE of 2.44% and a RMSE of 183.35. Despite this, it still demonstrated competitive performance. Additionally, the Gradient Boosting model exhibited commendable results, recording a MAPE of 3.34% and an RMSE of 247.72. These findings underscore the efficacy of Random Forest in achieving accurate pricing predictions, followed closely by Decision Trees, while Gradient Boosting also proves to be a viable option, albeit with slightly higher error metrics. The Random forest model was shown the least error among the three machine learning models. Therefore, the prediction of the IoT-enabled microwave oven was executed by the Random forest. The below table was shown as an example of a Random Forest regressor for predicting IoT-enabled microwave oven prices: This Table 5 presents the predicted prices generated by the Random Forest Regressor and their corresponding actual values. The data used for this table is derived from the K-Fold Cross Validation technique, specifically for Fold 3 testing, where the model's predictions are compared to the actual prices.

4.3.3. Data validation by K-Fold Cross Validation for Random Forest

The Random Forest model demonstrated superior performance in predicting pricing within the CE framework, exhibiting the lowest error compared to the other machine learning models tested and reported in Table 4. In order to enhance the robustness and reliability of the model, a rigorous data validation process was implemented, employing K-Fold cross-validation. The K-Fold Cross Validation method requires splitting the dataset into five separate folds, with each fold containing a unique subset of data. In each iteration of the validation process, one-fold was selected as the test set, consisting of 18 data points. The remaining four folds were combined to form the training set, which included a total of 72 data points. The implementation of a systematic rotation strategy ensured that each data point was utilized for testing exactly once, thereby mitigating the potential for bias in the evaluation of the model.

Fig. 13 presents the MAPE values for the Random Forest predictive model in this research, as observed across the five folds of K-Fold Cross Validation. This visualization provides valuable insights into the model's performance. In this particular context, the MAPE functions as a crucial metric for assessing the accuracy of price forecasts. The findings obtained from the five folds consistently demonstrate a notable level of accuracy. Fold 1 exhibits a notable characteristic with an exceptionally low MAPE of 1.86%. This indicates the model's proficiency in generating highly precise price predictions when subjected to testing using this specific subset of data. Fold 2, which exhibits a MAPE of 2.06%, consistently upholds its remarkable level of precision. Despite a marginal increase in the MAPE by 3.38%, Fold 3 remains within an acceptable range of error. Exhibit 4 demonstrates a notable MAPE of 1.40%, which is comparable to the level of precision observed in Fold 1. Fold 5, which exhibits a MAPE of 3.02%, demonstrates a notable degree of precision. The model's consistent and commendable predictive performance is evident in the overall Mean MAPE of 2.35%. This result highlights the robustness and reliability of the model in accurately predicting prices within the CE framework, providing managers with confidence in decision-making processes related to pricing strategies and resource allocation.

4.4. Comparison with conventional techniques

By comparing our work with existing mainstream techniques, the superiority of our proposed model can be elucidated. The comparisons can be described into two distinct aspects.

1. **Pioneering Research:** There is a significant void in prior research on CE concepts-based microwave ovens, positioning us as pioneers in incorporating IoT sensors into ovens and paving the way for implementing CE models to household electric products. When differentiating our model from traditional microwave ovens, the main differentiators are real-time data availability and enhanced user interaction. This capability facilitates users to optimize their oven operations by visualizing the impact of their usage in real time. Our proposed model will not only enhance user experience but also help to contribute to more sustainable practices in household appliance usage.
2. **Usage Data Monitoring:** Our model enables the precise monitoring of usage data, which provides users with insights into the true condition of the oven and helps to determine its residual value. Moreover, when this dataset is maintained and analyzed using machine learning techniques, it can accurately predict the resale value of the oven based on actual usage patterns. Additionally, this approach facilitates the categorization of components within the context of a CE, leveraging real usage data. In contrast, traditional ovens do not possess these capabilities, making it impossible to ascertain the actual condition and residual value of the appliance, thereby these differences underscore the superiority of our model over conventional ovens leveraging real usage data. In contrast, traditional ovens do not possess these capabilities, rendering it impossible to ascertain the true condition and residual value of the appliance, thereby highlighting the superiority of our model over conventional ovens.

Table 4
Model evaluation of Predicting IoT enable Microwave Oven.

Model	Average MAPE	Average RMSE
Decision Tree	3.34 %	247.72
Random Forest	2.35 %	173.33
Gradient Boosting	2.44 %	183.35

Table 5
Test data for fold 3 - Random forest regressor for predicting prices of IoT-enabled microwave oven.

Voltage (V)	Current (A)	Blade Rotations	Door closures	Actual Price (Taka)	Predicted Price (Taka)
84.41	11.90	271058.00	15762.00	3700.00	4054.00
63.81	7.99	94706.00	9143.00	7000.00	6986.00
78.24	11.44	255697.00	14270.00	4300.00	4380.00
20.29	4.51	13777.00	2310.00	8500.00	8424.00
106.61	14.41	344186.00	19776.00	2000.00	2003.00
37.36	6.82	61686.00	6126.00	7500.00	7462.00
75.87	10.64	154224.00	13282.00	5000.00	5007.00
44.98	7.37	80647.00	7398.00	7200.00	7134.00
20.61	4.57	20022.00	2649.00	8300.00	8352.00
79.86	11.78	261354.00	14928.00	4100.00	4188.50
67.53	8.74	111012.00	10433.00	6500.00	6090.00
18.79	4.14	6601.00	1602.00	8500.00	8559.00
21.28	4.70	24925.00	2804.00	8000.00	8243.00
77.96	11.36	245121.00	14003.00	4150.00	4485.00
88.19	12.10	276780.00	16267.00	3500.00	3689.00
67.73	9.00	113655.00	10721.00	5700.00	5626.00
99.64	13.51	309933.00	17711.00	2300.00	2306.00
87.32	12.01	275725.00	16036.00	3200.00	3799.00

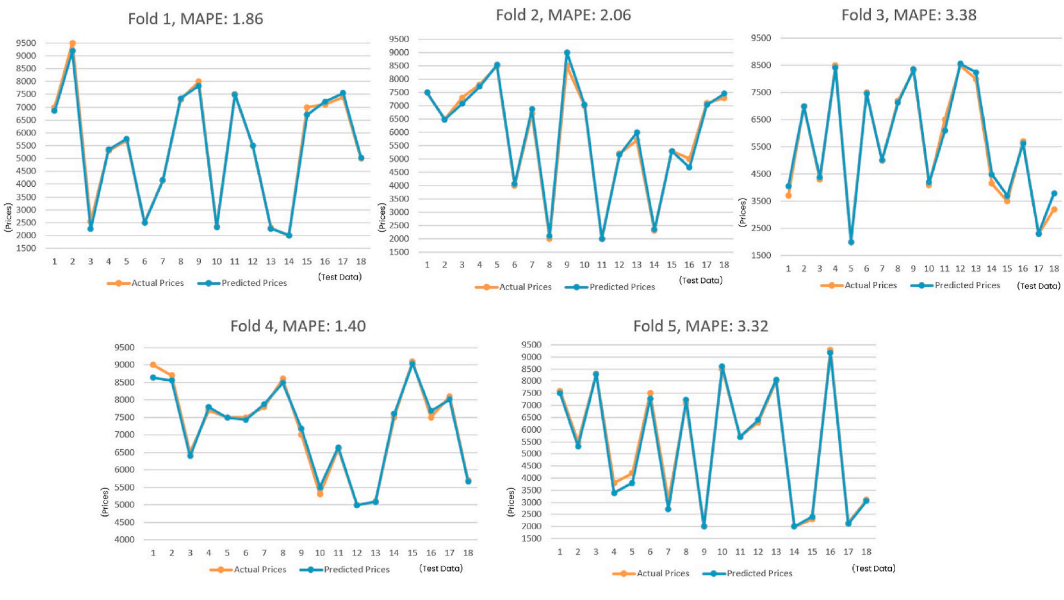


Fig. 13. Data validation of Random forest regressor.

5. Discussion

This study introduced IoT sensors into microwave ovens, aiming to enhance appliance management practices within the context of the CE. Through the installation of IoT sensors, including current sensors, voltage sensors, and limit switches, this study facilitated real-time monitoring of crucial parameters such as voltage, current consumption, door closures, and blade rotations. These sensors provided immediate access to data via a mobile app interface and systematically stored data in Google Sheets, offering dynamic insights into microwave oven performance and usage trends.

Furthermore, this research categorized IoT sensor data to predict the life cycle of microwave oven components, such as the voltage capacitor, rotational blade, and door enclosure. By analyzing voltage fluctuations, blade rotations, and determining the total count of door enclosure, this study classified these components into distinct phases within the CE (summarized and reported in Table 2), facilitating predictive maintenance procedures and resource optimization strategies.

The utilization of machine learning predictive models, namely Random Forest, Gradient Boosting, and Decision Tree, enabled accurate pricing predictions for IoT-enabled microwave ovens. Through extensive training and validation using K-Fold Cross Validation, these models demonstrated robust performance, with the Random Forest model exhibiting superior accuracy compared to other models. This validation process ensured the reliability and dependability of predictive models, empowering consumers to make informed decisions about microwave oven usage within the CE framework.

The MAPE values obtained from K-Fold Cross Validation provided valuable insights into the performance of the Random Forest predictive model. Across five-folds, the model consistently exhibited a notable level of accuracy, with Fold 1 demonstrating exceptional precision. The overall Mean MAPE of 2.35% highlights the reliability of the model in accurately predicting prices within the CE framework.

This research provides industry practitioners with actionable insights for optimizing product lifecycles and enhancing customer experiences through the utilization of real-time data acquired from IoT-enabled microwave ovens, a significant advancement over conventional techniques. The leveraging of this data will empower practitioners to make informed decisions that will enhance resource efficiency and mitigate waste, ultimately leading to more sustainable practices in appliance management. Additionally, the study elucidates the residual values of these ovens, which can substantiate their market price after initial usage. This information is crucial not only for manufacturers and retailers but also for the customers in getting the idea of competitive pricing strategies and understanding the long-term value of their products. Furthermore, this research acts as a significant resource for policymakers in promoting sustainability and fostering innovation. By promoting the adoption of CE practices, policymakers can facilitate the development and integration of IoT technologies in household appliances, thereby leading to a more sustainable future.

Thus, this study offers promising opportunities for enhancing appliance management practices and promoting sustainability within the CE through the integration of IoT sensors, machine learning models, and rigorous validation techniques. These advancements contribute to informed decision-making, efficient resource allocation, and optimized product lifecycles in the context of IoT-enabled microwave ovens.

6. Conclusion and future work

This research successfully implemented IoT sensors in microwave ovens, laying the groundwork for enhanced appliance management practices within the CE. The integration of current sensors, voltage sensors, and limit switches enabled real-time monitoring of critical parameters, offering dynamic insights into microwave oven performance and usage trends through mobile app and Google Sheets interfaces. Categorizing IoT sensor data facilitated the prediction of component life cycles, guiding predictive maintenance strategies. Additionally, machine learning models, particularly the Random Forest algorithm, accurately predicted residual value for IoT-enabled microwave ovens, validated through rigorous K-Fold Cross Validation. The consistently low MAPE across folds underscores the model's reliability in price forecasting, emphasizing its potential in promoting sustainable appliance management practices within the CE.

In addition to the technological advancements made in this study, integrating additional IoT sensors can expand monitoring capabilities to include temperature, humidity, and energy efficiency, providing comprehensive insights. Enhanced analysis of sensor data facilitates proactive maintenance and optimization by identifying patterns and anomalies. Extending machine learning to other appliances supports sustainable lifecycle management.

In the context of the IoT-enabled CE for sustainable appliance management, ensuring the security of connected devices, such as microwave ovens, is paramount. The increasing vulnerability of IoT devices to cyber threats—ranging from Denial-of-Service (DoS) and Distributed Denial-of-Service (DDoS) attacks to botnets and Man-in-the-Middle (MITM) attacks—poses significant risks to the integrity and reliability of smart appliances. According to Inayat et al. [42], learning based methods, particularly those leveraging deep learning (DL) approaches like Deep Belief Networks (DBN), Long Short Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN), have demonstrated significant efficacy in detecting and mitigating these threats. Implementing such robust and scalable cyber defense mechanisms is crucial for maintaining the secure and sustainable operation of IoT-enabled appliances. Hence, future research holds immense potential to significantly enhance the secure and sustainable management of IoT-enabled household appliances within a CE framework by addressing the critical areas of cybersecurity, sustainability, and user education. Therefore, through the prioritization of developing advanced security protocols, future research can play a pivotal role in safeguarding these appliances. This will, in turn, foster a more secure and sustainable CE, where technology not only improves convenience but also protects users and the environment from the risks associated with cyber threats.

Declarations ethics statement

This research included human participants, and informed consent was obtained from all participants prior to their involvement in the study. Their identities were enshrined and no personal identifiers were collected or disclosed in the study for protecting their privacy.

Data and code availability statement

The data, that has been used in this research, will be made available on request.

CRediT authorship contribution statement

Asif Iqbal: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sonia Akhter:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Conceptualization. **Shahed Mahmud:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Lion Mahmud Noyon:** Visualization, Validation, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e38609.

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