Intelligent resource management and decision support system for sustainable refuse-derived fuel production

by

Junaid Oosman Tahir

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Abstract

Municipal Solid Waste (MSW) represents a diverse array of materials promising substantial potential for reuse and recycling. MSW originates from residential, commercial, and construction sources and is generally divided into recyclable and non-recyclable categories. Specifically, within the non-recyclable portion lies the organic component, which can be utilized to harness energy. This reclaimable combustible segment, extracted from MSW, is termed "Refuse Derived Fuel" (RDF). Processes like RDF incineration convert this material into a range of valuable resources. This transformative process yields heat, electricity, and a diverse array of biofuels through gasification and pyrolysis. Among these biofuels are biomethane, dimethyl ether, methanol, syngas, bio-oil, biochar, etc. However, lack of operating plant data, uncertainties in process inputs, operating parameters, capital investments, waste composition, and product costs are some of the critical parameters that influence the performance indicator for waste treatment systems. In particular, the waste treatment system transforming municipal solid waste into RDF faces limitations in maintaining consistent production and quality control standards of RDF. The leading cause is the unwary biomass fuel supply chain decision-making, implicating many decisions associated with discovering the best waste diversion options and measuring their impact on the waste processing plants. Hence, municipal solid waste management requires integrated decision-making for sustainable waste treatment systems. Rigorous assessment is crucial for improving operational planning and addressing uncertainties in waste-to-energy applications.

The proposed study aims to tackle the challenges of assessing waste treatment system related to the RDF production at a material recovery facility (MRF) while integrating varied uncertainties. A decision support system is proposed for sustainable RDF production connecting four key components to form a comprehensive framework tailored for management and operational level hierarchies at any MRF. The framework includes, first an advanced computer vision system, developed to enhance the workflow of the waste characterization process at an MRF. This system enables precise waste detection and early mitigation planning for unsuitable compositions in RDF production. Secondly, the prior phase is integrated to a discrete simulation model, examining various production line configurations for high-quality RDF and consistent mass flow efficiency. These simulations yield optimal process plant configurations, ensuring alignment with specified RDF quality benchmarks. Third, knowing the calorific value aids in optimizing combustion for maximum energy extraction, assessing fuel quality for suitable applications, and estimating emissions for cleaner energy systems. Using chemical analysis, real-world experiments are executed to develop calorific value prediction models for processed RDF. These models aid operational decision-making and are cross- validated with existing ones for accuracy. Lastly, study integrates risk epidemiology into the Public-Private-Partnership (PPP) model to assess RDF plant economics and introduces a quantitative energy from waste (EfW) feasibility model, accounting for subjective biases in risk perceptions of groups involved in PPP.

The contributions of this study lay the foundation of efficient problem-solving and scientific solution methods for effective decision-making in waste management. This study's insights benefit various stakeholders profoundly. Managers at MRFs gain the ability to assess diverse scenarios, ensuring robust configurations amid input uncertainties. Operators aiming to elevate profits and RDF material quality find strategic guidance in these scenarios. Local and regional waste managers benefit from efficiency parameter modeling, enhancing waste stream redirection to facilities optimizing sorting. Policymakers, often facing knowledge gaps, find clarity in this study regarding material sorting intricacies and impacts of recycling policy. The proposed research can be extended to investigate the RDF production problems considering additional uncertain factors, such as fluctuations in waste composition and variability in market demand for RDF, as well as dynamic events like operational disruptions and policy changes in future work.

Preface

This thesis is the original work by Junaid OOsman Tahir. Listed below are five journal papers closely linked to this thesis, either published or already submitted.

1. Tahir, Junaid, Rafiq Ahmad, and Zighang Tian. "Calorific value prediction models of processed refuse derived fuel 3 using ultimate analysis." Biofuels 14.1 (2023): 69-78.

2. Tahir, Junaid, Zhigang Tian, Rafiq Ahmad, and Pablo Martinez. "Refuse-derived fuel-3 production simulation using network flow modeling: Predicting the uncertainty in quality standards." Fuel 345 (2023): 128168.

3. Tahir, Junaid, Zhigang Tian, Pablo Martinez, and Rafiq Ahmad. "Smart-sight: Video-based waste characterization for RDF-3 production." Waste Management 178 (2024): 144-154.

4. Tahir, Junaid, Zhigang Tian, Dr. Mohamad Kassem, Pablo Martinez, Rafiq Ahmad, (2024), "A Critical Analysis of Public Private Partnership Model in Energy from Waste Projects." Sustainable Futures (Accepted).

5. Tahir, Junaid, Pablo Martinez, Rafiq Ahmad, (2024), “Integrated Approaches to Sustainable Energy Recovery: A Critical Review of Municipal Solid Waste Conversion into Refuse-Derived Fuel in Material Recovery Facility.” Energy Conversion and Management (under-review).

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I am deeply grateful to my dear son, Salaar, and beloved wife, Zarfi, whose unwavering support and cherished companionship have been my pillars of strength. Finally, I extend my deepest appreciation to my parents for their continuous support, care, and encouragement, which has been influential in my academic pursuits and well-being.

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List of Abbreviations

MSW	Municipal Solid Waste
OECD	Organization for Economic Co-operation and Development (OECD)
WtE	Waste to Energy
HHV	Higher Heating Value
LHV	Lower Heating Value
MRF	Material Recovery Facility
EfW	Energy From Waste
VfM	Value For Money
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Square Error
PPP	Public Private Initiative
PFI	Private Finance Initiative
RDF	Refuse Derived Fuel
SRF	Solid Recovered Fuel
SPV	special purpose vehicle
CV	Computer Vision
O&M	Operations & Maintenance
AD	Anaerobic Digestion
RFQ	Request For Qualifications
RFP	Request For Proposal
EPC	Engineering Procurement Construction
SITA	Suez Recycling and Recovery UK
NPV	Net Present Value
AAE	Average Absolute Error
ABE	Average Biased Error
ASTM	American Society for Testing and

	Materials,
MJ/KG	Mega Joules per Kilo Gram
EN	European Standard
ISO	International Organization for Standardization.
YOLO	You Only Look Once
SUK	SITA UK
FEI	FortisBC Energy Inc

Chapter 1: Introduction

1.1 Research Background

1.1.1 Waste Generation

Globally, across many countries, the speed-up growth in population and urbanization has caused an upsurge in the generation of municipal solid waste (MSW). MSW is a heterogeneous mixture of various types of materials which varies in composition and volume depending on the type of waste generators including residential, commercial, construction and socioeconomic factors. As economies develop and populations grow, a general expectation of increased waste generation is often measured using metrics like waste per capita. At regional levels, a substantial amount of MSW is directed to landfills, resulting in a significant loss of valuable resources. This trend is especially projected to impact regions with significant proportions of burgeoning low-income and lower-middle-income countries, foreseeing the highest surge in waste production [1]. Several national and local governments have initiated measures to address waste production and processing, like sustainable source separation programs, extended producer responsibility etc. However, despite these efforts, over the years waste generation among OECD member countries has cumulatively increased by 9.3% between 2013 and 2020 [2]. Furthermore, solid waste does contribute to climate change in the form of CO_2 equivalent emissions. MSW is predicted to increase to 3.40 billion tons by 2050 [1] and significantly escalate the carbon footprint [3]. Globally CO_2 emissions have consistently risen with occasional declines due to global events such as the pandemic in 2019, the financial crisis in 2008, and the dissolution of the Soviet Union in 1991, resulting in a temporary reduction in emissions illustrated in Figure 1.1, [4]. When it comes to waste generation globally, USA and Denmark generate a higher amount of waste per capita whereas the least waste per capita is generated by Japan and

Columbia, as shown in Figure 1.2, [5].

This study focuses on waste management, mainly handled by local municipalities in a decentralized approach. In this context, the local jurisdictions strategize solid waste management programs based on local factors like funding, community layout, norms, and the publics' affordability for services. Municipal solid waste collection sources with physical composition considered in this study are shown in Figure 1.3. The four main waste collection streams included in the study are recyclable, garbage, organic waste, and yard waste. Other types of waste like medical waste, single-use plastics and waste-water sludge are not part of the study.

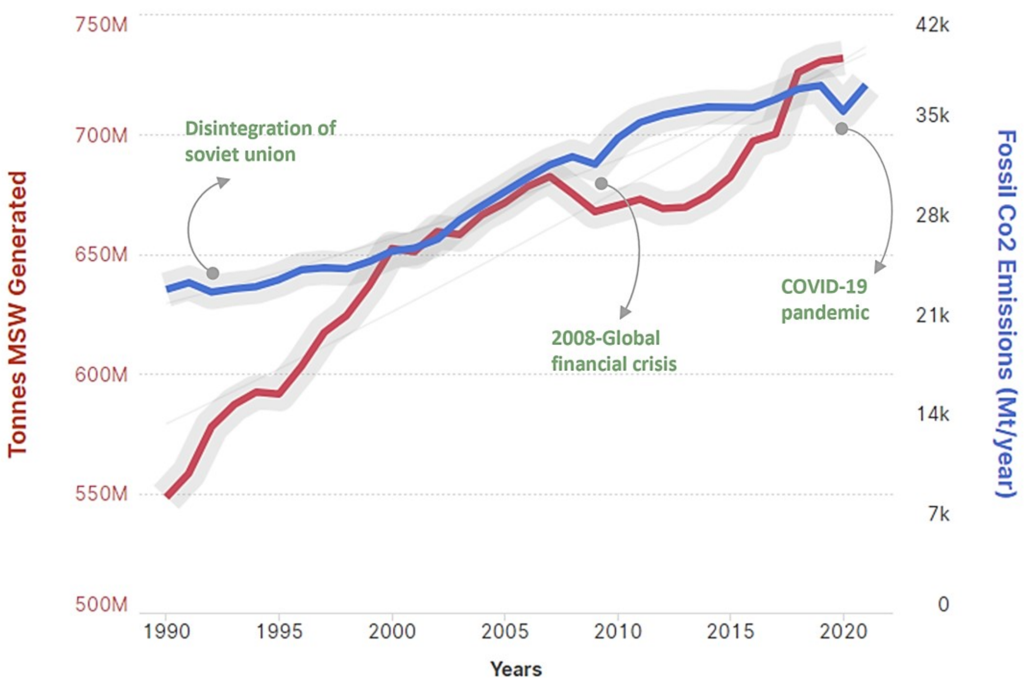

Figure 1.1: Over the years municipal solid waste generation (million-tonnes/year) of OECD economies and fossil CO_2 emissions (million-tonnes/year), have shown a growing trend, [2,4].

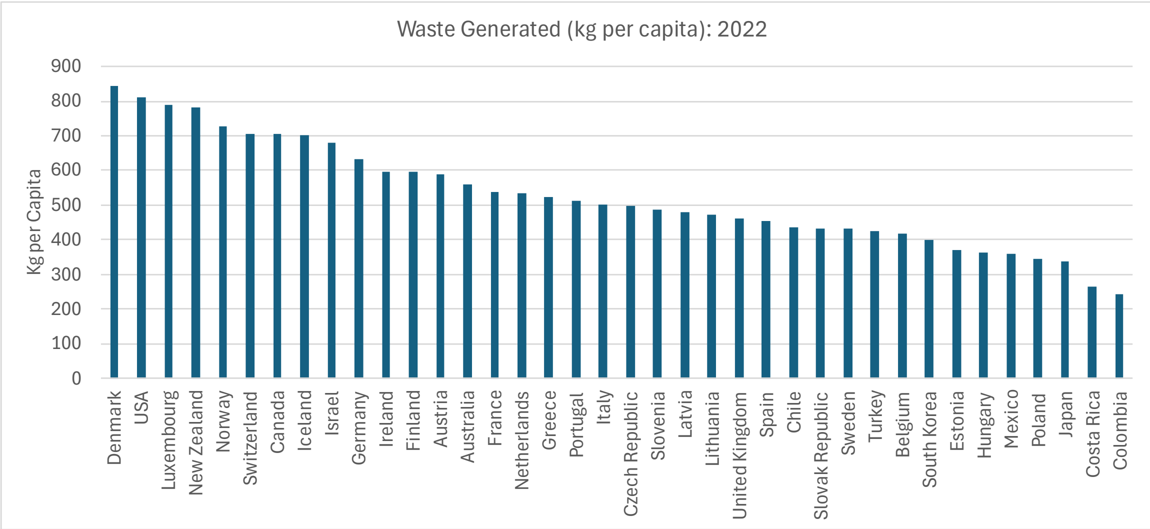

Figure 1.2: Municipal waste per-capita generation in 2022 for 38 countries, [5]

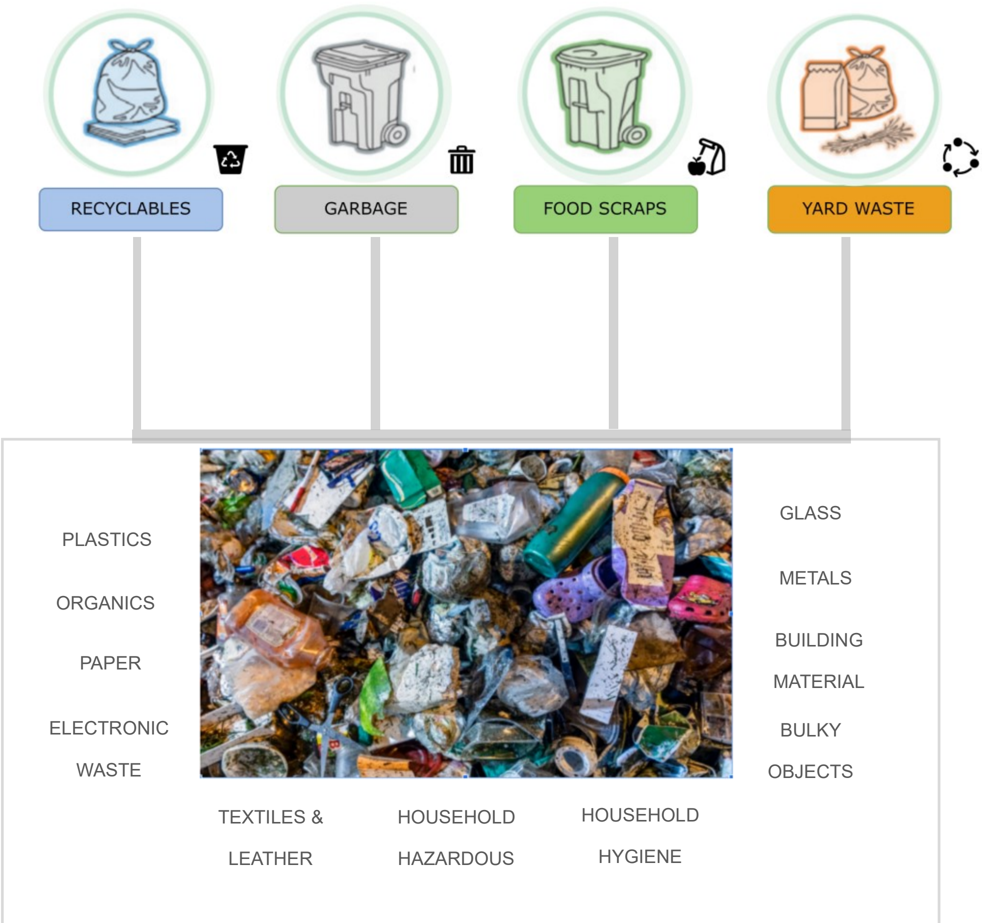

Figure 1.3: In scope municipal solid waste collection sources and physical composition

1.1.2 Energy Recovery from Waste

MSW is processed in various ways utilizing recycling, composting, energy production, and landfill disposal methods. Globally, 19 percent of the waste produced undergoes material recovery through recycling and composting, and 11 percent is treated through some form of incineration process to produce energy. The 33 percent of waste is not managed in an environmentally safe manner and the remaining is landfilled [1]. Figure 1.4 shows that South Korea has the highest recycling rate 61% and both Japan and Sweden incinerate major portion of the municipal solid waste generated.

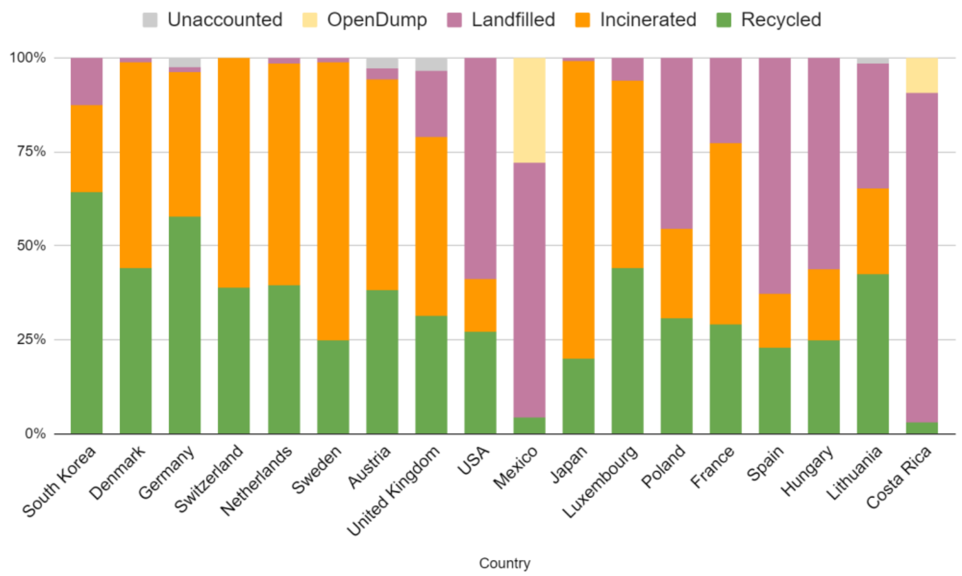

Figure 1.4: Waste Disposal strategies in selected countries, [5]

However, to mitigate the rising carbon footprint, the MSW can be transformed to generate energy and has the potential to replace a wide range of fossil fuel products [6]. To achieve this, the non-recyclable organic fraction within MSW serves as a valuable feedstock and right after collection it is initially processed to separate out biodegradables, lignocellulosic waste and Refused Derived Fuel (RDF) for effective resource recovery [7]. These extracted fractions from MSW can undergo either Biological or Thermal treatment using specialized technologies such as anaerobic digestion (AD), incineration, combined heat and power (CHP) plants, gasification, and pyrolysis[8]. These advanced methods pave the way for transforming waste into energy. The primary challenge encountered in Waste to Energy (WtE) initiatives often emerges during the preliminary waste treatment for thermochemical processing [7]. Therefore, the scope of this study is limited to the conversion of MSW exclusively into high-quality RDF. This emphasis is crucial as the composition of RDF serves as a fundamental input for modeling and simulating incineration, gasification, and pyrolysis processes. Figure 1.5 shows the process of transforming MSW into RDF and energy products. Initially, the waste collection process begins at the source generators and collected waste progresses to the Material Recovery Facility (MRF) for thermomechanical treatment to process and sort the waste.

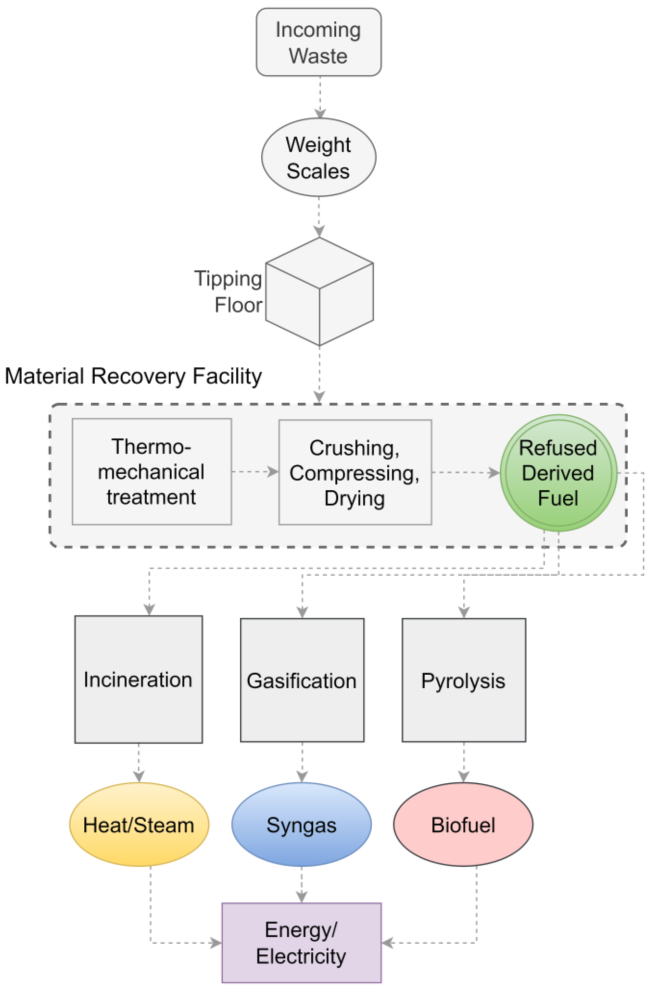

Figure 1.5: Transformation of MSW into Refuse Derived Fuel and energy

Thermo-mechanical treatment of waste is prominent due to distinct features, efficiently removing the recyclable and non-combustible materials from MSW using unique sequences of material recovery units [9] and producing a great quality RDF having higher heating value (HHV) [10]. From RDF, a range of energy products can be derived, including heat, power, and biofuels (Biomethane/Biochar). Waste incineration is the preferred option for treating MSW-derived RDF [11]. There are 800 existing WtE facilities using thermal treatment with the option of energy recovery by treating waste. Canada has only five of them, treating municipal solid waste and recovering heat or steam from the treated waste [12]. A few facilities are planned to be built in different regions in Canada. Cement manufacturing facilities in Canada would like to increase the use of MSW as an alternative energy source, which is a potential waste diversion option as compared to conventional incineration or pyrolysis treatment for waste. Table 1.1 below shows the number of WtE facilities treating MSW in operation and planned for construction in Canada.

Table 1.1: Number of EFW facilities treating MSW in operation and planned for construction in Canada, after [12].

Canada	**Large WtE Facilities (Treating Capacity>25t/day)**	**Small WtE Facilities (Treating Capacity<10t/mo)**	**Brand new WtE Facilities Planned (Large or Small)**	**Brand new Biofuel WtE Facilities Planned (Large or Small)**
BC	1			1
AB	1	420	1	1
SK				
MB				
ON	1		4	1
QC	1	2	2	7
NB				
NS				
NL				
PE	1			
NU				
NT				
YT				

1.1.3 Refuse Derived Fuel

Dr. Jerome Collins, named RDF in 1973, and the American Society for Testing and Materials (ASTM) has outlined several forms of RDF based on the methods of its preparation and the particle size representation illustrated in Table 1.2, [13]. This study is specifically focused on the RDF-3 category, which involves the sorting, screening, and shredding of MSW. This fuel category undergoes a comprehensive processing aimed at removing metal, glass, and other inorganic materials to refine the final fuel product in shredded form.

Several properties of RDF such as calorific value, moisture content, amount of chlorine, sulfur and ash content are important when it is used in cement production plants or any other application [14]. Yet, pinpointing consistent values for these properties is challenging due to their heavy reliance on the waste source. For example, the different calorific values associated with RDF based of its sources are shown in Figure 1.6, [15].

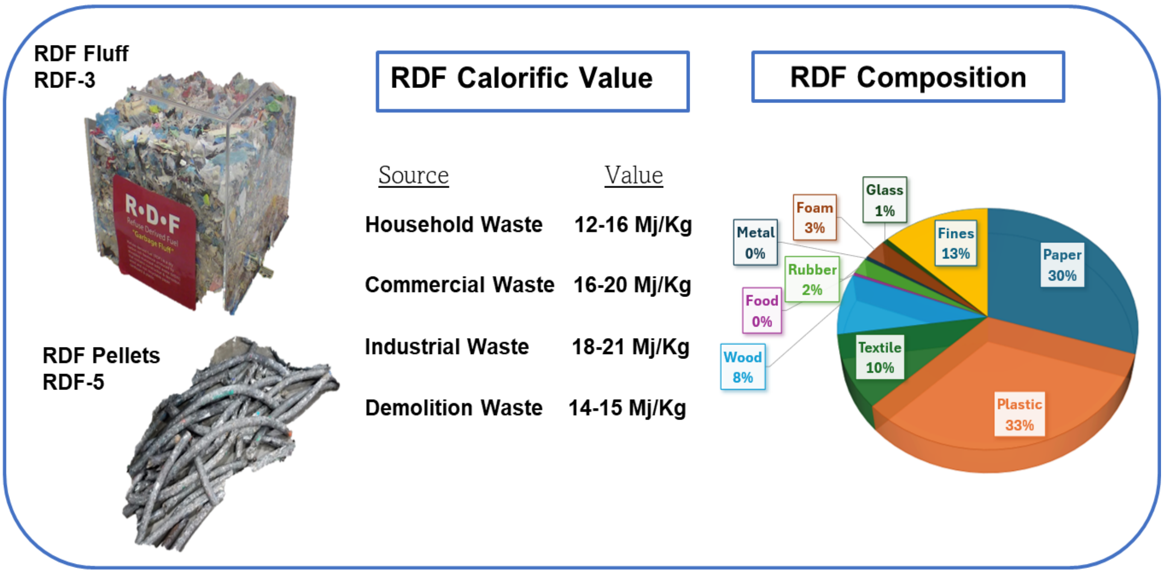

Figure 1.6: Final RDF-3 & RDF-5 samples, calorific values of RDF produced from different sources and composition, [13], [18].

Table 1.2: RDF Types and their processing methods, [13]

RDF Category	Description	Particle Size	Processing Method
RDF-1	Utilizing discarded waste as fuel	Variable	No specific processing
RDF-2	Processing waste into coarse particles	Coarse	Potential magnetic separation
RDF-3	Shredded MSW fuel, 95% passes 50mm mesh	Shredded	Removal of metal, glass, inorganic materials
RDF-4	Transforming waste into powder form	Powder	Grinding process
RDF-5	Densifying combustible waste into pellets	Densified	Compression into pellets, slugs, etc.
RDF-6	Converting combustible waste into liquid	Liquid	Transformation into liquid form
RDF-7	Converting combustible waste into gas	Gas	Gasification process

The research has shown that many mathematical models presented in the past utilized ultimate analysis to predict the higher heating value (HHV) for various categories found in Biomass. But all the models are limited to the type of biomass used as references and often cannot be extrapolated to a different kind of substance such as RDF, also very few models exist to estimate HHV for urban wastes like MSW and RDF [16]. Improved and deeper studies are required to be conducted with a distinct group of RDFs to prove the robustness of the models previously developed in the literature.

1.1.4 Material Recovery Facility

The MRF are essential centers designed to precisely sort various waste components. Within these centers, the intricate operation involves sorting recyclable inorganic materials like plastics and metals, organic substances ideal for composting, and combustible materials tailored for energy production. In the realm of waste-to-energy (WtE) applications, this study focuses on specific MRFs dedicated to RDF production and its varied types. The facility is equipped with an array of waste sorting units, including primary shredders, ferrous separators, eddy currents, wind sifters, waste

screens, secondary shredders, dryers, and surge bins [9]. The sequence of these units and the process design play a vital role in the recovery and purity maximization of the sorted waste. Mathematical modeling of various waste sorting unit chain structures and process optimizations have been examined [17]. Additionally, RDF production line configurations studied by [18], [19], [20] also provide a good reference for comparing the performance metrics of an MRF for RDF production located in Canada, and Italy.
However, the production of a high-quality RDF or SRF is impacted by the composition of the input waste stream and the design of the material recovery facility (MRF) which is comprised of multistage waste separation processes or units. The composition of the output waste stream and its quantities are calculated by means of mass balance [21] and this is generally done using semi-empirical methods due to the lack of available information on the performance of these operational units [22]. Moreover, a thorough evaluation of RDF quality standards (EN 15539) across European countries offers essential benchmarks for assessing and ensuring RDF quality within the context of waste management practices [23]. This aspect has a significant impact on the final product recognition because an RDF produced according to a defined quality assurance procedure can further become a certified "solid recovered fuel" (SRF) [23]. These standards promote their safe use in energy conversion activities and for the general trust of the public.

Material recovery facilities within regional waste management systems hold the potential for integration with thermochemical processes within existing standalone WtE technologies [24]. The concept of waste-integrated biorefineries represents a significant stride, enabling the more efficient utilization of various fractions of MSW compared to the isolated operation of conventional WtE processes. This integration promises enhanced resource recovery and optimization within the waste management framework.

1.1.5 Waste to Biofuel Fuel Supply Chain Decision Making

Using RDF as an alternative and renewable energy source is a significant step for today's world to counter its energy demands as well as to reduce its dependency on fossil fuels for mitigating climate change. However, the major barrier to developing and implementing such innovative solutions is the cost of waste to the biofuel supply chain and uncertainty in MSW source generation [25]. Energy from waste has the potential to replace a wide range of fossil fuels, however existing biofuel supply chain implicates many decisions associated with waste type selection, collection, pretreatment, production, storage, conversion to bioenergy, and biofuel sales. The inherent abrasiveness of RDF presents a risk to process equipment[26], resulting in decreased efficiency and shortened lifetime. Furthermore, the amalgamation of diverse materials within RDF can cause issues like reactor blockages, often requiring restarts to rectify the situation [27]. The performance indicators of WtE processes are significantly impacted by uncertainties stemming from various factors. These include the absence of operational facility data, uncertainties in process inputs and parameters [27], dependency on cumbersome laboratory procedure for waste characterization and analysis [28], capital investments and product costs [29]. So, a major investment in using MSW to RDF as an alternative energy resource calls for vigilant decision-making in all aspects of the biofuel supply chain.

In this context, depending on their timeframe, three significant decision-making categories are strategic, tactical, and operational [30]. Strategic decisions entail long-term decisions that are difficult to change in a short time and have a long-lasting impact on the supply chain. Tactical decisions in the supply chain can range from a few months to a year depending on the strategic goals defined in the earlier stage and bridge the gap between strategic and operational decisions. In contrast to strategic and tactical decisions, operational-level decisions focus on short-term activities conducted on a day-to-day or weekly basis and ensure continuous operations of the facilities. Research in the past focused on strategic and tactical level decisions, whereas less emphasis is placed on operational decisions and combined strategic or tactical levels with operational decisions [25]. The three decision categories can be mapped across four key biomass supply chain functional processes, including biomass supply and preprocessing, biofuel production, biofuel blending and distribution, and biofuel sales. There is a consensus in the literature that two or more of these decision categories should be modeled or optimized together to improve supply chain performance [31]. The planning and supply chain categories can be designed vertically and horizontally, providing an effective framework for waste-to-biofuel supply chain planning. In this study, a hybrid model is employed, which analyzes the three categories of decision-making in tandem with the application of the RDF-3 production plant.

In developing countries, most energy from waste projects are funded by public-private partnerships (PPP) at both national and municipal authority levels [32]. It is a form of long-term collaboration between public and private parties sharing their skills and assuming different levels of implicated risks and rewards in WtE infrastructure delivery, substantiated contractually for a definite duration. Such an arrangement enables the public sector to undertake projects they could not finance internally or through loans and grants. However, a few opponents argue against such arrangements for infrastructure delivery projects. The public sector can build attractive incentives in PPP, which could be misleading regarding budget and schedules and are usually absent in the conventional infrastructure delivery model.

Similarly, the governments must pay a premium to incentivize private contractors to assume any risks. Usually, PPP financing costs are higher for the private sector because of high borrowing interest rates that vary during the projects' long duration [33]. Lastly, in the event of project failure, the public sector can transfer the loss of extra tab to the taxpayer through increased taxes or some reduction in public services [34]. Despite these concerns, studies on the value of money with PPP in WtE are missing.

1.2 Motivation and Methodology

The main motivation for conducting this research is to address the existing gap in maintaining the quality standards of RDF production, aiming to uncover sustainable practices that establish the operational and technical conditions ideal for consistently achieving high-quality RDF output at MRF. Thus, the major constraint is sustainability in converting RDF to a certified, self-declared, and nationally recognized SRF. In response to this challenge, a framework is proposed to develop an intelligent and integrated decision support system to achieve sustainable waste treatment processes at MRF. The architecture proposed for this study is presented in Figure 1.7, while the detailed methodology applied is depicted in Figure 1.8. The decision support system addresses challenges within the MRF on both managerial and operational fronts.

At management level, an improved mixed risk epistemology is deployed where a quantitative probabilistic model using the Monte Carlo simulation method is developed that will be impactful to intricately depict and analyze the influence of lifecycle risks on operational phase costs and profitability for WtE projects. These risks encompass factors like the quality of service, often governed by contractual obligations, which are typically delegated to the operation and maintenance (O&M) contractor. The improved mathematical model would accurately depict the O&M contract components, encompassing various technical, payment, and incentive variables. It considers their fluctuations and dynamic interactions, ultimately influencing the financial outcomes and overall feasibility of the operational phase. This will assist identifying common risks associated with WtE technologies prevailing around unplanned maintenance, infeed waste reduction, market price, unsustainable debts, and policy changes. Also, a detailed survey will be conducted to bring perspectives of stakeholders involved in public private partnerships for procuring WtE facilities. The outputs of this level are vital to provide financial viability of projects and feed its recommendations to the operational level.

At the operational level, the proposed methodology targets three significant problem areas that directly influence both the operational sustainability and the quality of RDF production. First, the quality of the produced RDF significantly relies on the composition of in-feed waste and waste characterization method applied for auditing purposes, a process that is both time-consuming and fraught with potential hazards. This study focuses on enhancing the workflow of the waste characterization process at an MRF by deploying computer vision techniques to detect and classify waste based on video feeds as shown in Figure 1.8. The proposed waste characterization system would not only aid in the accurate detection of waste but also facilitates early-stage decision-making regarding potential mitigation strategies for waste compositions unsuitable for RDF production. The outputs of this stage are waste composition probability distributions and feed at inputs to the next stage.

Secondly, based on the conventional framework of waste management activities, the proposed methodology constitutes an extension to facilitate the integration of an assessment of a selected set of uncertainties for adding value in waste to the biofuel supply chain. The new approach demonstrates the addition of the above factors using network flow modeling, enhanced discrete event simulation and statistical modeling technique. The foundations of the model are based on assumptions like emphasis on general representation but not physical properties of MRF. The model provides improvements to operating conditions and enables prediction for quality standards of RDF, enabling the waste management authority to meet their outlined quality specification for the final product. However, the RDF distribution and transport related decisions are out of scope in this study. The outputs of this stage are RDF quality, productivity, supply data and optimal plant operating conditions.

Lastly, new empirical models will be introduced to predict the calorific value(Mj/kg) of RDF. Linear and machine learning models are developed to predict the RDF calorific values. The estimated calorific value results will undergo comparison with established models found in the existing literature to validate the robustness and reliability of the newly proposed models.

Each identified problem will undergo validation through a series of systematic computational experiments using the proposed methods. These experiments will include the adoption of various baseline benchmarks for comprehensive comparative studies. Additionally, real-world case studies will be conducted using authentic data sourced from operational Material Recovery Facilities (MRFs). These case studies will showcase the effectiveness of the enhanced methods in resolving practical issues at both management and operational levels. The proposed framework yields a decision support system comprising four intelligent solutions developed through this research.

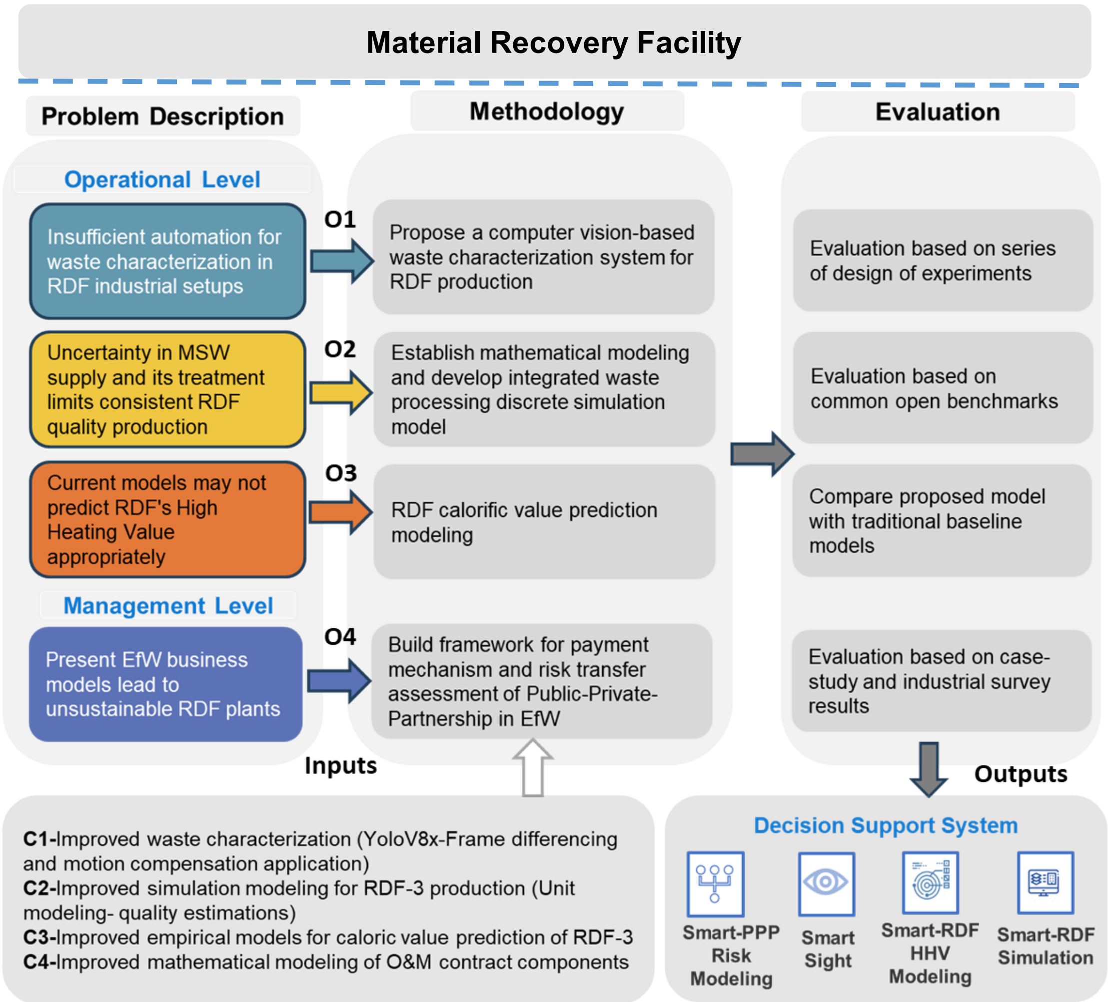

Figure 1.7: Overview of the proposed architecture.

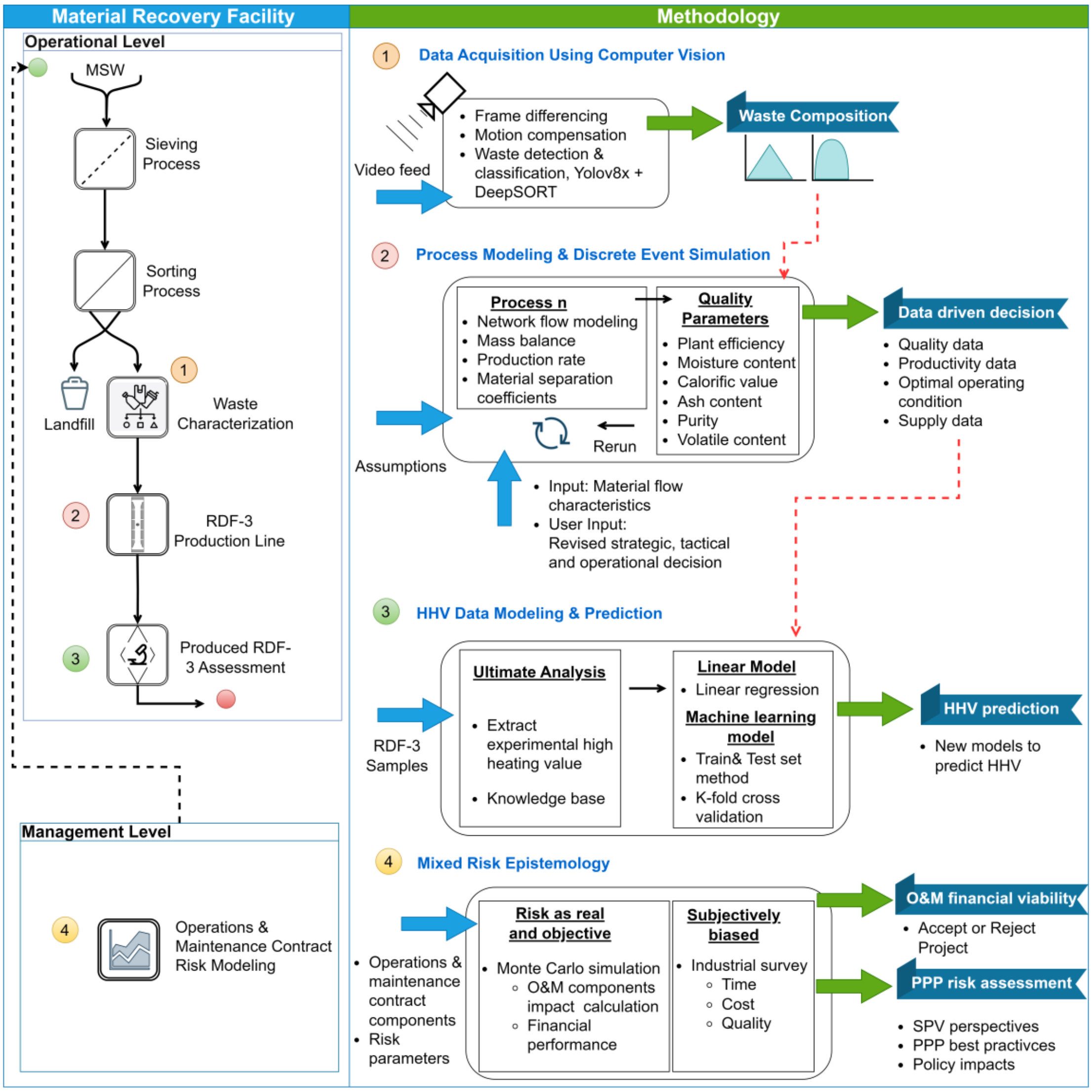

Figure 1.8: Detailed outline of the methodology applied in this study

1.3 Thesis Objectives

The main objective of this research is to "develop an intelligent framework for technical assessment and economic feasibility of an RDF production plant using stochastics process techniques and statistical methods, which will support management and operational level decisions for mitigating uncertainty in maintaining consistent production and quality control standards of RDF". The detailed research objectives of this study are outlined as follows:

O1. Using a computer vision approach to integrate a video-based monitoring strategy for sustainable RDF-3 production.

O2. Create a simulation model of a material recovery facility, which can support revisions in the strategic, tactical, and operational level decisions integrating uncertainties affecting its performance.

O3. Develop a calorific value prediction model and validate its accuracy with previous prediction models of RDF-3.

O4. Incorporate risk modeling for Public-Private Partnerships into the operations and maintenance of energy-from-waste applications, like RDF production.

1.4 Thesis Outline

Chapter 1: Research Background

This chapter provides the research background surrounding the production of waste to RDF conversion and focuses on associated uncertainties involved in decision-making at material recovery facilities producing RDF. The research motivation and methodology are then introduced. A brief statement on the research objectives of the thesis and an overview of the framework are also presented in this chapter.

Chapter 2: Literature Review

This chapter summarizes the research progress on using RDF as a renewable energy resource and its sustainability problems, including the process for RDF quality monitoring, uncertainty modeling, and PPP in WtE projects.

Chapter 3: RDF-3 Production and Characterization

This chapter delves into developing a computer vision application for precise municipal solid waste characterization, commencing with a mechanical sorting line employing bag breakers and trommel screens. It encompasses a comprehensive characterization process post-trommel screen, capturing waste from single and multi-family sources.

The Smart-Sight application's development and validation within a practical Materials Recovery Facility (MRF) are central, aiding in predictive RDF-3 composition assessment.

Chapter 4: Simulation Model for RDF-3 Production

Here, a simulation model for Material Recovery Facilities (MRFs) producing RDF-3 is constructed. It supports strategic, tactical, and operational decisions while incorporating uncertainties affecting MRF performance. The model enhances operational conditions and predicts RDF quality standards, validated against real-world MRF data.

Chapter 5: Predictive Models for RDF Calorific Value

This chapter introduces predictive models for RDF calorific value, leveraging ultimate elemental analysis. Empirical and machine learning methods yield accurate predictions, surpassing previously published models. These models demonstrate improved accuracy, especially the machine learning models, offering effective complex correlation handling.

Chapter 6: PPP Models in EfW Projects

A comparative analysis of PPP models in Energy from Waste (EfW) projects in the UK and Canada is undertaken. It introduces a novel quantitative probabilistic model simulating EfW feasibility, considering risks in O&M contract. This model accurately captures the multifaceted impact of variables, emphasizing the significance of modeling these variables for financial viability. The study highlights inherent risks in EfW technologies and supports PPP models' superiority over traditional models in the EfW sector.

Chapter 7: Finally, this chapter presents the research work completed in this thesis. The limitations and future works are also discussed in this chapter.

Chapter 2: Literature Review

2.1 Overview

In this chapter a systematic literature review (SLR) is presented with focus on the critical aspects of energy-from-waste (EfW) projects, starting with the research methodology that lays the foundation for systematic investigation. In sustainable EfW projects, the estimation of calorific value is a key component, where different methods and models are explored to accurately assess the energy potential of waste. This is closely linked to the characterization of municipal solid waste, which is essential for determining the composition and properties of waste, with continuous waste characterization and computer vision techniques playing pivotal roles in enhancing the accuracy of waste analysis and sorting.

The quality of refuse-derived fuel (RDF) is another crucial aspect, with various factors impacting its measures. This directly influences decisions in the biomass fuel supply chain, highlighting the importance of quality assessment in optimizing energy recovery. Public-private partnerships (PPP) are identified as instrumental in the successful implementation of EfW projects, with their role, trends, and risk modeling being key considerations for effective collaboration between the public and private sectors.

The chapter concludes with a discussion on research gaps, indicating the need for further exploration in areas such as advanced waste characterization techniques, optimization of RDF quality, and innovative PPP models. This comprehensive overview not only connects the various components of EfW projects but also underscores the interdependencies between them, paving the way for a holistic approach to sustainable waste management and energy recovery.

2.2 Research Methodology

To achieve the research objectives of this study, the list of academic publications was gathered from Scopus database due to the wide range of coverage and better choice for inter-disciplinary research topics [35]. Figure 2.1 shows the flowchart of the systematic literature review (SLR) research methodology [36], applied in conducting the literature review of this study, which includes three sequential phases that are explained in the following subsections.

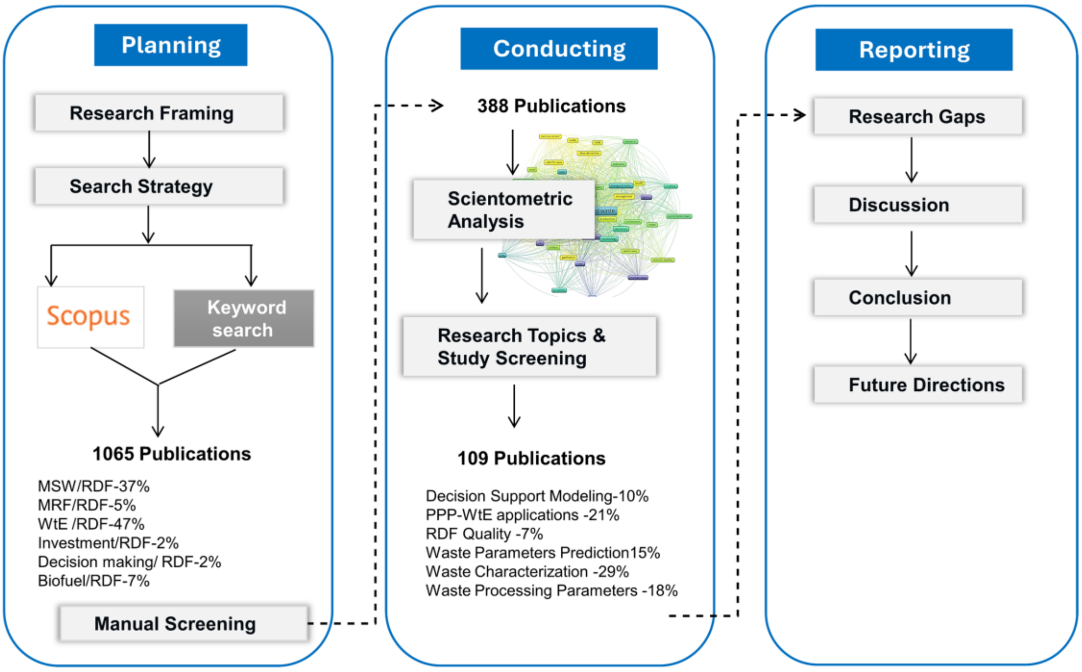

Figure 2.1: Research methodology, showing keywords, number of publications found.

2.2.1 Planning Phase

This phase identifies research questions that guide the selection of relevant studies, methodology, data extraction and synthesis, as well as the review protocol. The following four research questions are formulated according to the role of RDF in WtE applications,

a) What newer techniques are available for composition analysis of MSW for RDF production, and how can they help decrease reliance on labor-intensive laboratory procedures?

b) How do different models compare when estimating the calorific value of RDF or biomass within solid waste management?

c) What research studies emphasize the development and implementation of decision support systems to enhance quality within RDF production?

d) What are the primary limitations in RDF production operations and maintenance for WtE projects operating under the PPP model?

The research protocol is conducted in SCOPUS. The search history is set to last 25 years, and there is a total of 1065 studies identified using research questions related to keyword combinations that included "Refuse Derived Fuel" along with associated terms such as "Municipal Solid Waste," "Material Recovery Facility," "Biofuel," "Waste to energy" and "investments." Supplementary material (S8) shows the selected keywords, number of studies, and search queries. This approach is designed to capture a comprehensive set of studies related to RDF and its interconnections with other critical aspects of waste management for RDF production and its applications. The keyword search in Scopus is set as title/abstract/keywords to acquire all the publications containing the selected keywords for current studies on RDF. The process of filtering out the searched papers is also summarized in Figure 1. For the review process, only papers published in peer-reviewed journals or conference proceedings in the English language are considered. Book reviews and editorials are excluded to ensure uniformity in the research aims and methods of all selected papers. To further refine the selection, the source titles and abstracts are reviewed. The total number of papers that are thereby selected for deep focus in this study amounts to 388. In the next phase of the SLR, all of the selected publications undergo rigorous screening and are subject to bibliometric and scientometric analysis, as well as quality assessment.

2.2.2 Conducting Phase

In the conducting phase, 388 review studies are investigated with their metadata extracted, analyzed, and synthesized. This section provides a comprehensive analysis of the reviewed papers, and the following sections delve into exploring, analyzing, and synthesizing the data.

Furthermore, a scientometric analysis is carried out to pinpoint key research areas pertaining to the underlying topic [37]. Through network modeling and visualization, scientometric research seeks to analyze the intellectual landscape of a knowledge domain. This approach enables the identification of key questions that researchers aim to address and highlights the methods authors have developed to achieve their objectives. To construct and map the knowledge domain intersection between the 388 publications, keyword co-occurrence within the research area is analyzed using VOSviewer. This tool is selected for its ability to visually represent the results of scientometric analysis. The output from VOSviewer is a distance-based map, where the spatial distance between any two items visually indicates the strength of their relationship: the greater the distance, the weaker the relationship. Additionally, the size of each item label correlates directly with the frequency of the keyword across publications, while different colors distinguish various knowledge domains as identified by VOSviewer's clustering technique.

Finally, citation analysis is conducted with the unit of analysis set to documents. The relatedness of items is determined based on the number of times authors cite each other, providing an aggregate representation of the research field and offering evidence for subsequent clustering in research areas. Additionally, burst detection sheds light on the relative changes in significance over time, helping identify trends and shifts in RDF production. This approach contrasts with previous analyses that merely offer a static overview of the field.

A scientific criterion is identified as a quality check funnel to narrow down further the list of publications based on the objective, methodology, and the contributions presented. Additionally, journals published by reputable publishers are recognized as high-quality research and are, therefore, included in the review. In the subsequent eligibility phase, the focus narrowed to assessing the full text of the articles that passed the initial screening. The goal of the quality assessment is to evaluate the selected articles based on their relevance to RDF production in MRFs, research quality, and the presence of recommendations for further research and future work in this area. The authors used a scoring scale of 1-10 for each paper, assigning scores for each criterion (0, 0.5, 1). The scores are as follows: 1 indicates the paper fully met the assessment criteria, 0.5 indicates partial compliance, and 0 indicates a lack of compliance. Papers scoring 5 or higher are included. The assessment criteria were:

a) AC1: Was the research objective clearly defined in terms of RDF production?
b) AC2: Has the study been cited by other research in RDF production?
c) AC3: Does the study specifically address a phase of RDF processing in MRFs?
d) AC4: Does the study detail a specific RDF processing challenge or scenario?
e) AC5: Is the experimental design suitable for studying RDF processes?
f) AC6: Are experiments conducted with a relevant RDF dataset?
g) AC7: Is there a clear justification for the chosen method or technique?
h) AC8: Is the method or technique compared with other RDF processing methods?
i) AC9: Are the results of the study thoroughly evaluated?
j) AC10: Is there evidence that the method improved RDF production outcomes?

Each article is evaluated against the above-mentioned criteria, which may consider the scope of the study, its relevance to the field, and the article's contribution to the literature on the topic. Articles that do not meet these criteria are excluded. After a thorough review process, 109 publications are precisely selected for their detailed examination of the relationship between RDF, its high-quality production, sustainable operations, and applications within WtE projects. The next sections highlight the results.

2.2.3 Reporting Phase

This phase presents the results and findings from the literature review. It also includes the review framework and suggests future directions for further research. The results in this phase are detailed throughout the remainder of chapter 2.

The keyword search strategies outlined in Section 2.2.1 are utilized to uncover pertinent academic articles in journals, as summarized in Table 2.1. A significant portion of the academic literature on RDF applications is found in journals that encompass MSW, material recovery facility, biofuel supply, and PPP fields, including Waste Management, Waste Management and Research, Fuel, Bioresource Technology, and Journal of Environmental Management. Among these journals, Waste Management is the journal that includes the most publications on these topics

Table 2.1: List of most widely used academic journals and conference proceedings from January 1993 to February 2024.

Journal Title	**Number of Articles**	**% of Total Publication**
Waste Management	92	16%
Waste Management and Research	31	6%
Fuel	20	4%
Bioresource Technology	19	3%
Journal of Environmental Management	15	3%
Journal of Material Cycles and Waste Management	13	2%
Resources and Conservation	11	2%
Environmental Science and Technology	10	2%
Waste and Biomass Valorization	10	2%
Waste Management & Research	10	2%
WIT Transactions on Ecology and the Environment	10	2%
Chemical Engineering Transactions	9	2%
Environmental Science and Pollution Research	9	2%
Fuel Processing Technology	9	2%
International Journal of Life Cycle Assessment	9	2%
Renewable Energy	8	1%
Applied Thermal Engineering	7	1%
Energy and Fuels	7	1%

Figure 2.2 illustrates the annual variation in the number of publications on this research topic, in journals proceedings. Since 2009-2010, publications on RDF applications in selected applications have exhibited a consistent upward trend, with notable surges in 2016 (a 56% increase in publications) and 2022 (a 24% increase). Interestingly, these peaks align with the initial development of technologies in solid waste management [38], [39] and the rise of big data techniques [40], respectively. It's worth noting that this study includes only the publications from the first two months of 2024, which

explains the comparatively lower-than-expected number of publications for that year.

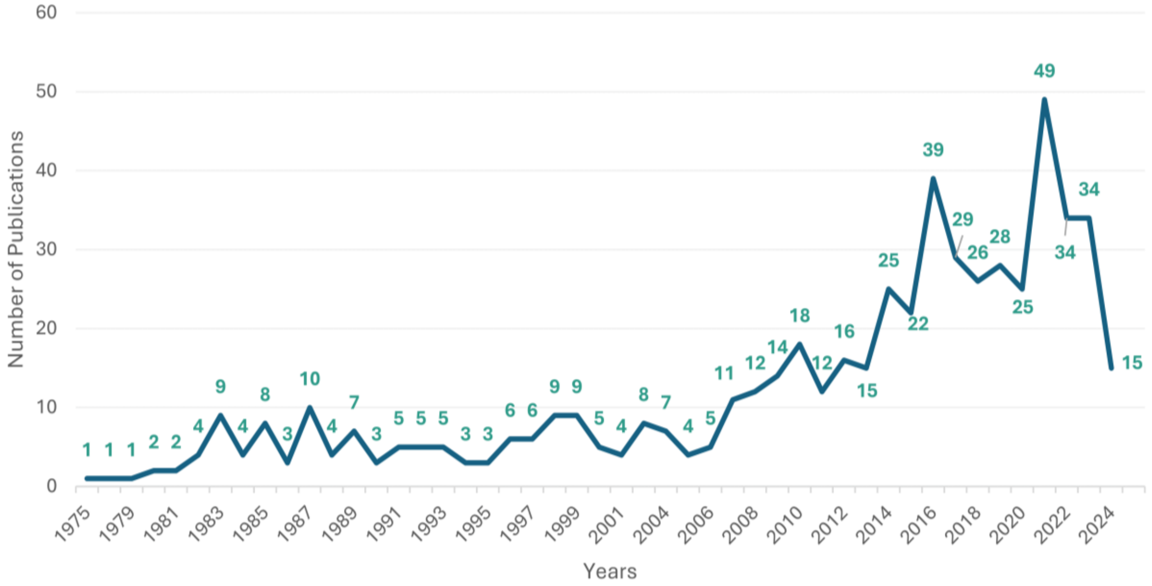

Figure 2.2: Historical trend of published studies in refuse derived fuel applications (period 1975-2024).

The study leverages a synthesis of interconnected topics to present a cohesive narrative that effectively bridges theoretical research with practical applications. This approach enhances the understanding of integrated waste management solutions, showcasing how interconnected insights can drive innovation and efficiency in the waste-to-energy recovery field. A threshold is set, requiring a minimum of five occurrences for a keyword to be included in the analysis, as depicted in Figure 2.3. This results in a map with 42 nodes, 583 links, and a total link strength of 2806. Table 2.2 summarizes the keyword occurrences and each individual node strength, and the map is illustrated in Figure 2.3.

This analysis unveiled interconnected research topics. The initial cluster (in purple) encompasses significant areas such as "Moisture", "Chlorine", "Calorific value", "Characterization", "Combustion," and "Theoretical study," critical to RDF applications. The subsequent cluster (in pink) highlights themes like "Decision making," "Environmental impact," "Energy policy" "investments," and "Sustainability" as crucial areas of research in this domain. Similarly, "quality control", "Solid recovered fuel", "Waste products" and "mechanical biological treatment" are other topics highlighted in this research. The rigorous assessment at this stage ensures that only studies that are directly pertinent and meet the research quality standards are included. Additionally, this phase may also include a supplementary search forward and backward looking at references from the selected articles and works that cite them, thereby potentially introducing a few additional records that are relevant for inclusion.

Table 2.2: List of selected keywords and relevant network data

Keyword	**Occurrences**	**Links**	**Total link strength**	**Avg. pub. Year**
Refuse derived fuels	217	40	642	2013
Municipal solid waste	171	40	445	2015
Waste management	120	40	365	2012
Waste incineration	118	39	387	2016
Combustion	85	38	246	2008
Gasification	80	37	253	2014
Waste treatment	75	37	281	2013
Biomass	66	37	188	2012
Pyrolysis	62	34	193	2013
Calorific value	61	35	204	2016
Land fill	44	30	152	2013
Biofuels	42	33	95	2016
Environmental impact	41	31	136	2010
Chlorine	40	28	146	2014
Anaerobic digestion	35	23	86	2012
Waste products	35	30	87	2012
Waste-to-energy	33	33	117	2015
Gas emissions	27	26	97	2016
Greenhouse gases	27	26	99	2018
Methane	27	27	71	2009
Thermogravimetric analysis	27	26	105	2016
Theoretical study	25	10	15	1984
Moisture	24	27	87	2017
Decision making	23	28	76	2015
Life cycle assessment	23	24	85	2017
Chemical analysis	22	32	78	2012
Sustainable development	21	27	72	2019
Cements	20	27	70	2018
Waste disposal facilities	18	28	65	2018
Particle size	17	24	66	2014

Plastics	17	23	55	2015
Plastic	15	24	65	2013
Characterization	14	17	40	2008
Chemical composition	14	25	68	2013
Investments	14	20	37	2019
Mechanical biological treatment	14	20	51	2016
Pelletizing	14	16	49	2013
Solid recovered fuel	13	27	61	2015
Sustainability	13	20	45	2019
Syngas	13	20	57	2019
Energy policy	12	17	37	2020
Quality control	10	20	38	2014

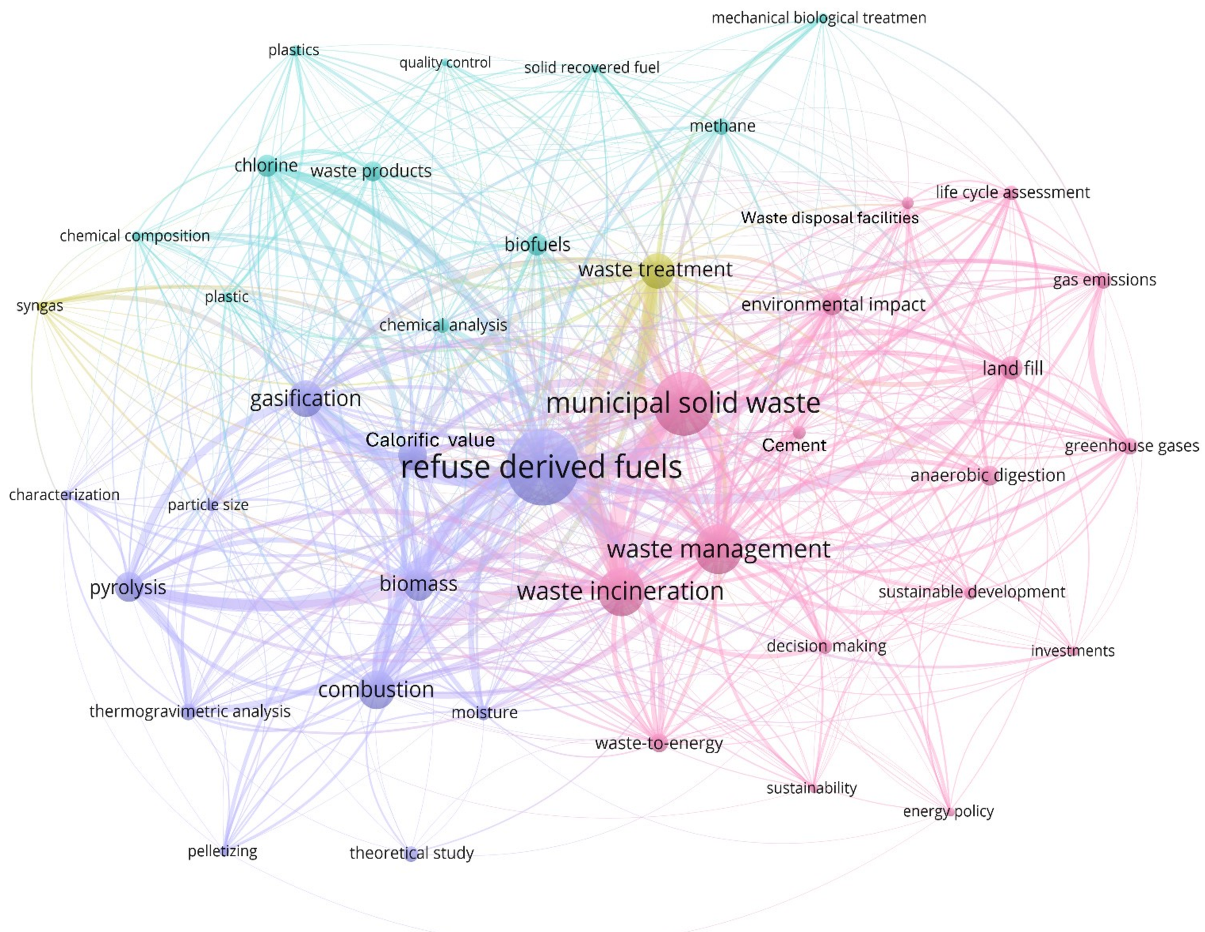

Figure 2.3: A general network of co-occurring relevant research topics (2003-2023) retrieved from the literature. Number of studies according to publication year and application fields.

Keyword co-occurrence networks are static snapshots of the research field, not reflecting temporal changes. However, VOSviewer introduces a time-zone perspective by representing each node with the average year in which that keyword was cited in the literature. Figure 2.4 shows the evolution of RDF studies and shows that characteristics of RDF, energy policy, investments, sustainability, and waste disposal facilities are a few emerging topics in recent times.

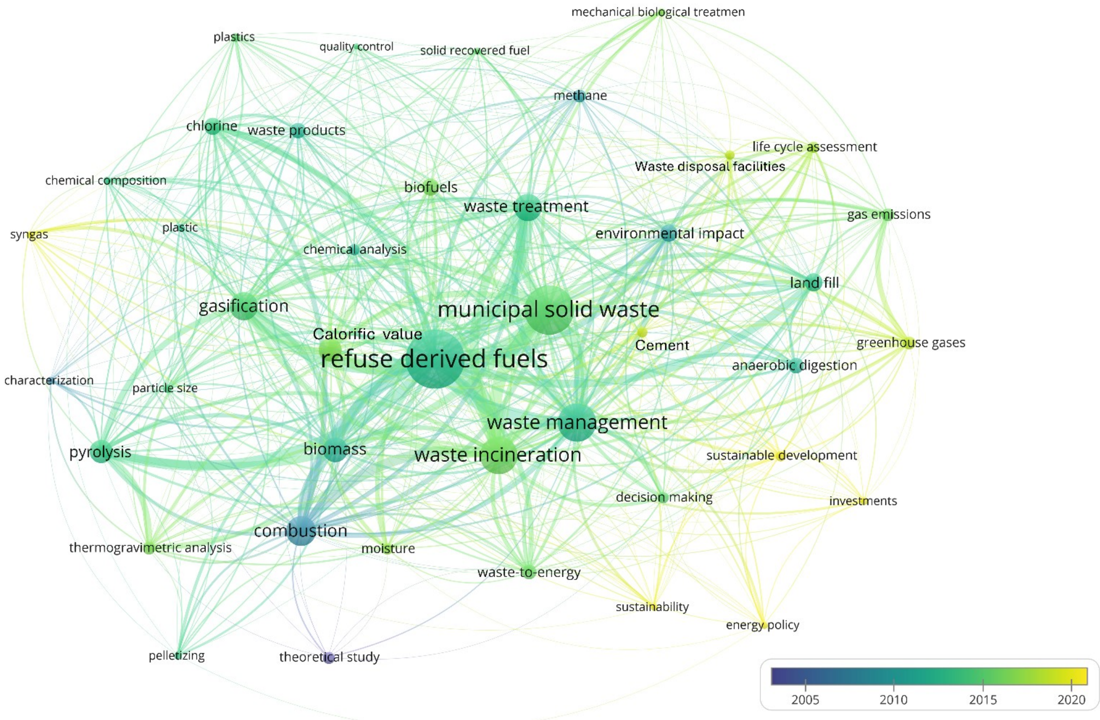

Figure 2.4: Network of co-occurring keywords timeline

Data synthesis was facilitated by extracting and summarizing pertinent information, encompassing dataset specifics into the following categories, “Decision Support Modeling”, “PPP-WtE applications”, “RDF-Quality”, “Waste Characteristics Prediction”, “Waste Characterization”, and “Waste Process Parameters”. This comprehensive approach aided in streamlining the data synthesis process. Finally, 109 publications were selected for their direct exploration of the relationship between RDF, its high-quality production, sustainable operations, and applications within WtE.

Figure 2.5 shows how the number of publications on the research topic under review varies each year. Publications on waste characterization, PPP in waste to energy, and waste processing parameters show an overall upward trend from 2015 to 2022. Table 2.3 presents the most cited studies within six key areas of our research focus highlighted before. The table lists the authors and publication years alongside the number of citations each study has received, illustrating the influence and relevance of these works in the field. (Castillo-Villar et al., 2017; Sarc and Lorber, 2013) [20], [41] are widely acknowledged for their seminal work on assessing RDF production quality. Their research is pivotal in classifying RDF according to SRF standards and analyzing biomass quality variance in biofuel production, ensuring that RDF meets stringent sustainability criteria. In the category of process parameters prediction, (Bairamzadeh et al., 2018; Clavreul et al., 2012) [42], [43] have significantly contributed by demonstrating how uncertainty analysis can enhance sensitivity analysis within waste management systems. (Channiwala and Parikh, 2002; Yin, 2011) [44], [45] are renowned for their predictive models of waste parameters. Similarly, (Buah et al., 2007; Shi et al., 2016) [28], [46] have garnered recognition for their studies on waste characterization of municipal solid waste (MSW) using pyrolysis and thermogravimetric techniques. In a comprehensive systematic review, (Vitorino de Souza Melaré et al., 2017) [47] emphasized the importance of decision support modeling in addressing challenges across various waste management sectors, employing tools such as mind maps. (Costi et al., 2004) [48] has made notable contributions by presenting foundational models and optimizations for decision support systems that aid in sizing recycling and waste disposal operations. From a PPP perspective, (Song et al., 2013a) [49] stand out as the most cited authors for their research on global trends in PPPs and risk identification in WtE incineration projects, with (Wu et al., 2018) [50] also making significant contributions to the field.

All these aspects are prominently featured in the main sections of these publications. Consequently, this lays a solid foundation for the subsequent sections, where these threads are woven into a comprehensive narrative, contributing to a deeper understanding and paving the way for future research endeavors.

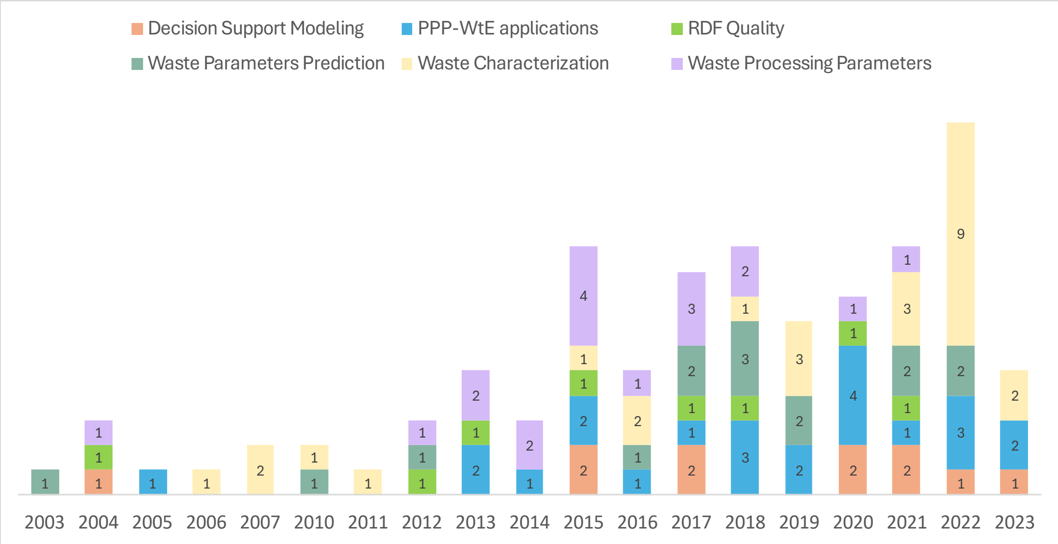

Figure 2.5: Number of studies according to publication year and application fields.

Table 2.3: Overview of relevant categories in the SLR and top citied authors

#	Category	Author/Year	Citations
1	**RDF Quality**	(Sarc and Lorber, 2013; Mbt et al., 2015)	153
		(Castillo-Villar et al., 2017)	71
		(De Filippis et al., 2004).	57
		(Velis et al., 2012)	55
		(Aboytes-Ojeda et al., 2022)	35
		(Manyà et al., 2015).	30
		(Mirkouei et al., 2016)	12
		(Ouigmane et al., 2021b)	5
		(Tahir et al., 2023b)	1
2	**Process Parameters Predictions**	(Clavreul et al., 2012)	357
		(Rotter et al., 2004)	215
		(Bairamzadeh et al., 2018)	175
		(Pressley et al., 2015)	162
		(Arena and Di Gregorio, 2014)	153
		(Diaz et al., 1982)	109
		(Velis et al., 2013)	80
		(Bessi et al., 2016)	64
		(Antmann et al., 2013)	43
		(Ip et al., 2018)	43
		(Ardolino et al., 2017)	34
		(Nasrullah et al., 2017)	33
		(Vanegas et al., 2015)	19
		(Tanguay-Rioux et al., 2021)	14

	(Mariapaola Testa et al., 2015)	12
	(Raymond, 2017)	12
	(Russo and Verda, 2020)	12
	(Shi et al., 2015)	3
3 Waste Parameters Prediction	(Channiwala and Parikh, 2002)	2554
	(Yin, 2011)	584
	(Vargas-Moreno et al., 2012)	310
	(Kathiravale et al., 2003)	287
	(Shi et al., 2016)	172
	(Xing et al., 2019)	125
	(Ozyuguran et al., 2018)	113
	(Boumanchar et al., 2019)	112
	(Samadi et al., 2021)	59
	(Yaka et al., 2022)	31
	(Galhano dos Santos and Bordado, 2018)	27
	(Dashti et al., 2021)	23
	(Sebastian et al., 2019)	21
	(Dodo et al., 2022)	19
	(Alves et al., 2018)	6
	(Tahir et al., 2023a)	1
4 Waste Characterization	(Buah et al., 2007)	198
	(Shi et al., 2016)	172
	(Ma et al., 2010)	142
	(Cozzani et al., 1995)	123
	(Vassilev et al., 1999)	100
	(Lu and Chen, 2022a)	75
	(Rana et al., 2018)	62
	(Hwang et al., 2007)	54
	(Zaini et al., 2019)	32
	(Rotter et al., 2011)	29
	(Robinson et al., 2016)	28
	(Garcia Lopez et al., 2018)	30
	(Agrawal, 1988)	27
	(Rada et al., 2006)	17
	(Silva et al., 2015)	15
	(Okoligwe et al., 2022)	9
	(Sbrolini Tiburcio et al., 2021)	9
	(Okoligwe et al., 2022)	8
	(Âriņa et al., 2020)	6
	(Ouigmane et al., 2021a)	4
	(Thawani et al., 2022)	3
	(Akdemir et al., 2023)	1
	(Cuingnet et al., 2022)	1

	(Tahir et al., 2024)	0
	(Saravanan and Dhinagaran, 2023)	0
5 Decision Support Modeling	(Vitorino de Souza Melaré et al., 2017)	268
	(Costi et al., 2004)	146
	(Zahraee et al., 2020)	114
	(Sharifzadeh et al., 2015)	107
	(Mirkouei et al., 2016)	102
	(Yılmaz Balaman and Selim, 2015)	40
	(Burli et al., 2021)	17
	(Akhtari et al., 2020)	13
	(Pishvaee et al., 2021b)	9
	(Patel et al., 2023)	3
	(Gautam et al., 2022)	1
6 PPP-WtE applications	(Song et al., 2016, 2013b)	467
	(Wu et al., 2018, 2017)	231
	(Xu et al., 2015)	93
	(Fantozzi et al., 2014)	59
	(Spoann et al., 2019)	53
	(Arbulú et al., 2016)	50
	(Forsyth, 2005)	41
	(Saadeh et al., 2019)	38
	(Khawaja et al., 2021)	24
	(Dolla and Laishram, 2021a)	23
	(Zhang and Wang, 2018)	22
	(Lu et al., 2022)	15
	(Wang and Zhang, 2018)	14
	(Cui et al., 2020)	13
	(Cao et al., 2022)	8
	(Bourtsalas, 2023)	5
	(Hou et al., 2022)	3
	(Utama et al., 2020)	1

In this context, the comprehensive data synthesis from the scientometric analysis and quality assessment helped categorize key findings into five topics which set a detailed empirical backdrop for the forthcoming detailed discussions. Each of these categories not only reflects a distinct aspect of waste management and energy production but also interlinks to form a cohesive understanding. These interconnections are crucial for developing integrated solutions that are more effective and sustainable. For example, improvements in RDF quality can enhance the outcomes of waste-to-energy applications (PPP-WtE), thereby making the systems more efficient and environmentally compliant.

The subsequent sections highlight the insights into “Waste Characteristics Prediction” which enhances understanding of how different waste compositions influence RDF's calorific value, crucial for optimizing energy recovery. Secondly, “Waste Characterization” provides a foundational knowledge base that supports the detailed examination of waste types and properties, which are essential for effective segregation and energy production treatment in subsequent processes. Third, drawing from the “RDF-Quality” findings, this topic probes into the standards and methodologies employed to ensure the high quality of RDF, which is critical for consistent energy production and environmental compliance. Fourth; leveraging the “Decision Support Modeling” insights, this part explores strategic, tactical, and operational decisions that drive the efficiency and sustainability of the biomass fuel supply chain. Lastly, the accumulated knowledge on “PPP-WtE applications” sheds emphasis on how collaborative efforts between public and private sectors can enhance the implementation and management of EfW projects, thereby ensuring sustainable and economically viable waste management solutions.

This structured exploration ensures a thorough narrative that not only addresses the intricate dynamics of managing RDF and waste-to-energy systems but also prepares the groundwork for future advancements in the field.

2.3 Waste Characteristics Estimation

2.3.1 Estimation Methods

Utilization of RDF as a fuel requires familiarity with its heating value, which is a very significant parameter and is often stated as the higher heating value (HHV) [51]. The HHV refers to the total energy released by a kilogram of fuel when it is completely burnt out and normally measured in mega joules per kilogram. Unlike HHV, the low heating value (LHV) quantifies the heat released from burning a substance while keeping the resulting water vapor in a gaseous state. The measurement of these properties is expensive and requires time, which has prompted many previous works to focus their attention on determining mathematical models to predict HHV values for various categories of Biomass [52]. According to Channiwala [44], RDF's calorific value is dependent on its chemical composition during the combustion process. In this study, basic characterization involves four key measurements: determining physical composition [53], moisture content [54], conducting chemical composition (proximate-ultimate analysis), and determining the heating value, all shown in Figure 2.6. These assessments collectively provide fundamental insights into the composition and energy potential of the RDF material. The elemental composition of RDF on a dry and ash-free basis includes Carbon, Hydrogen, Oxygen, Nitrogen and Sulphur contents, and the weight percentages of these elements inside RDF can be found using the ultimate analysis [45]. Thus, the crucial parameter of HHV in waste or biomass fuels demonstrates a direct correlation with their ultimate analyses. The laboratory samples for analysis are prepared using the following ASTM E829-23 method [55]. Subsequently, the sample's particle size is reduced through shredding, resulting in the air-dried finely ground laboratory sample. This finely ground sample is separated and stored in an air-tight container, designated as the air-dried analysis sample. These specific samples are utilized for conducting various analyses shown in Figure 2.6.

The ultimate analysis is normally conducted according to standards like ASTM 5373 [56] , ASTM D4239 – 18 [57] or E775-15 [58], whereas the calorific value calculation is based on ASTM D5865 [59] or ASTM E711 [60] methods and experiments are conducted using a Bomb calorimeter and thermogravimetric analyzer [61]. The only drawback of using such composition analysis is related to representative samples, which may be either small or specific from the location where collected. Nonetheless, another method which is also used for HHV prediction applications is known as proximate analysis. The correlation involving four independent variables from proximate analysis (via ASTM D121 [62]), moisture, fixed carbon, volatile matter, and ash contents with HHV, exhibits the least estimation error, making it a viable choice for future applications [63].

However, Xing [64] proposed models for HHV prediction of biomass using machine learning approaches demonstrating ultimate-based models show better performances even with fewer samples. The results in that study showed that newly developed models which are based on the ultimate analysis give better predictions ($R^2 > 0.90$) and the carbon and hydrogen fractions hold the significant places for having major impacts on the HHV. Thus, complex non-linear models developed using innovative techniques like machine learning are desirable to accurately predict the calorific value of biomass fuels and can significantly influence the operational stability of waste processing facilities.

A recent study incorporated an assessment of CO_2 emissions and potential cost savings achievable by substituting coal combustion with RDF [65]. This assessment focused on waste-derived fuels with heat values equal to or exceeding 20 MJ/kg, indicating their suitability for this substitution analysis. The study emphasized the potential for substantial savings: an estimated 64 kilotons/year of coal and $8.69M (USD) could be conserved by utilizing RDF as a viable energy replacement alternative.

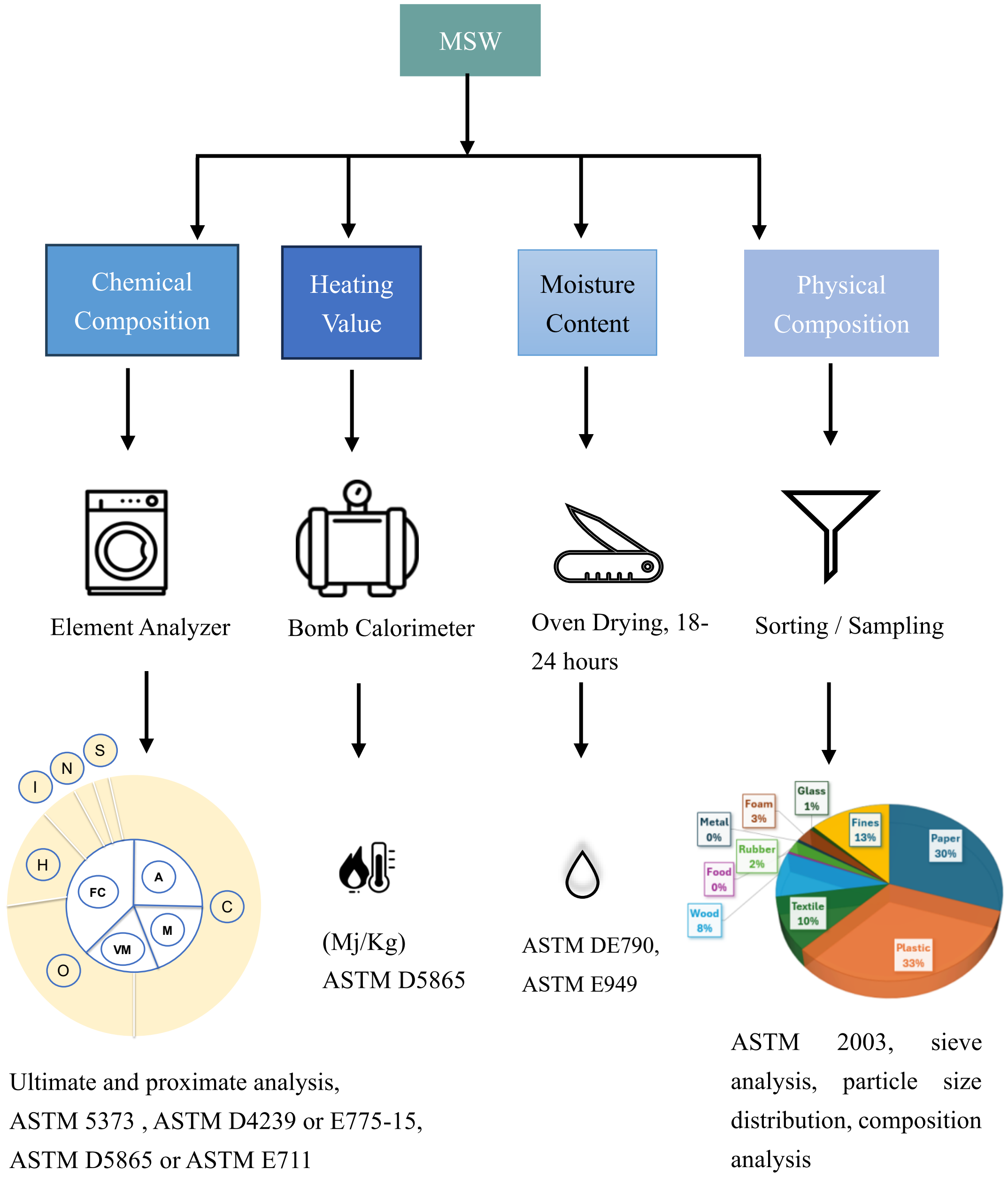

Figure 2.6: MSW is typically analyzed using four key methods, 1) moisture content determination, 2) physical composition, 3) chemical composition, 4) heating value determination

2.3.2 Estimation Models

Literature shows that many mathematical models presented in the past utilized ultimate analysis to predict the HHV for various categories found in Biomass. In 1880, Dulong provided the first model for calculating the heating value [66]. Both statistical and heuristic methods e.g linear regression, multi-layer neural networks, and genetic programming are prominent methods employed to predict HHV value using the ultimate analysis [67] and [68]. Advanced machine learning algorithms like artificial neural networks, Support vector machine regression and Random forest regression as mentioned by [64], [69], [70],[71], are new methods successfully applied to predict HHV for biomass fuels with variable training and validation datasets. Figure 2.7 shows the list of methods applied for such applications in the literature. The exploration primarily emphasizes the utilization of linear regression and artificial neural networks methods in determining the Higher Heating Value (HHV) of RDF-type materials. These methods show that better models can be devised with improved statistical efficiencies in the heating value predictions for biomass fuels.

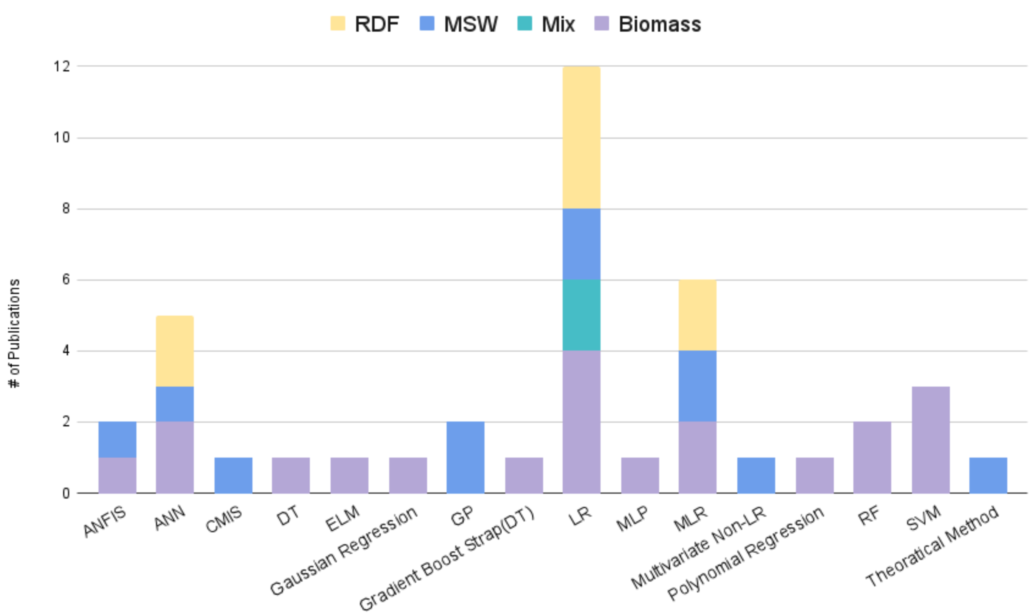

Figure 2.7: Statistical and Heuristic methods used for HHV predictions of various waste types extracted from publications between (2003-2023).

To illustrate the practical application of the updated physicochemical properties of individual waste components, Roshni et al.[72] presented a study to simplify the theoretical estimation of waste characteristics by experimentally analyzing individual components within mixed MSW feed on an as-received basis. In this approach both ultimate and proximate analysis are conducted using empirical equations. This approach minimizes the need for labor-intensive and economically complex experiments. Similarly, Ozyuguran et.al.[73] presented the linear and non-linear empirical equations to predict heat value for thirty-nine different material types with varying physical characteristics. For comparison purposes, the previously established empirical models for predicting HHV based on the ultimate analysis of similar waste types from the literature are shown in Table 2.4.

Additionally, the models' performance is usually depicted through scatter plots, showcasing the relationship between model-predicted and observed values. The assessment of the developed models utilized statistical indicators like R^2, mean average precision error (MAPE), root mean square error (RMSE), correlation coefficient (CC), average biased error(ABE), etc. [71], [73], [74]. These parameters were calculated based on the variance between observed and predicted values of HHV or LHV. But all the models are limited to the type of biomass used as references and often cannot be extrapolated to a different kind of substance such as RDF, also very few models exist to estimate HHV for urban wastes like MSW and RDF [16]. Improved and deeper studies are required to be conducted with a distinct group of RDFs to prove the robustness of the models previously developed in the literature. Further to this, it has been discovered that the literature did not elaborate on the type of RDF used for modelling HHV equations. In this context, previous studies did not highlight the line configuration consisting of material recovery units or material separation parameters of a facility used in prediction models which can have a significant impact on the quality of the RDF produced. Now the question arrives, can the existing correlations be used to determine or predict the HHV of the RDF and are they appropriate enough to be applied?.

Table 2.4: Established Models for HHV Prediction of Similar Waste Residue

Model #	HHV equation (MJ/kg)	Author	Waste Residue	Year
Eq 2.1	$\left[140.96\, C + 602.14\left(H - \frac{O}{8}\right) + 39.82\, S + 42.75\left(\frac{O}{2}\right) - 104\, N + 89.29\left(H - \frac{O}{16}\right)\right] \text{x}\ 0.002326$	Wilson DL[75].	MSW	1972
Eq 2.2	0.328C + 1.419H + 0.0928S	Channiwala [44]	MSW	2002
Eq 2.3	0.4373C − 0.3059	Channiwala [44]	MSW	2002
Eq 2.4	370.8 C + 1112.4 H - 139.1O+317.8 N + 139.1 S	Meraz L[76]	MSW	2003
Eq 2.5	0.416638C − 0.570017H + 0.259031O + 0.598955 N + 5.829078	Kathiravale [77].	MSW	2003
Eq 2.6	0.336C+1.419H+0.94S−0.145	Reza B[78]	RDF	2013
Eq 2.7	0.350 C+1.01 H−0.0826 O	Shi H[28]	MSW	2016
Eq 2.8	0.40C+0.32H	Rui Galhano[79]	RDF	2017
Eq 2.9	0.4531C	Rui Galhano[79]	RDF	2017
Eq 2.10	0.4191C+0.6523 (H- $\frac{O}{8}$)+ 18.4007 S	Octávio [16]	MSW	2018
Eq 2.11	0.3805 C+0.7700 H-4.0219	Boumanchar[67]	MSW	2019
Eq 2.12	$2.775 + H + 0.004027\, C + 0.004027\, C^2 + \frac{0.05706}{H - 12.97} + \frac{0.02323}{H - 6.661} + \frac{0.009398}{H - 5.961} + \frac{12.97 - H}{H^3 - 5.922\, C}$	Boumanchar[67]	MSW	2019

2.4 Characterization of Municipal Solid Waste

2.4.1 Continuous Waste Characterization

Municipal Solid Waste (MSW) is typically categorized based on its source or material type, outlining its physical composition. Yet, in Waste-to-Energy (WTE) facility design, additional elements like moisture, volatile and fixed carbon content, non-combustible proportions, chlorine, and sulfur content are vital. These factors inform technology selection, furnace/boiler capacity determination, and auxiliary facility design, including flue gas cleanup equipment [28]. Processing MSW is increasingly challenging because of futile decision-making and fragmented integration in sustainable waste treatment processes, causing a substantial wastage of resources in landfills. In response, the continuous sorting of MSW and its transformation into a combustible fraction called refuse derived fuel (RDF) represents an effective measure to curtail resource depletion in landfills and shift towards alternative energy solutions. This approach aims to diminish reliance on conventional fossil fuels. However, RDF production must adhere to precise technical specifications, primarily dictated by its end-users or local municipalities. This aspect significantly influences the final product's recognition, elevating RDF to meet the highest quality of solid recovered fuel (SRF) standards described by [23]. To achieve this goal, the recovery and purity of the sorted material must be ensured, and the cost of the waste separation process must be reduced [18], [80]. At present, the quality of the RDF is checked at the end of the sorting line by manually collecting the samples and sending them to laboratories at the MRF for further composition and chemical analysis. This is an expensive and time-consuming process and untimely for making any substantial improvements in RDF quality [52]. Even with timely sampling, MRF managers assume similarity in waste compositions for long periods of time, which leads to incorrect energy generation estimations and economic uncertainty. To enhance the quality of produced RDF, it is imperative to shift focus towards upfront waste characterization, enabling more proactive quality control measures. Also, the operations of the MRF require frequent waste stream characterizations to adjust feedstock quantities and meet the required final RDF specifications defined for parameters like calorific value, ash content, or moisture content among others, [81]. Thus, the dependency of sorting equipment separation coefficients on the in-feed MSW composition has yet to be explored.

2.4.2 Computer Vision for Waste Composition Analysis

Over the years, advancements in computer vision (CV) technologies, driven by improved computational power and algorithms, have significantly enhanced the efficiency of waste sorting and recycling processes in waste management. A review conducted by [82] presents a detailed comparison of popular machine learning algorithms (ANN, SVM, decision trees, rule-based classifiers, etc.) and object detection networks (Xception, AlexNet, ResNet, DenseNet) to accomplish various tasks like waste recognition-classification and waste detection using R-CNN, Fast R-CNN, Retinet, YOLO, VGG structures for industrial, commercial, institutional, and residential-municipal waste materials. There are also studies which have explored the application of computer vision-based waste characterization in several other domains, including aluminum streams [83] and medical waste [84]. Use of hyperspectral imaging combined with artificial intelligence models for detecting chlorine in RDF [26], [85]. Sheng et al.[86] developed smart bins for collecting metal, plastic, paper, and general waste by integrating sensor data and a machine learning framework. Thermal imaging for waste classification by [87] and restoring value of damaged materials by [88] are also captivating applications. Another promising approach was presented by Standley et al.[89] in which a model is developed for deriving a physical attribute, such as an object's mass, from its image. In this context, there are various open-source image data sets for various purposes, such as multiple object detection and single object recognition of a wide range of waste types. Some notable examples include (DataCluster Labs,[90]; Koskinopoulou et al.[91]; Mohamed, 2021 [92]; Sekar, 2019 [93]; Yang and Thung [94]). In a systematic review by Abdallah et al.[95], it is mentioned that using CV models in their original state sets an additional challenge, emphasizing the need for tailored adaptations to fit the complexities of MSW management. Similarly, researchers often employ simplified environments and synthetic datasets in their studies. So the future research should focus on real-world complex functions and apply computer vision to industrial waste characterization and sorting applications,[96].

Residential waste collected from single-family (SF) or curbside units, multi-family (MF) or apartment buildings /complexes, undergoes initial processing like hand sorting and mechanical separation using bag-breaker and trommel screens. Fabrice et al.[18] presented a study that emphasized the pivotal role of trommel screens. This critical sorting unit influences recovery rates and the quality of output streams in a standard MRF. Sequenced at the conditioning stages of the MSW sorting process, the trommel unit segregates materials based on their physical properties [27]. Typically, the trommel screen's output undergoes additional shredding or washing stages, which subsequently reduces the possibility of identifying distinct waste components, as noted by Onyinyechi et al.[97]. The waste residues collected after processing at various stages of the trommel unit maintain fraction size within a range of 5 to 23 cm and go through a manual waste characterization procedure before being directed via conveyors to the RDF production line [27]. This characterization aims to assess and predict the potential quality of RDF beforehand that can be produced to support operational decisions using computer vision. Such assessments can be facilitated using discrete-event simulation models as described by Junaid et al.[81]. The mass balance along with recovery of useful waste particles is significantly influenced by the size of the separation screens installed on the trommel units [27]. For such waste sorting at disposal facilities, the practical deployment of CV for automatic waste sorting requires significantly more research efforts to tackle the waste detection problems.

2.4.3 Computer Vision at Waste Sorting Facilities

Within waste sorting facilities, a computer vision-enabled waste classification system basically binds hardware and software elements. The hardware typically involves an inexpensive camera, functioning as the system's "eyes." Complementing this, the software comprises a set of sophisticated computer algorithms serving as the system's "brain.". These systems facilitate the identification of waste objects, creating an integrated and efficient waste sorting mechanism. Table 2.5 shows the implementation of various software and hardware solutions to detect and sort waste at sorting facilities .

The application method highlights the expansion of CV solutions across environments for waste monitoring or detection. Simplified methods lack real-world complexities, while Roadside, Conveyor, and Bin demonstrate practical real-world applications. Carolis et al.[85], presented an improved YOLOv3 network model to perform garbage detection and recognition in outdoor environments.

Table 2.5: Computer vision software/Hardware application for various waste type at sorting facility

Author	**Environment**	**Waste**	**Technology Used**	**Application Method**
Tachwali et al, 2007 [98]	Indoor	Recycling	Software	Conveyor
Mittal et al, 2016 [99]	Outdoor	MSW	Software	Roadside
Singh et al, 2017 [100]	Outdoor	MSW	Software	Roadside
Chu et al, 2018 [101]	Indoor	MSW	Software/Hardware	Simplified
Gundupalli et al, 2018 [102]	Indoor	Recycling	Software/Hardware	Conveyor
Ku et al, 2019 [103]	Indoor	C&DW	Software/Hardware	Conveyor
Wang et al, 2019 [104]	Indoor	Recycling	Software	Conveyor
Chen et al, 2020 [84]	Indoor	Medical	Software	Bin
Nowakowski et al, 2020 [105]	Outdoor	Electronics	Software	Simplified
Carolis et al, 2021 [106]	Outdoor	MSW	Software	Roadside
Koskinopoulou et al, 2021[91]	Indoor	Recycling	Software/Hardware	Conveyor

2.5 RDF Quality Measures

The characteristics of waste fuels like RDF are calorific value, particle size, impurities, chlorine content, sulfur content, fluorine content, ash content, moisture content, and heavy metals content. These characteristics are used for the quality classification of different types of RDF [20]. This aspect holds a significant impact on the final product recognition because an RDF produced according to a defined quality assurance procedure can further become a certified “solid recovered fuel” (SRF) [23], [107]. SRF is a subset of the larger family of RDF, and its quality is well known and defined according to standards such as EN-15359 and ISO-21640. These standards promote their safe use in energy conversion activities and for the general trust of the public.

Manyà et al.[97] discovered RDF pyrolysis dependence on temperature and heating rate, advocating further research into their impact on char yields and volatile release. RDF inclusion in feedstock enhances carbonization, prompting exploration of RDF-biomass co-pyrolysis for waste management and increased char production. Higher temperatures improve RDF-derived char reactivity, indicating potential for better carbon dispersion. Inorganic components in RDF boost char reactivity, highlighting MSW-derived RDF's for efficient biofuel production.

2.5.1 Factors Impacting Quality Measures

The production of a high-quality RDF or SRF is impacted by the composition of the input waste stream and the design of the material recovery facility (MRF) comprising of the multistage waste separation processes or units [9],[108], [109]. The composition of the output waste stream and its quantities are calculated by means of mass balance [21] and this is generally done using semi-empirical methods due to the lack of available information on the performance of these operational units [22]. Thus, the major constraint is sustainability in converting RDF to a certified, self-declared, and nationally recognized SRF. Antonio et al.[74], presented an extensive technical study on RDF production plant design to investigate the feasibility of producing a high calorific value product. The method used in the study involved testing various choices of process equipment and their utilization in different configurations in an RDF production line. Further, the study provides the heating value and mass efficiency in each configuration for defining the most suitable plants able to meet the required RDF quality levels at minimum cost. Yet, a few of the major constraints in utilizing this type of method are the evolving change in waste compositions, available newer waste treatment technologies, and stricter environmental regulations that were not present at the time of disclosure of this method. These points recommend propounding the reevaluation of this method and incorporating more uncertainties into the technical analysis.

Vera et al. presented a material flow analysis of RDF production processes [110]. The study showed how chemical characteristics of refuse-derived fuels (RDF) can be modified by mechanical operations to reach and assure quality targets. Similarly, Edo-Alcon et al studied how the chemical and physical characteristics of RDF are influenced by input waste streams and processing technologies [111]. Using this idea, Nasrullah et al. [112] studied the influence of three input feedstocks such as MSW, construction, and other industrial waste, on the quality of the produced RDF in terms of its characteristics, recovered energy, and mass balance in a mechanical treatment plant. In the study, the results of the quality parameters were validated by laboratory analysis. The effect of external uncertainties such as fluctuations in input waste composition and internal uncertainties such as energy consumption of the equipment on the performance of two different plant configurations are also studied under an exergoeconomic perspective [42].

The recovery of a particular material in the output stream of an operational unit depends on the estimated separation parameters to characterize the performance of the MRF. A separation parameter is a value between 0 and 1 that defines a corresponding input stream that ends up in a specific output stream. In this context, Diaz et al. and Palmer used recovery factor transfer functions to estimate the material flow of various waste materials in each unit in an MRF [113], [114]. Another approach introduced by Vanegas et al.[115] focused on defining the material separation models from a probabilistic point of view using Bayesian separation. This method defines the probability for routing the desired material and non-desired material. Similarly, a network flow model introduced by Testa et al. provided a groundbreaking framework representing an MRF with multiple output units and recirculating streams [17]. In this context, Fabrice et al.[18] presented a modern line configuration consisting of material recovery units and compared the material separation parameters of those units with similar parameters found in the literature [25]. The study revealed that variations in the separation parameters of material recovery units can significantly impact the quality of the RDF produced. In the same way, Karine Ip et al. discussed how uncertainty and variations in the parameters affect the performance of the network flow models [80]. The study incorporated uncertainty in the input material composition and based on that, it estimated the separation parameters of the operational sorting units. However, newer line configurations need to be tested. Research efforts should provide new data covering more waste characterizations while providing operating conditions and feedstock compositions affecting an MRF output stream composition such as RDF.

2.5.2 Decisions in the Biomass Fuel Supply Chain

One of the other major barriers to developing and implementing waste to biofuel solutions is the cost of biomass to the biofuel supply chain and uncertainty in biomass source generation [116]. The biomass supply chain implicates many decisions associated with biomass type selection, collection, pretreatment, production or harvest, storage, conversion to bioenergy, and biofuel sales. Depending on their timeframe, decision-making can be divided into three significant categories, strategic, tactical, and operational [30]. Strategic decisions entail long-term decisions that are difficult to change in a short time and have a long-lasting impact on the supply chain. At this level, uncertainties include technology policies and regulations, climate conditions, emerging waste treatment technologies, and environmental effects. Tactical decisions in the supply chain can range from a few months to a year, depending on the strategic goals defined in the earlier stage and they bridge the gap between strategic and operational decisions. The uncertainties at this level include RDF production planning, RDF demand forecasting, equipment performance etc. In contrast to strategic and tactical decisions, operational-level decisions focus on short-term activities conducted on a day-to-day or weekly basis and ensure continuous operations of the facilities, e.g., monitoring standards and quality of produced RDF or scheduling related tasks. The studies in the past tackled several sources of uncertainty affecting decision-making in the design and planning of the biomass to biofuel supply chain from aspects like feedstock selection [117], location and capacity design [118], selection of technology [119], or feedstock seasonality [120] among others. In this context, many publications in the literature focus on strategic and tactical level decisions, whereas less emphasis is placed on operational decisions and combined strategic or tactical levels with operational decisions [25], [121].

In the literature, researchers have adopted various modeling approaches for the efficient planning of biomass supply chains. The most dominant techniques are distinguished as mathematical programming, simulation, and geographic information system (GIS) based modeling [122]. Piedro et al. classified uncertainty-modeling approaches into four groups: analytical methods, models based on artificial intelligence, models based on simulation, and hybrid methods [40], [123]. The scope of this study is limited to simulation modeling [124] and decision sciences, as this area is not explored adequately for implicating uncertainty in RDF supply chain planning. Only a few references are available using the simulation method for these purposes as described in a study by Bairamzadeh et al.[42].

2.6 Public Private Partnership (PPP) in EfW Projects

2.6.1 Role of Public Private Partnership

In developing countries, most energy from waste (EfW) projects are funded by public-private partnerships (PPP) at both national and municipal authority levels [32]. The PPP is a globally recognized model used to deliver infrastructure-based projects or services funded by private investors instead of the traditional public sector models. It is a form of long-term collaboration between public and private parties sharing their skills and assuming different levels of implicated risks and rewards in EfW infrastructure delivery, substantiated contractually for a definite duration. Such an arrangement enables the public sector to undertake projects they could not finance internally or through loans and grants.

In 1997, the UK Government launched the PFI (Private Finance Initiative) scheme to modernize its new infrastructure [125], and close to 700 projects were signed by 2017. Later, incorporating the UK government's 2018 decision to suspend all PFI, this move highlighted the need for new models that better balance private investment with public accountability and value for money. The UK's PFI model enacting trifling variations was later adopted in Canada and the rest of the world. The concept of PFI differs among countries; for example, in Canada, PPP is referred to as P3, and in the UK, it is referred to as PF2 or simply the old PFI. The distinction in financing structures between PFI and PPP significantly impacts their implementation and outcomes. PFI financial options could include bank debts, bonds market, mortgages, or lease finance. PFI projects typically involve a high degree of leverage, with the Special Purpose Vehicle (SPV) relying heavily on debt financing [126]. This structure can lead to a focus on short-term financial returns and a higher cost of capital, as the private sector seeks to cover the debt service and generate profits. The reliance on debt also increases the financial risk associated with these projects, which can be transferred to the public sector in the form of higher long-term payments. Figure 2.8 depicts this typical setup of a PFI scheme and the main participants including the public sector, SPV, sponsors and various categories of subcontractors in a project. Financial companies are critical actors in PFI transctions, as they engage in various functions such as arranging debt, providing debt and equity, and offering financial consultation. Moreover, these entities play a pivotal role in ensuring that the operations involving multiple companies are executed seamlessly in accordance with the established financial plans.

In contrast, PPPs offer a more flexible approach to financing, allowing for a broader mix of financial instruments. This flexibility can enable a more balanced allocation of risks and returns between the public and private sectors. For example, the use of equity financing in PPPs can align the interests of private investors with the long-term success of the project, as their returns are more directly linked to the project's performance. Additionally, PPPs can incorporate various revenue streams, such as user fees or government payments, which can provide a more stable financial foundation for the project [127].

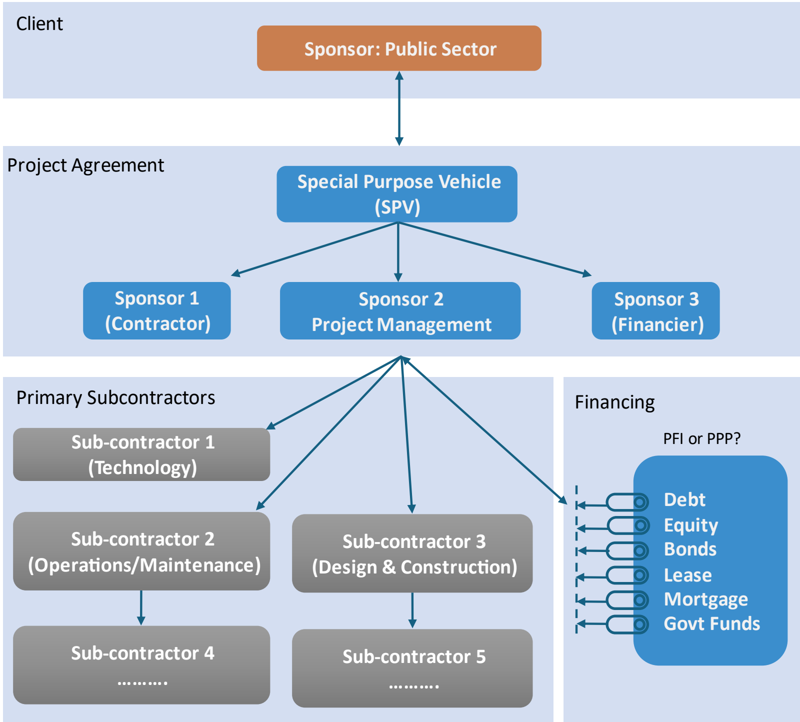

Figure 2.8: Standard configuration of a PFI/PPP framework based on financing options

In a PPP, the structure allows involved parties more freedom to structure their contributions. Another major underlying difference is that PPP can be structured as a joint venture or via contract. Figure 2.9 shows different models inside PPP, which are additional ways the public sector can deliver infrastructure projects. It reflects the inherent nature of how contracts for private entity from public partners can be designed to incorporate element of risk management for design, build, finance, operations, and maintenance tasks in projects.

Governments across the globe continue adapting PPPs in the development of critical public infrastructure as it is the most suitable model to deliver infrastructure on time and on-budget [128]. This is because PPPs not only provide taxpayers value-for-money (VfM) by transferring project-related risks to the contractor but also ensure that completed projects in the future are operated and maintained in good condition[33], [129]. VfM is defined as the optimum combination of whole-of-life cost and quality and fitness for the good or service that fulfills the user requirements [130]. The five interrelated VfM drivers in infrastructure-related projects are the sector management skills brought to the project by the private sector; the effective risk allocation; the long-term nature of the contract; and the effective performance measurement and competition [131].

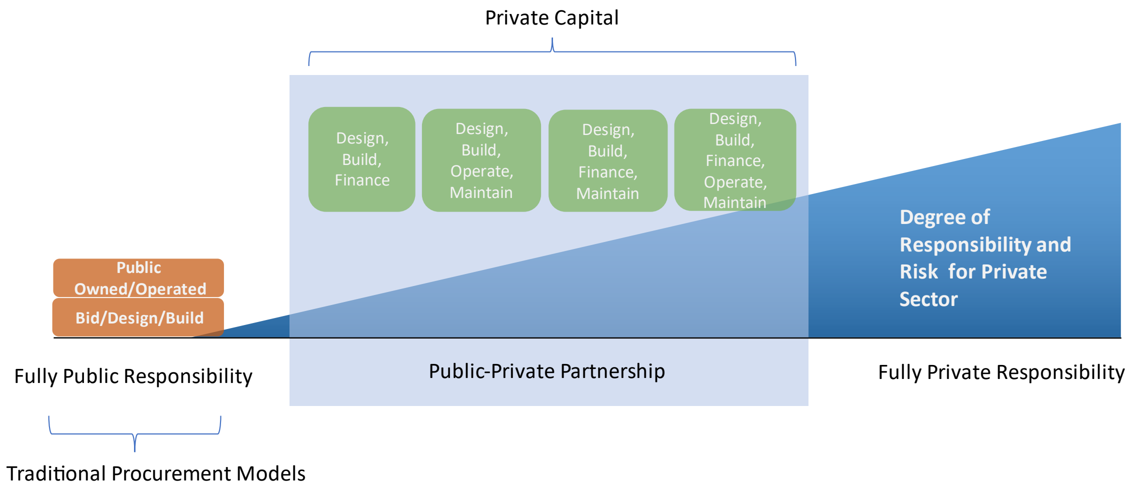

Figure 2.9: Infrastructure delivery under PPP models, adapted from the Canadian Council for public-private partnerships [132]

However, a few opponents argue against such arrangements for infrastructure delivery projects. The public sector can build attractive incentives in PPP, which could be misleading regarding budget and schedules and are usually absent in the conventional infrastructure delivery model. Similarly, the government must pay a premium to incentivize the private contractor to assume any risks. Usually, PPP financing costs are higher for the private sector because of high borrowing interest rates that vary during the projects' long duration [33]. Lastly, in the event of project failure, the public sector can transfer the loss of extra tab to the taxpayer through increased taxes or some reduction in public services [34].

2.6.2 PPP Trends in Energy from Waste Projects

Energy from waste initiative carry a range of benefits for the environment and its investors, like clean energy production, less load on landfills, lower greenhouse gas emissions, and grants from the public sector for scaling sustainable processes. In EfW applications, cutting-edge technologies are incorporated, converting waste into heat, electricity, and other fuels [133]. China procured 463 EfW plants (using incineration technology) by 2020 due to an exponential increase in municipal solid waste generation [134] . To mitigate this challenge and improve energy recovery from waste, researchers are focusing on other technologies like pyrolysis, anaerobic digestion, and gasification processes[135], [136], [137]. However, from the public policy perspective, EfW projects are a flutter on government investments due to financial risks and natural implications like COVID-19 [138]. In past years, governments in various countries have incorporated PPPs or PFIs as a solution to deliver public infrastructures[34], [139], [140]. Following a PPP approach, new infrastructure projects, like EfW, could be delivered where most of the risk is shared by the private sector, payments and final bills are not immediately due as contracts prolong from 25 to 30 years [141]. This philosophy suits governments and ensures reliable and stable contract payments (transactions) from taxpayers' money or other funds. From a sustainable point of view, the equity structure among private and public bodies is vital for maintaining the performance of PPP projects [142]. Figure 2.10 below shows the total number of EfW facilities operational in the UK. Seventeen more facilities are still under construction [143]. Table 2.6 exhibits seventy EfW operational plants with a classification of contracts from 1973 to 2022 adopting various technologies in the UK.

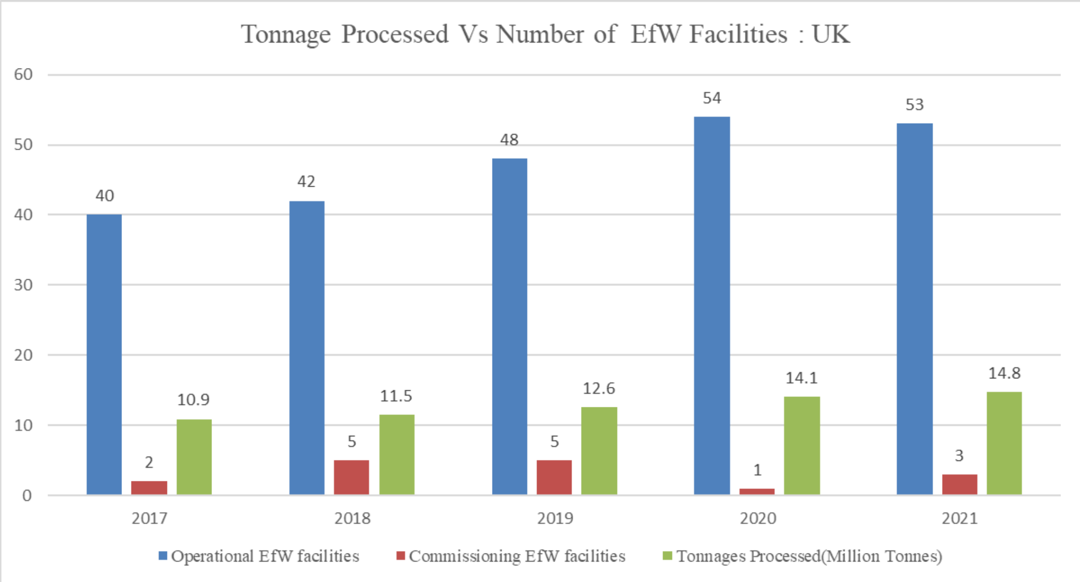

Figure 2.10: Number of UK EfW facilities and total tonnage of waste processed at EfWs in 2017-2021, adapted from [143]

Table 2.6: Energy from Waste (EfW) – Incineration , Advanced Conversion Technology (ACT), Biodrying Mechanical & Biological Treatment (BMBT), Landfill Mechanical & Biological Treatment (LFMBT),M (merchant facility) - private sector initiative, [144]

Contract Classification	PPP				PFI			M
Year Operational	BMBT	EfW (ACT)	EfW (Incineration)	LFMBT	BMBT	EfW (Incineration)	LFMBT	EfW (Incineration)
1973-1994			5					
1997-2004	1		6			2		
2005-2011	1		5	1	2		1	
2012-2016	8		7		3	6	1	
2017-2022	1	1	11			1		7
Total	11	1	34	1	5	9	2	7

Recent projects in Canada provide indicators that because of growing pressure to reduce the amount of waste going to landfills, the government at municipal and provincial levels is undergoing a change by adopting P3 in procuring EfW infrastructure.

Provinces like Quebec, Ontario, Alberta, and British Columbia have EfW facilities, among which a few are procured under the P3 model, as shown in Table 2.7,[145].

Table 2.7: Publicly owned solid waste assets, Infrastructure Canada, 2022, adapted from [145]

	Composting facilities	**Materials recovery facilities**	**Anaerobic digestion facilities**	**Incinerators**	**Energy from waste facilities**
Newfoundland & Labrador	8	14	0	0	2
Prince Edward Island	1	1	0	0	1
Nova Scotia	12	11	0	0	0
New Brunswick	4	8	0	0	6
Quebec	28	108	4	4	3
Ontario	64	45	6	0	4
Manitoba	32	37	1	3	1
Saskatchewan	82	35	0	0	1
Alberta	32	104	8	15	2
British Columbia	27	31	2	0	2
Yukon	3	0	0	0	0
Northwest Territories	1	5	0	0	0
Nunavut	0	0	0	0	0
Total	294	399	21	22	22

2.6.3 PPP Risk Modeling in EfW Projects

Researchers have focused on modelling potential risks impacting EfW projects, such as economic, political, technological, environmental, and societal factors [146]. Fantozzi et al.[147] presented a study of risks in 2014 associated with PPP in bioenergy technology projects. This research study focused on the six categories of risks that have a paramount influence on various PPP topologies. It concluded that PPPs could effectively reduce risk in the bioenergy business for the public sector. Zhang et al.[148] conducted research in 2019, bundling a questionnaire survey and a professional validation to identify twenty-one risks related to incineration PPP projects. The study identified that studies on risks of PPP projects in the past normally analysed risks individually based on risk sorting and statistical analysis and neglected their direct casual interrelationships, where one risk factor, 'Change in law', directly caused nine other risk factors. Among a few are operating cost overrun, public opposition, revenue, and government and private sector decision-making risks. Another study by Caiyun et al. in 2019 showed that environmental pollution, lack of supporting infrastructure, government credit, public opposition, government decision-making, and flawed legal and monitoring systems are the top risks touching the growth of EfW incineration PPP projects in China [149]. From a financing perspective, the Asian Development Bank (ADB) declared China to be an active proponent of PPP for EfW and provided screening parameters for investing in EfW in PPP topology [150].

Overall, limited studies are adopting advanced technologies besides incineration for EfW in PPP. Recently, Dolla et al.[151] emphasized considering the nuances of technology in PPP procurement projects. The study identified twenty-two influential risk factors from the literature. It showed the variation of risks criticality measured associated with the four EfW treatment technologies (biomethane, RDF to power, incineration, pyrolysis & gasification). Each technology brings a set of critical risks which are mitigated by the public and private sectors. The risks such as waste volume, revenue, and market risk are among the critical one's that directly affect the financial viability of energy from municipal solid waste (MSW) in PPP projects. Various risk occurrence probability forecasting models are available in the literature for improving the accuracy in estimating risk magnitude in PPP EfW projects. Wang et al. presented a risk occurrence probability forecasting model using the Bayesian updating approach (ROPFM-B) [152]. Zhang et al.[148] deployed DEMATEL (decision-making trial and evaluation laboratory) method to prioritize the risks and then analyze the interrelationships between them to identify critical risks. Another study by Cheng et al.[153] used DEMATEL method to identify pivotal risks such as government decision-making, credit, and supervision behavior risks, along with legal, policy, revenue, cost, and management capacity risks. These risks, positioned at varying levels within a hierarchical structure, often act as catalysts for other risks. Deriving a risk evaluation index is also a common way of prioritizing risks. Jokar et al. developed a method in accordance with fuzzy AHP (analytical hierarchy process) and fuzzy TOPSIS (a technique for order of preference by similarity to ideal solution) to obtain the priority of risk factors and choose the optimal contractor company for projects [154]. Another methodology based on weighted multi-granulation fuzzy rough sets (MGFRSs) to perform risk evaluation for PPP EfW incineration plant projects was introduced by Chao et al.[155]. An additional research framework is developed for risk allocation between public and private bodies in easing decision-making for EfW in PPPs by deploying adaptive neuro-fuzzy inference systems (ANFIS) [156]. Wang et al.,(2023) highlighted the importance of PPPs for construction waste recycling in China, pinpointing risk allocation and benefit distribution as pivotal for project success. Their research advances this field by crafting a novel Best-worst multi–criteria decision-making method combined with a comprehensive fuzzy evaluation (BWM–FCE) risk assessment model, aimed at refining risk assessment for key stakeholders in construction waste recycling PPP projects, thus offering a holistic strategy to improve project efficacy in developing nations contexts [157]. The other important aspect of identifying and allocating risks in PPP projects is financial risk modeling. The major influences like capital costs, operations & maintenance costs, inflation, and discount rate forge risks for the positive and negative net present values (NPV), which could lead to rejection or acceptance of the project [158], [159].

It is concluded from the literature review that previous studies provide a vital understanding of the risk identification of PPP in numerous industries. With a focus on operations and maintenance (O&M) risk assessment of EfW in PPP projects, the preceding research is identified and presented in Table 2.8, highlighting former focus areas, methodology, and analysis techniques deployed. Specific to EfW technology studies, a few studies have [148], [151] focused on mixed research methods for risk identification and analysis of PPP projects in China and India. The PPP studies using mixed risk epistemology methods are not explored in the literature for EfW applications in UK and Canada.

Table 2.8: Previous studies on operations & maintenance risk assessment in PPP for EfW applications

Ref	Authors	Focus Area	Research Methodology	Analysis Technique
[160]	Song et al. 2013	Incineration technology	Subjective risk epistemology	General response strategies
[147]	Fantozzi et al. 2014	Bioenergy technology	Objective risk epistemology	Economic feasibility analysis
[161]	Song et al. 2015	Incineration technology	Objective risk epistemology	Simulation and Fuzzy Multi-objective Programming
[162]	Wu et al. 2017	Various EfW technologies	Objective risk epistemology	Fuzzy synthetic evaluation analysis
[50]	Wu et al. 2018	Incineration technology	Subjective risk epistemology	Linguistic modeling
[148]	Zhang et al. 2018	Incineration technology	Subjective risk epistemology	Causal risk relationship modeling
[152]	Wang et al. 2018	Incineration technology	Objective risk epistemology	Bayesian analytic approach
[163]	Spoann et al. 2019	Waste management	Subjective risk epistemology	Success and efficiency factor approach
[151]	Dolla et al. 2020	Various EfW technologies	Subjective risk epistemology	Risk allocation mechanism modeling
[156]	Utama et al. 2020	Incineration technology	Subjective risk epistemology	ANFIS modeling
[134]	Cao et al. 2022	Incineration technology	Subjective risk epistemology	Risk assessment
[142]	Hou et al. 2022	General	Objective risk epistemology	Multi-objective programming model

2.7 Discussion and Research gaps

This section applies a systematic review to delve into the ongoing research on RDF-3 production for EfW applications. Its contribution stands as a valuable addition to this field, offering scholars and managers a deeper insight into the evolving trends and challenges within waste-to-energy decision-making at MRF. The challenges and research issues identified in this research are summarized in Figure 2.11 and discussed below,

- O1. Waste recognition typically requires individual waste items against simple backgrounds, which are often not representative of real-world scenarios. In most cases, waste materials are scattered or overlapped in complex settings. Therefore, this study will expand the application of computer vision techniques for waste composition analysis in the real-world environment, where tools like smartphones could aid MRF in distinguishing various single and multi-family wastes. The accuracy of the proposed solution from this study will be assessed in an MRF for validation purposes.

- O2. Contemporary solid waste management methods lack sustainability, particularly concerning quality RDF-3 production operations. Therefore, this study attempts to develop a framework for the technical assessment of material recovery facilities that can support revisions in the strategic, tactical, and operational level decisions integrating different waste treatment technologies considering varied uncertainties affecting its performance selected in the scope as shown in Table 2.9. Additionally, this study delves into various modeling approaches used in relevant research within this domain. It offers an insightful exploration of diverse modeling methodologies employed in similar contexts by other research works. This comparative analysis contributes to a broader understanding of the modeling landscape, providing a valuable reference for researchers and practitioners in the field. The developed model would provide the best operating conditions and prediction for quality standards of RDF-3. The results of this study will be tested in an MRF for validation purposes. The model shall assist with scenario-based analysis, which can save huge costs and support the overall decision-making process.
- O3. Various HHV prediction models are proposed in the literature, and to validate the existing models in literature, comprehensive studies using specific RDF types are necessary. Moreover, the literature fails to provide specifics about the types of RDF utilized in modeling HHV equations, as well as the unit-level procedures involved in its preparation. After the detailed literature review, twelve established models were found relevant to RDF, as shown in Table 2.4, and would be used to validate the performance of models developed in this study.

- O4. This study will contribute to the gap in the literature on PPP in EfW projects by supporting the analysis of operations and maintenance of incineration and anaerobic digestion technologies. A stochastics modeling technique and survey analysis approach would be explored that can process identified risk uncertainties as input and model the impact of those on the economic feasibility of an O&M contract. Results of this would provide empirical evidence to stakeholders within the waste management sector about the VfM of PPP in EfW projects.

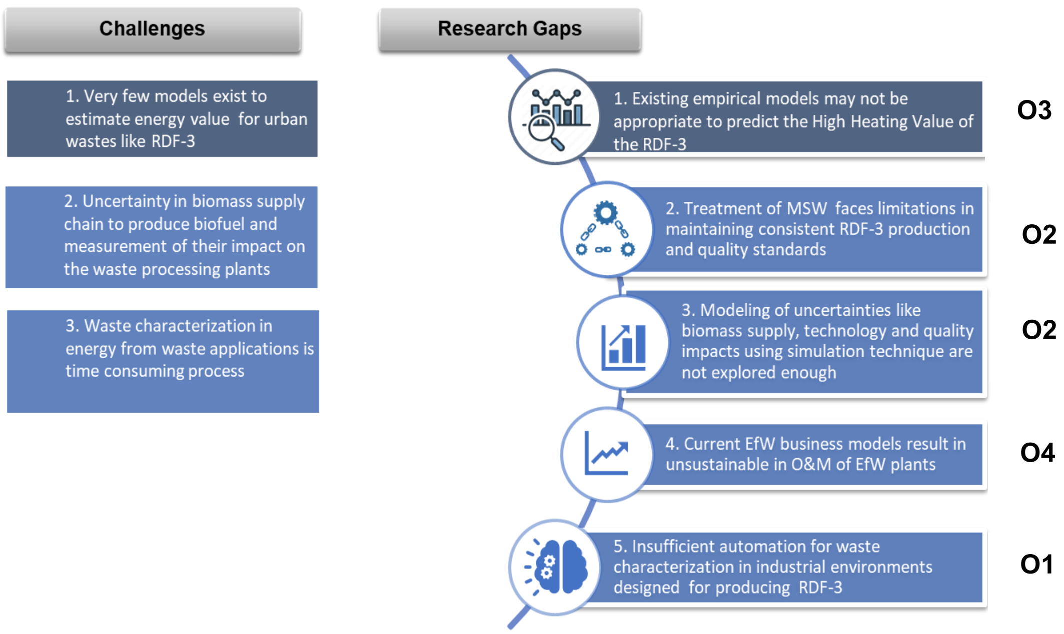

Figure 2.11: Challenges and research gaps in using RDF as renewable energy resource

The literature review presented diverse references that elucidate the framework devised for strategic, tactical, and operational decisions concerning biomass supply chain. Several studies have utilized different modeling approaches, each targeting specific types of uncertainty as outlined in Table 2.9. This research study compares with other studies across six modeling approaches, considering a selected set of strategic, tactical, and operational decisions, as well as types of uncertainty. Upon comparison, it is revealed that this study addresses various gaps in the research field.

Table 2.9: Comparison of frameworks from literature with underlying study for strategic(S), tactical(T) and operational(O) decisions in the scope of this study. Legend: ✓ indicates authors have used methodology and tackled the decisions in the biomass supply chain in a broad sense.

References	**Modeling approach**							**S**		**T**		**O**			**Type of Uncertainty**		
	Statistical Method	Mathematical Programming	Survey or Experimental Methods	Heuristic Methods	Stochastic Process	Theoretical Methods	GIS/Other	Technology Upgrade	Biomass market Selection	Waste Selection /Composition	Technology performance	Biomass yield	Biomass Quality	O&M Risks	Random	Epistemic	Deep Uncertainty
Bairamzadeh et al,2017[42]		☑									☑				☑	☑	☑
Castillo et al, 2017 [41]					☑						☑		☑		☑		
Nunes et al, 2023[164]		☑			☑								☑		☑		
Aboytes-ojeda et al, 2022[165]					☑								☑		☑		
Mohseni et al, 2016[166]		☑					☑					☑			☑		
Testa et al, 2015[17]		☑		☑				☑		☑	☑	☑	☑		☑		
Sebastian et al, 2022[72]						☑				☑			☑				
Ip et al, 2018[80]		☑			☑						☑	☑	☑		☑		
Arina et al, 2020[167]			☑									☑	☑				
Tanguay et al, 2021,[18]		☑			☑			☑			☑	☑	☑		☑		
Sharma et al, 2013[168]		☑					☑					☑			☑		
Dolla et al, 2021[151]			☑						☑		☑			☑		☑	
Nasrullah et al, 2017,			☑								☑	☑	☑				
This Research	☑		☑	☑	☑			☑	☑	☑	☑	☑	☑	☑	☑	☑	

This literature review systematically explores the current research landscape surrounding RDF production for EfW applications, identifying existing research gaps that future studies could address. It serves as a foundational reference for academics and practitioners by shedding light on trends and challenges in waste-to-energy decision-making within MRFs. In literature, it is identified that waste recognition typically involves individual waste items placed against simplistic backgrounds, which do not reflect complex real-world scenarios where waste materials are often scattered or overlapping. In response, it has been suggested to extend the application of computer vision techniques to analyze waste composition in realistic environments. Tools such as smartphones could aid MRF staff in differentiating between different waste types, with the effectiveness of these solutions to be validated in an MRF setting.

Similarly, it is also highlighted in the literature that current solid waste management practices often lack sustainability, especially concerning the production of high-quality RDF. New frameworks for the technical assessment of MRFs are required to be proposed to support improvements in strategic, tactical, and operational decisions. This involves integrating various waste treatment technologies under different conditions of uncertainty. Additionally, the literature review explores various modeling approaches documented in related research, providing a comparative analysis of these methodologies to enrich understanding and serve as a resource for future modeling efforts. The models developed aim to establish optimal operating conditions and standards for RDF production, with validation tests conducted in MRF settings. These models are designed to facilitate scenario-based analyses, potentially leading to significant cost savings and improved decision-making.

The literature review reveals several models for predicting higher heating values (HHV) of RDF yet notes the need for comprehensive studies using specific RDF types to validate these models. Additionally, it is often pointed out that the literature lacks detailed descriptions of the RDF types used in HHV models and the procedures involved in their preparation. Thirteen established models relevant to RDF have been identified and are listed in Table S3; these models will be employed to validate the

performance of newly developed models in this study.
Despite the wealth of knowledge in this field, the analysis of literature reveals certain limitations. As highlighted in Section 2.2.1, publication keywords capture the primary focus of research in this area. However, the keyword co-occurrence map (Figure 3) may display weak links and isolated terms, suggesting fragmented knowledge in the field. The primary RDF applications in WtE are limited due to the influence of chlorine in waste streams, with minimal interconnections between them.
Finally, the literature indicates a significant gap concerning PPP in EfW projects, specifically focusing on the operational and maintenance aspects of incineration and anaerobic digestion technologies. Various machine learning, stochastic modeling techniques, and survey analysis approaches are being explored to process identified risk uncertainties and model their economic impact on the feasibility of O&M contracts. The findings from this study are expected to provide empirical evidence to stakeholders within the waste management sector about the value for money of PPPs in EfW projects.

2.8 Conclusion

RDF has started to transform key aspects of WtE applications, drawing growing interest from researchers and practitioners. This study aims to investigate the status and global trends of research on RDF. While numerous literature reviews have already been conducted, this paper represents the first comprehensive scientometric study of the field, analyzing 1065 journal articles using an SLR approach. The key journals are identified, alongside the state of the research field and prominent topics in RDF research for WtE applications. The findings reveal that substantial progress has been made, yet much work remains to be done.
In summary, this chapter provides a literature review addressing research gaps at the operational and management levels in an MRF, aiming to achieve the objectives to address the existing gap in maintaining the quality standards of RDF production; this review aims to uncover sustainable practices that establish the operational and technical conditions ideal for consistently achieving high-quality RDF output at MRFs. The

detailed research methodology explains various methods and models for estimating the calorific value of RDF-type waste materials. It also highlights methods for continuous waste characterization and the application of computer vision for waste composition analysis. It identifies different standards for quality control measures of RDF and factors affecting these measures. While this study makes valuable contributions, it is essential to consider the limitations. The findings are influenced by the initial keyword selection and the scope of current literature. Thus, future research is needed to tackle the identified issues and provide solutions. Furthermore, conducting similar studies in the future will help monitor and understand the evolving nature of this field. The next chapter will concentrate on the first identified objective of this study, related to developing a computer vision application to precisely characterize municipal solid waste from single and multi-family sources. This process is designed to evaluate and forecast the potential physical composition by mass of RDF-3.

Chapter 3: Video-Based Waste Characterization for RDF-3 Production

3.1 Overview

In this chapter a computer vision application that can accurately characterize municipal solid waste originating from single and multi-family waste is developed. The process begins with the utilization of bag breakers and trommel screens within a mechanical sorting line at MRF, segregating bulky waste, non-combustible material, and hazardous waste. Subsequently, the residues from the trommel screen move along conveyors before entering the shredding phase at the RDF-3 production plant. This comprehensive characterization process is deployed immediately right after the trommel screen, encompassing waste from both single and multi-family sources.

A fundamental aspect of this study involves the collection of a dataset comprising high-quality images capturing waste ranging from 12.7cm to 23cm, segregated by the trommel unit. The culmination of this effort is the development and testing of the Smart-Sight application, validated within a practical Materials Recovery Facility (MRF). Figure 3.1 illustrates the waste residues post-processing at different stages within the trommel unit. These residues maintain a fraction size ranging from 5cm to 23 cm and undergo a manual waste characterization process. Subsequently, they are directed through conveyors to the RDF-3 production line. This characterization process serves the purpose of assessing and predicting the potential physical composition of RDF-3 in advance, aiding operational decision-making processes.

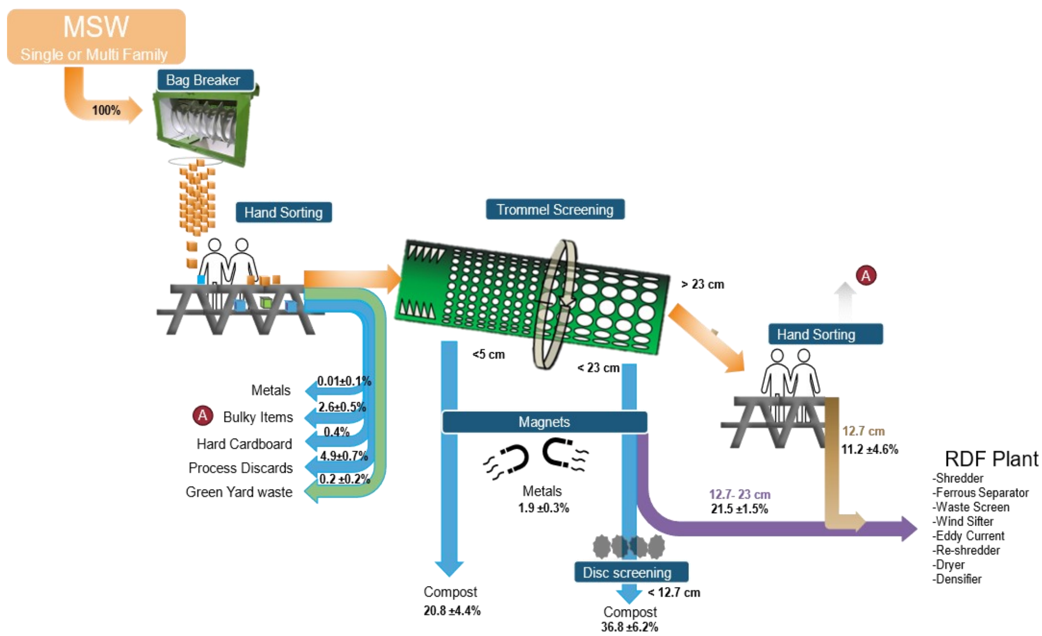

Figure 3.1: Mass balance of the initial waste processing at an MRF in Edmonton, values are averaged at ± 95% confidence interval.

3.2 Methodology

The block diagram outlining the various stages of the research methodology is presented in Figure 3.2. Stage-1 involves the collection of RDF source samples ranging from 12.7 to 23cm, [169] .These samples are gathered at different intervals from a system operational within an MRF, as illustrated in Figure 3.1. Subsequently, these samples are analyzed in the MRF laboratory to validate the findings obtained through the proposed method. Stage-2 involves the preparation of a dataset from the collected samples, followed by training of classification and object detection models. Stage-3 uses an artificial intelligence human-machine interface(HMI) application developed by integrating model from stage 2 and Python /Flask frameworks with computer vision techniques like Frane’s algorithm and frame differencing methods, for automated characterization of RDF waste source. For object detection to be applied successfully in waste characterization, it is essential to consider the RDF source stream as consisting of distinct and identifiable waste fragments. These fragments can be quantified by calculating the area of their respective bounding boxes and subsequently comparing these measurements with the total area encompassing all the detected waste. The ultimate results generated by this process offer analytical insights into the composition by mass of the detected waste, all in accordance with the proposed methodology. Each of the stages are presented in detail in the following subsections.

3.2.1 Stage 1: Dataset Collection & Preparation

3.2.1.1 Waste Sample Collection

Both SF and MF wastes are processed as described in Figure 3.1 and during the process, samples are systematically collected at 15-minute intervals over a two-hour duration. Subsequently, these collected samples are combined in specific proportions to create a homogeneous blend. This blending approach offers flexibility in ensuring the feedstock meets the specified requirements. In this study, two wet basis samples each for SF and MF, were systematically acquired using half-size deep aluminum trays, each having a capacity of 128 ounces. Care was taken to uniformly fill each tray to its maximum capacity, adhering to a standardized procedure to ensure consistent volume among all samples. Notably, the mass of the material gathered in each tray exhibited variability, ranging from 450 grams to 650 grams. The composition of msw samples comprised paper, cardboard, rigid plastics, film plastics, food waste, yard waste, diapers/ napkins, other combustibles, metal, glass, other non-combustibles materials and woodchips presented by Junaid et al.[170]. This study considers thirteen waste components divided into three high-level waste categories, including inert materials, compostables, and combustibles, as shown in Appendix section (A4).

3.2.1.2 Laboratory Waste Characterization Method

The waste characterization process completed in the lab involves several key steps to facilitate physical separation. . Samples obtained from the trommel outputs underwent a separation process using a shaker device (Model: Sellbergs Eng.; type: LB/LO). The shaker is used to aid in the sorting process for enhancing efficiency as it generally separates materials that tend to stick or adhere together and ensures their distinct collection. Following this step, the waste samples undergo manual sorting into three primary categories, combustibles, compostables and inert materials. Further subcategories of these sorted materials are detailed in the Appendix (A4). Afterwards, the waste samples are subjected to oven drying at approx. 70ºC for 18-24 hours. Each category of waste is individually weighed, and its weight is calculated as a percentage relative to the total dry weight of the entire sample, as per Eq(3.1) below,

$$\text{Composition (\%)} = \frac{\text{Weight of each waste category}}{\text{Total dry weight of the materials sorted}} \quad \text{.......Eq.(3.1)}$$

Additionally, the moisture content for each sample obtained post trommel screening is calculated proportionally based on its composition and the measured moisture content of its sub-categories. The moisture content range within the particle size 12.7 cm to 23 cm for the MF material : Mean = 32.3%, Std Dev = 10.56% and SF material: Mean = 34.54%, Std Dev = 8.56%.

3.2.1.3 Dataset Preparation

The dataset utilized in this study comprises images obtained from waste samples collected at the MRF, as well as open datasets made accessible by (DataCluster Labs, 2021 [90]; Koskinopoulou et al.[91]; Mohamed, 2021

[92]; Sekar, 2019 [93]; Yang and Thung, 2016, [94]) in their Garbage Classification dataset. The dataset includes a variety of washed and unwashed waste samples from SF and MF streams utilized for model training and illustrating the true nature of waste as it typically exists in the facility environment. A total of 3100 images were gathered from all sources. The data annotation process involved manual labeling of the desired thirteen waste classes in the collected dataset using visual object tagging tool (VoTT). The annotations are generated first in JSON format due to limitations of the tagging tool and latter converted to YOLO Darknet format. Next, data augmentation is performed to enrich and expand the dataset. This serves to improve the model's ability to generalize and prevent overfitting. Additionally, it allows the model to learn a broader range of relevant features. In this study, Albumentations, a Python library known for its speed and flexibility in image augmentations is harnessed, Buslaev et al.[171]. A variety of augmentation techniques such as flipping, rotation, noise addition, blurring, and brightness adjustments are used onto the images. The final dataset is comprised of a total of 3960 images with annotations and Figure 3.3 shows the class distribution in the dataset. For training the object detection model, the dataset is split into 80% for training, 15% for validation, and 5% for testing. A Python script is developed that takes the dataset of images and labels, splits it into training, validation, and test sets, and organizes them into separate directories, ensuring that an equal class distribution is maintained, especially for the validation set, Carolis et al.[106].

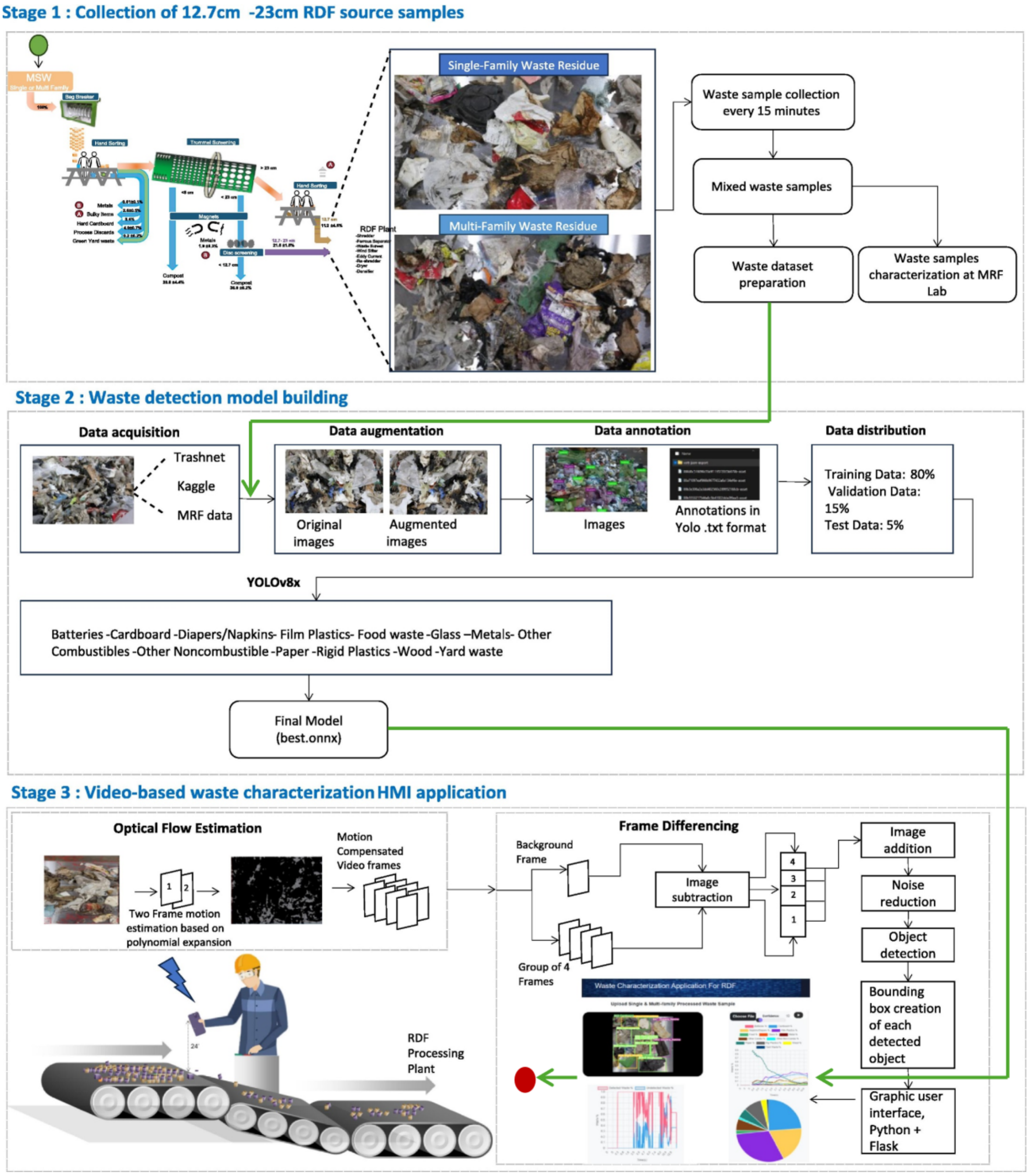

Figure 3.2: Proposed methodology for waste characterization system to enhance RDF-3 production quality

Distribution of waste classes in the used dataset and few samples of the sorted waste components for data annotation and labeling purposes

Values of hypermeters used for the objection detection method

Input size=640 x 640, Batch size=16, Learning rate = Lr_0,Lr_f=0.01, Momentum=0.937, Weight decay=0.0005, Training time=2.5 hours,   Epochs=300

Training and validation curves for model development

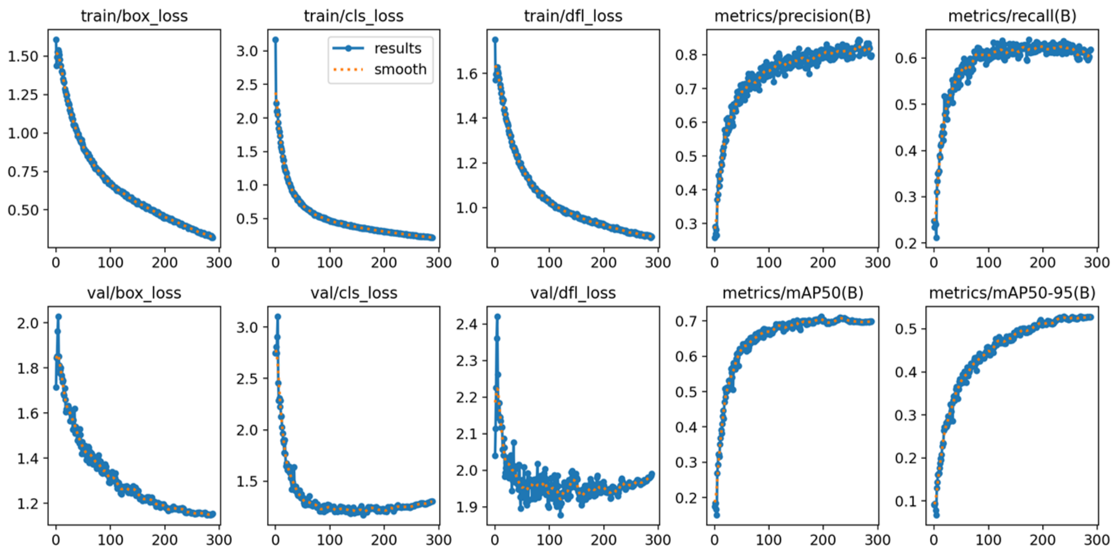

Figure 3.3: Stage 2 includes – Distribution of sorted waste components for annotation/labeling purposes, object detection hyperparameters determination, and training/validation curve plotting for model development

3.2.2 Stage 2: Waste Detection Model

Detecting waste in video streams presents a complex challenge. In this study, we addressed this challenge by deploying the YOLO (You Only Look Once) architecture, which is known for its speed and superior performance when compared to other detection methods such as R-CNN and deformable parts models (DPM) as mentioned by Redmon et al.[172]. In terms of detection accuracy, there are several versions of YOLO available, including YOLOX, YOLOR, YOLOv3, scaled YOLOv5, YOLOv7 (s-m-l), and YOLOv8 (s-m-l-x). Carolis et al.[106], presented an improved YOLOv3 network model to perform garbage detection and recognition in outdoor environments. In this study, YOLOv8x model is adopted for indoor waste classification and detection.YOLOv8x has demonstrated the highest accuracy, along with a lightweight network design. This approach incorporates effective feature fusion techniques, resulting in more precise and improved detection outcomes for small objects in complex scenes, Lou et al.[173]. The YOLOv8x is implemented in PyTorch, and initially a pretrained version of the algorithm on the COCO dataset is used to save time by utilizing learned features (weights/biases), which are easily transferred to the new dataset. This involves initializing model parameters using transfer learning and subsequent fine-tuning on a custom dataset, as detailed in sections 3.2.1.1-3.2.1.3. A NVIDIA GeForce RTX 3090 is used to train all models with the pre-installed CUDA version 12.1 available from PyTorch. Figure 3.3 shows hyperparameters and their value for the model along with the training and validation loss curves obtained during training phase. The characteristics of the learning curves provide evidence of a well-suited model, as observed in the bounding box regression, classification, and deformable convolution layer loss plots. Throughout the training process, both training and validation losses steadily decrease until they converge to a stable point, with minimal divergence between their final loss values. The positively classified instances (precision) of the trained model reaches 76.2% and the average precision of the model at the intersection over union threshold is 71.6% (mAP@0.5).

3.2.3 Stage 3: Image Pre-processing

In this study, image preprocessing is required to ensure and evaluate the accuracy of the results obtained from the waste detection model and posterior waste characterization. This is due to the reality in which image data is collected in the MRF using the system described in Figure 3.2. Cameras are subjected to vibrations and, generally, unexpected motions during daily operations. The below algorithms are used to mitigate the negative impacts of the system dynamics on the data collected.

3.2.3.1 Motion Estimation

As shown in Figure 3.2, the camera looks down on the waste stream, moving on a conveyor belt coming out of the trommel and onto the RDF production line. The expected motion seen in the image is the waste stream moving along with the conveyor belt, while the background remains static. A dense optical flow method can be used to estimate motion from two consecutive frames of a video feed, (Dheeraj et al., 2022[174]). Here, the objective is to compensate for potential camera motion between frames, allowing a focus on the desired motion of objects (waste streams) within the scene. Generally, optical flow refers to the movement of individual pixels on the image plane (Turaga., 2010[175]). It is a method used to estimate how picture intensities change over time and correspond to the movement of objects in the scene. The intensity at a point in a picture is expressed as a function of space and time as $E(x, y, t)$. This point progresses to a new position $(x + \triangle x, y + \triangle y)$ after a certain time $\triangle t$, and the intensity of that point can be stated as $E(x + \triangle x, y + \triangle y, t + \triangle t)$. Under the above assumptions,

$$E(x, y, t) = E(x + \triangle x, y + \triangle y, t + \triangle t) \quad \text{..........Eq.(3.2)}$$

Applying Taylor series approximation on RHS provides,

$E(x + \triangle x, y + \triangle y, t + \triangle t) = E(x, y, t) + \frac{\Delta E}{\Delta x} \triangle x + \frac{\Delta E}{\Delta y} \triangle y + \frac{\Delta E}{\Delta t} \triangle t$………Eq.(3.3)

Now substitute Eq(3.3) in Eq(3.2),

$\frac{\Delta E}{\Delta x} \triangle x + \frac{\Delta E}{\Delta y} \triangle y + \frac{\Delta E}{\Delta t} \triangle t = 0$ …… Eq.(3.4)

The optical flow equation is derived from the above by dividing with $\triangle t$

$\frac{\Delta E}{\Delta x} \mu + \frac{\Delta E}{\Delta y} \nu + \frac{\Delta E}{\Delta t} = 0$ ………. Eq.(3.5)

Here , $\mu = \frac{\Delta x}{\Delta t}$ and $\nu = \frac{\Delta y}{\Delta t}$, defines how fast the intensity changes moving across the image. For calculating the optical flow vectors for all pixels in each frame, Farneback's method is used as proposed in (Farnebäck, 2003[176]). This method provides a two-frame motion estimate based on quadratic polynomial expansion. The initial step involves approximating the neighborhoods of both frames with quadratic polynomials. This approximation is efficiently achieved through the polynomial expansion transform . As presented in Eq(3.6),

$f(x) = x^T M x + b^T x + c$ …….. Eq.(3.6)

where **M** is a matrix, **b** a vector and **c** a scalar. By studying how an exact polynomial transform during translation, a method for estimating displacement fields from the coefficients of the polynomial expansion is derived. For comprehensive analysis of dense optical flow, OpenCV offers a method known as calcOpticalFlowFarneback() which includes ten parameters to configure during the implementation. Adjusting these parameters can significantly impact the speed and accuracy of the optical flow calculation, however they will be further discussed in the results section. Appendix section (A6) shows a sample of the outcome of the integrated motion compensation technique, utilizing two polynomial expansions.

3.2.3.2 Waste Detection using Frame Differencing:

An issue with using machine learning approaches to quantify waste is that the stochasticity makes it difficult to trust the results on a frame-by-frame basis. With an expected performance of 70% precision on waste detection, a simple approach is developed to easily quantify (but not classify) the total waste in each video frame. This way, it will allow to compare the detected waste by both methods, by motion and by machine learning, and evaluate the detection rates of the proposed approach. For this, frame differencing is used, a straightforward and computationally efficient algorithm, for detecting moving objects through video monitoring. This approach is particularly suitable for identifying moving objects in indoor environments (Thapa et al.[177]). As shown in Figure 3.2 (stage 3), the first step in frame differencing involves reading several (four or eight usually) consecutive frames from a video sequence, stated as $R_i(x, y)$, where i is a sequence of frames. In the second step, RGB images are converted into grayscale images. The third step involves the creation of a background image, where we read the video file and randomly select 35-50 frames. Then, the median frame from this selection is calculated, which serves as the background model. Finally, the initial four consecutive frames are subtracted from the background, as outlined in Eq(3.7), where $MO_i(x, y)$ presents moving objects in each frame.

$MO_i(x,y) = R(x,y) - R_i(x,y)$ …… Eq.(3.7)

$MO(x,y) = \sum_{i=0}^{4} MO_i(x,y)$ ………. Eq.(3.8)

In the fourth step, the differences are accumulated as shown in Eq(3.8), which highlights the maximum displacement of an object within the sequence of frames. In the fifth step, a morphological opening and closing process is used to eliminate noise from the resultant image. This final image is represented in black and white, where the black background surrounds the objects, and the displacement of these objects is indicated by connected white pixels. Further, contour detection is used to identify object boundaries within the binary mask, using the "cv2.findContours" function from OpenCV. These contours are essentially lists of coordinates outlining object boundaries. To reduce memory usage and remove noise, small contours are filtered out with areas less than 500 or 1000 square pixels. The remaining, larger contours have their minimum area bounding rectangles extracted and are visualized, offering a basic estimation of the waste objects' positions and sizes.

3.2.3.3 Waste Quantity Calculation and Composition Analysis

To calculate the area of number of detected moving object (n), the ratio of non-zero white pixels (Px_W_i) within in the frame and the total number of pixels (Px_T) in the frame are computed. This task is completed using "cv2.countNonZero()" function and calculating (image height x image width). This ratio effectively quantifies the proportion of the frame occupied by the objects. Summing these individual ratios provides the total quantity of waste detected, as presented in Eq(3.9). This step is crucial since the detections made by the YOLOv8x model (section 3.2.2) also provide width and height information for the thirteen waste classes. The areas obtained from the bounding boxes calculated using Eq(3.10), by the YOLOv8x model for every detected object i of type j, are compared to the areas calculated through the frame differencing algorithm. This comparison helps quantify the waste composition percentage within the incoming waste stream compiled using Eq(3.11).

$$Area_{FD} = \sum_{i}^{n} \frac{Px\_W_i}{Px\_T} \text{ .... Eq.(3.9)}$$

$$Area\_Yolo_{ij} = \sum_{ij}^{13} W_{ij}\ x\ H_{ij} \text{ .... Eq.(3.10)}$$

$$\%Comp_i = \frac{Area\_Yolo_i}{Area_{FD}} \text{ .... Eq. (3.11)}$$

$$MW_i = (\%Comp_i\ x\ 0.00397)\ x\ BD_i \text{ .... Eq.3.12)}$$

$$MD_i = \frac{MW_i\,x\,(1-MC_i)}{\sum_i^{13} MW_i\,x\,(1-MC_i)} \text{ ....Eq.3.13)}$$

In addressing the volume-to-mass conversion, the method adopted involves utilizing computer vision methods to acquire the percentage distribution of waste composition by volume for all waste classes. This distribution is subsequently applied to the cumulative volume capacity of tray (0.00397 m^3) in which the samples are systematically collected and the known bulk density of waste classes, as outlined in Eq(3.12). The outcome of this procedure yields estimations of the wet mass (MW) for all waste classes i. Subsequently, Eq(3.13) is used to perform the conversion from wet mass to dry mass (MD). This conversion process entails multiplying the calculated wet masses by the complement of post-trommel screened moisture content probability distributions and then dividing the result by the total sum of the calculated dry mass proportion for all waste components. This process yields the composition (%) by mass. This comprehensive calculation accounts for all waste components and their respective moisture content's seasonal variations. Appendix (A15) includes the data collected for density and moisture contents.

3.3 Implementation Results & Discussion

This section presents the results of experiments conducted in the current research. Firstly, the software application and interface information are presented, in addition to the waste composition analysis results. Next, the performance of the YOLOv8x model in the waste characterization system is assessed. Afterwards, the system is tested and validated on new data to confirm its performance. Then, the waste characterization results obtained are compared to ones obtained from analysis in a laboratory following current MRF practice. Finally, we conclude by highlighting the significance of the entire system.

3.3.1 HMI Application

The trained YOLOv8x waste detection model is saved in ONNX format, which is an open and versatile format for machine-learning models. ONNX facilitates the seamless deployment of models across different machine learning frameworks and tools. The model is integrated with an application built using Flask framework and Python. Figure 3.4 shows the layout of the application. The graphic user interface offers three input options: 'Choose video file,' 'Confidence interval slider,' and 'Play button.' When the application is initiated, the user selects a video for analysis, configures the confidence interval for object detection, and initiates the analysis by clicking the 'Play button.' The software then begins processing the video using the framework depicted above in Figure 3.2. The outcomes are presented through pie charts, showcasing in real-time the percentage breakdown of identified waste objects, alongside additional charts that reveal the detected waste types at each second of the video and the total percentage of detected/undetected waste. For waste detection and operational planning purposes, this information is of significant value. This approach helps efficiently determine the characteristics of waste in a timely manner and take preemptive measures at early stages. Such measures are instrumental in decreasing the amount of inert and compostable waste in RDF feedstocks, thereby mitigating potential economic losses

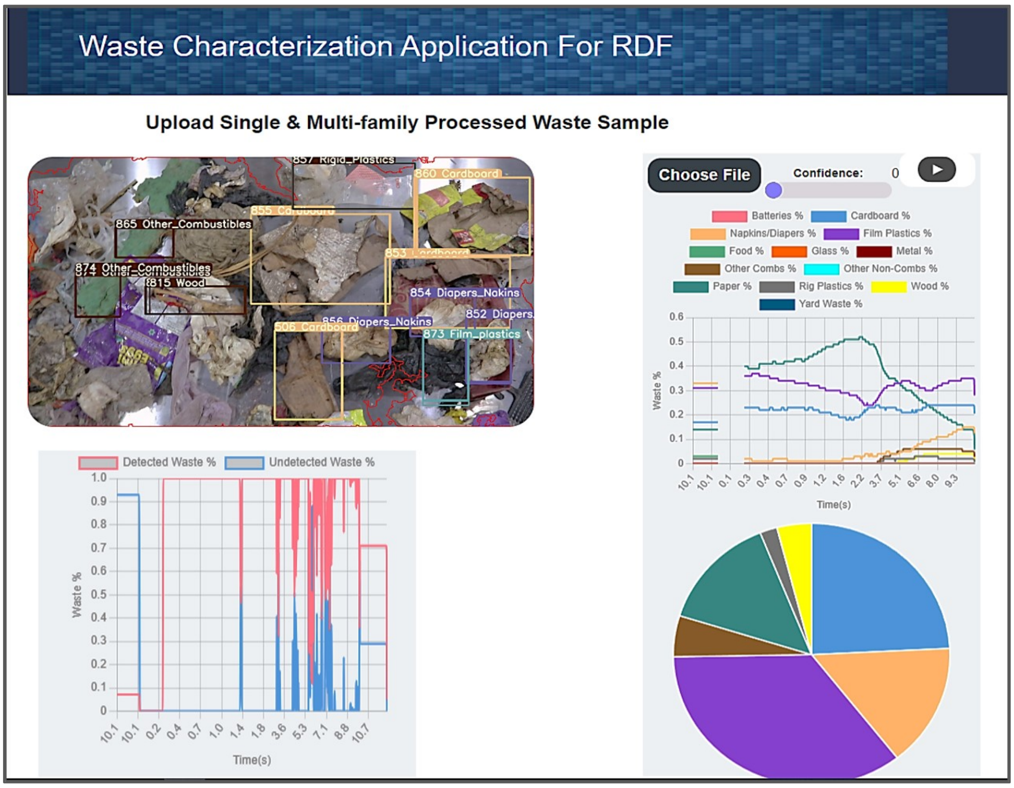

Figure 3.4: Layout of the waste characterization application

3.3.2 Detection Model Results

The performance of the model based on the YOLOv8x algorithm is evaluated using a validation dataset. This validation set consists of 15% of the total images, comprising an equal distribution of 45 pictures across all thirteen classes. The performance is presented in the form of a confusion matrix and uses common metrics for measuring the performance of deep learning models presented in the literature, such as overall accuracy, precision, recall, and F1 scores by Khan et al.[178]. As shown in Figure 3.5, the model exhibits susceptibility to confusion when distinguishing between certain waste classes. For example, it has categorized seven instances of rigid plastics among film plastics (2), glass (3), and metal (2). This confusion may stem from challenges in recognizing distinct waste type patterns and delineating specific contour features. Table 3.1 shows that the model has achieved an overall accuracy of 70% ,which is calculated using equation 3.14 , average precision of 76.2%, average recall of 69%, and average F1-score of 72.2%. The performance results for the 'Film Plastics' class are comparatively lower than those for the other classes. This disparity is attributed to the sensitivity of object detection approaches to occlusion and transparency which occurs more often with film plastics than for other classes. This model is built from the ground up, and to improve the performance of the 'Film Plastics' class, it could be beneficial to increase the number of images specifically for this class. It is concluded that detection models are inherently more complex compared to classification models. This complexity arises because an image may contain multiple objects, each of which can belong to the same or different classes.

$$\text{Accuracy} = \frac{\text{Number of images correctly classified}}{\text{Total images}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad \text{Eq.3.14)}$$

Table 3.1: Results of waste detection model

Waste Components	Precision	Recall	mAP50	mAP50-95	F1 Score
Batteries	0.78	0.66	0.69	0.40	0.71
Cardboard	0.69	0.83	0.79	0.59	0.75
Diapers/Napkins	0.84	0.63	0.71	0.52	0.72
Film Plastics	0.45	0.42	0.39	0.29	0.43
Food waste	0.76	0.58	0.61	0.43	0.66
Glass	0.93	0.70	0.84	0.63	0.80
Metals	0.86	0.90	0.90	0.72	0.87
Other Combustibles	0.85	0.51	0.62	0.44	0.64
Other Noncombustible	0.72	0.63	0.65	0.47	0.67
Paper	0.79	0.73	0.73	0.49	0.76
Rigid Plastics	0.72	0.73	0.76	0.65	0.72
Wood	0.77	0.80	0.83	0.57	0.78
Yard waste	0.75	0.83	0.79	0.58	0.79
Average	**0.762**	**0.69**	**0.716**	**0.52**	**0.722**
Overall Accuracy	**70%**				

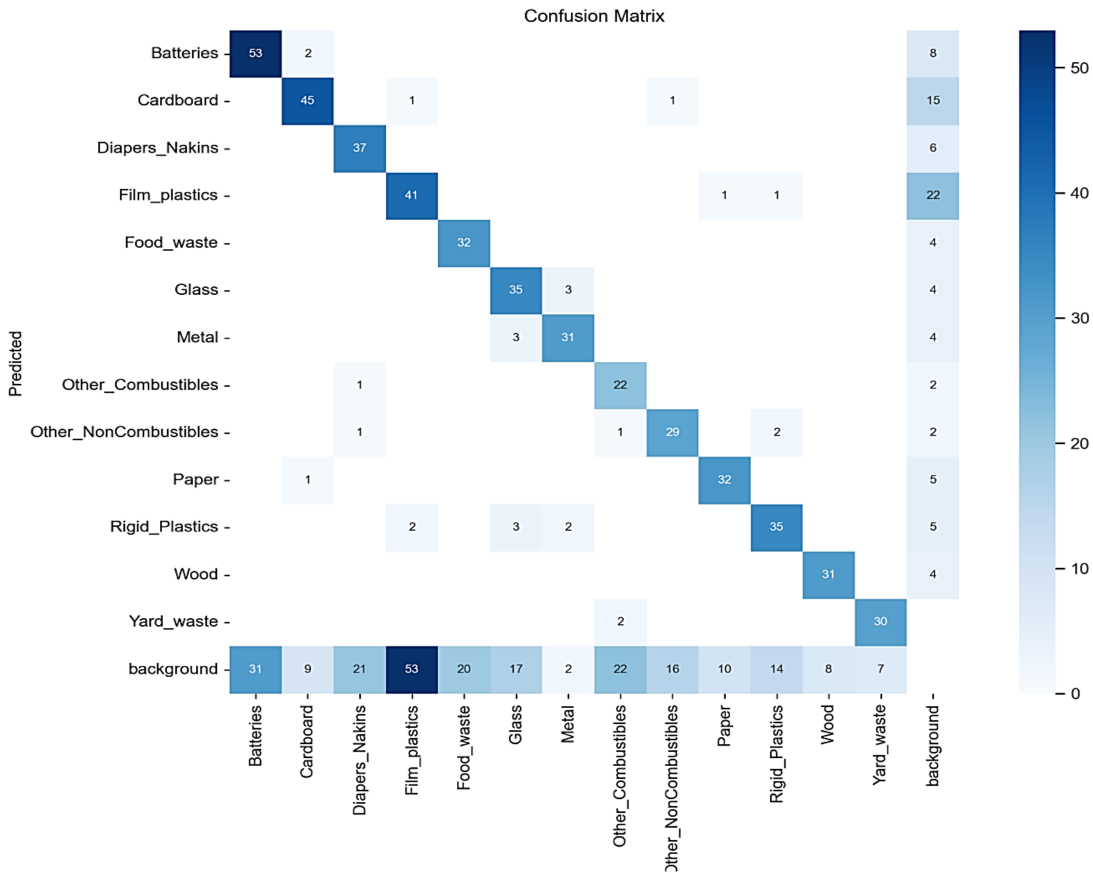

Figure 3.5: Confusion matrix of waste detection results

3.3.3 Waste Characterization Results

The average accuracy of the predictions across all waste classes is 70%. The preceding error in accuracy primarily stems from video frames with too many correct but excessively predicted boundary boxes. To address this, confidence filters can be used to minimize bounding box regression and eliminate bounding boxes with low confidence levels. This approach ensures that the most reliable object detections are considered while reducing the impact of overly predicted boundary boxes. In contrast, the number of frames containing incorrectly characterized objects is limited and did not significantly contribute to incorrect results. The low accuracy challenge seemed to arise from a need for more iterations and the presence of particularly challenging examples for the detection model, which required additional time to adapt. Also, the impact of the learning rate can be explored in the future for such applications.

In addition, mAP@50 is used as a metric to evaluate models' errors on the validation set. Notably, after 200 epochs, the fluctuations in the average precision error across all classes remained relatively constant, fluctuating around 0.71. Figure 3.6 shows the outcomes of the waste characterization application developed in section 3.3.1. Videos are taken from MRF conveyors, capturing different fractions of waste materials as they fell after trommel screening. These videos are then loaded onto the application for analysis. Overall, it can be observed that the application performed reasonably well under various conditions achieving a processing speed of approximately between 25 and 29 FPS (frames per second) enabling real-time performance with not substantial computational power. It's important to note that dominant factors influencing the accuracy of predictions are the lighting conditions, the height of camera placement and the monitoring durations. Brighter spaces tend to yield more accurate waste composition estimations. Likewise, it was determined that placing the camera at a height between 24 to 28 inches is ideal for handheld devices. Additionally, it is observed that longer video durations increased the requirement for motion compensation, which is computationally intensive but provides high accuracy. To validate the results, a limited number of waste samples are collected directly from the conveyors and sent to the lab for analysis. Operational constraints limited the number of samples that could be analyzed in the lab.

3.3.3.1 Validation of the Estimated Waste Composition

For validation purposes, samples of single-family and multifamily waste residues which were collected on as received basis are gathered from the conveyor and after their computer vision inspection are sent to the lab for analysis, as discussed in section 3.2.1.2. The lab typically provides results of the experimental analysis on a dry basis after an extended duration. Upon comparing the results obtained from the proposed application (using Eq 3.9 to Eq3.13) on dry basis and those from the lab, it is observed that the mean absolute error (MAE) between the experimental waste composition values from the lab and the estimated value from the application is reasonably low. Given that RDF is a heterogeneous mix of various materials that vary in composition and volume, achieving a 70% accuracy in predicting its characterization with minimal error is considerably positive. This accuracy value gives a holistic view of the developed model's performance across all waste categories, indicating that 70% of all waste items were classified correctly by the model. Figure 3.6 also displays the mean absolute error in the estimated values for thirteen waste types across all the collected samples. The larger error displacement in the estimation arrived from sample 3 for classes like film plastics, rigid-plastics, and paper. Sample 4 also showed estimation variations for paper, and rigid -plastics. When these waste types are grouped into the three high-level categories, it becomes evident that the difference between the estimated and observed values is minimal. This is shown in Table 3.2. The combustibles category accounts for the largest portion of compositions in both the laboratory and the Smart-Sight model, followed by compostable materials. A detailed breakdown of each waste component is provided in Appendix (A4).

Table 3.2: Comparison between the experimentally observed and estimated waste composition values, assessed for three high-level waste categories. Waste components details are presented in Appendix (A5)

Categories	**Lab Result S1**	**Prediction S1**	**Lab Result S2**	**Prediction S2**	**Lab Result S3**	**Prediction S3**	**Lab Result S4**	**Prediction S4**
Inert	0.39%	3.06%	0.27%	1.38%	2.84%	1.83%	1.41%	0.00%
Combustibles	75.80%	84.48%	66.96%	89.00%	94.46%	95.65%	73.75%	80.03%
Compostable	23.82%	12.47%	32.76%	9.52%	2.70%	2.52%	24.87%	19.97%

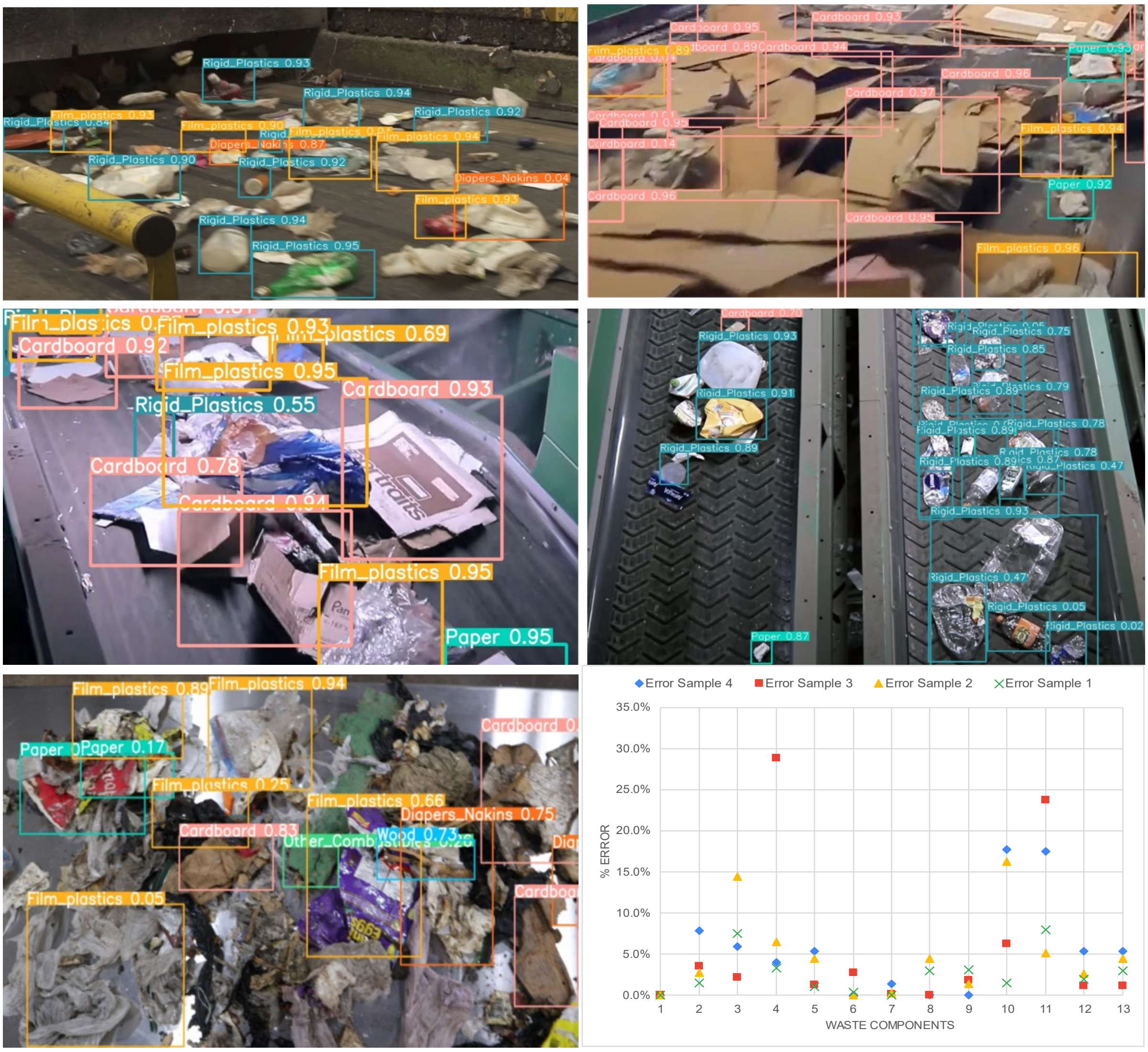

Figure 3.6: Prediction results of the proposed waste characterization application tested for indoor industrial environment. It also illustrates the percentage of error in estimating waste composition for four samples, covering thirteen waste components(-Batteries-1, Cardboard-2, Diapers/Napkin-3s, Film Plastics-4, Food Waste-5, Glas-6s, Metals-7, Other Combustibles-8, Other Noncombustible-9, Paper-10, Rigid Plastics-11, Wood-12, Yard Waste-13)

3.3.4 Parameters of Influence and Limitations

The proposed approach is specifically designed for waste streams where individual items can be detected on a conveyor. It operates under the assumption that every waste item on the conveyor can be accurately characterized under normal conditions. From the algorithm's perspective, the frame differencing technique brings some limitations. For example, it is only tailored for detecting moving objects in videos and may require a waiting period to establish background models, most likely not limiting its real-time capabilities. However, this technique works well with stationary cameras but is less practical for moving ones and close objects may be falsely identified as a single object, posing a challenge.

Similarly, for successfully implementing two-frame motion estimation, determining the best parameter values for the cv2.calcOpticalFlowFarneback function necessitates experimentation and a deep understanding of the unique characteristics of acquired data and detailed objectives. Figure 3.6 shows the result of the applied motion compensation technique using two polynomial expansions with the following parameters, pyr_scale: 0.5, levels: 3, winsize: 15, iterations: 3, poly_n: 9, poly_sigma: 12, flags: 0. Future studies can explore optimizing these parameters for enhancing the waste characterization application, but the reported parameters have been optimized in this study empirically

3.3.5 Comparison With Other Studies

In this chapter, the authors have extended the application of work from Carolis et al., 2020[106] by conducting a comprehensive analysis of thirteen low-level and three high-level waste categories. It utilizes the latest version of the YOLOv8x object detection algorithm. The achieved average precision (AP) for waste characterization is 0.76, and the mAP@50 is 0.716, which represents an improvement compared to the 0.68 precision and 0.59 mAP@50 in previous study by Carolis et al. for similar source of waste material. In contrast to the study conducted by Cuingnet et al.[83], this chapter introduces an alternative method for detecting metals, including aluminum with an average precision of 0.86, thereby extending the scope of prior research. In waste management, factors such as the configuration of material recovery lines, parameters for the separation of material recovery units, and the composition of municipal waste used for producing targeted materials can profoundly influence the quality of RDF produced, Fabrice et al.[18]. This uncertainty in establishing quality standards for RDF is highly relevant to operational decisions within the plant. The new proposed method in this chapter contributes to reducing reliance on laborious and time-consuming efforts required for the waste characterization of RDF material providing accurate, immediate, and continuous information on waste composition. The new method integrated with previous work from Junaid et al., 2023a[81] will facilitate improved decision-making at tactical and operational levels within the material recovery facility.

3.4 Conclusion

This study proposes a unique waste characterization system for detecting single and multifamily waste for enhancing quality of RDF-3 production. The latest YOLOv8x object detection algorithm is employed to train a model capable of detecting inert, combustible, and compostable waste types with an overall accuracy of 70% and mAP@50 of 0.716. The proposed system demonstrates both accuracy and flexibility, making it suitable for real-world scenarios without being hindered by indoor environments. The integration of motion compensation and frame differencing techniques in this study considerably alleviates challenges commonly encountered in waste detection applications. While these algorithms effectively solve the identification of physical composition problem in terms of quality RDF production, the investment to obtain the optimized solution remains high. Hence, imperative algorithmic enhancements are needed to achieve high-quality solutions more efficiently, reducing computational costs.

From the algorithm's perspective, the frame differencing technique brings some limitations. For example, it is only tailored for detecting moving objects in videos and may require a waiting period to establish background models which may limit its real-time capabilities. However, this technique works well with stationary cameras but is less practical for moving ones and close objects may be falsely identified as a single object, posing a challenge. In the study, a notable disparity in classification primarily emerged when dealing with plastics and rigid plastics. It is imperative to acknowledge the importance of discriminating among various types of plastics, given their marked differences in calorific values and chlorine content. This facet of this research offers promising opportunities for future extensions and investigations. One particularly promising avenue worth exploring is the utilization of near-infrared spectroscopy, renowned for its efficacy in distinguishing between various polymers based on their distinct spectral signatures. Embracing this approach could lead to exciting advancements and progress within our research in this field.

The proposed system in this study offers valuable assistance to waste management practitioners interested in implementing AI techniques for waste characterization and integrating smart solutions into their material recovery facilities. This system not only aids in the accurate detection of waste but also facilitates early-stage decision-making regarding potential mitigation strategies for waste compositions unsuitable for RDF production.

In the upcoming chapter, the outputs pertaining to the physical compositions of waste from the developed tool will be utilized as one of the inputs for the next stage, which addresses the second objective of the study. This subsequent chapter focuses on creating a simulation model for a material recovery facility that produces RDF-3. The simulation's objective is to facilitate revisions in strategic, tactical, and operational decisions by integrating diverse waste treatment technologies and accounting for uncertainties that impact its performance.

Chapter 4: Quality RDF-3 Production Modeling in a Material Recovery Facility

4.1 Overview

This chapter considers creating a simulation model of a material recovery facility producing RDF-3, which can support revisions in the strategic, tactical, and operational level decisions integrating different waste treatment technologies considering varied uncertainties affecting its performance. The developed model supports revisions in the strategic, tactical, and operational decision levels and is integrated with varied uncertainties like probability distributions of in-feed waste compositions, moisture content, and calorific value of individual waste components, affecting the energy performance of an MRF. The model provides improvements to operating conditions and enables prediction for quality standards of RDF, enabling the waste management authority to meet their outlined quality specification for the final product. The validation of the model is conducted in a way, where the quality measures of the final product collected from an MRF are compared with the estimated values those from the simulation. The comparison reveals that precision in results from the developed model, in all performed tests is consistent with actual observed results, inferring the developed simulation model as a viable tool for estimating quality measures for RDF. The foundations of the model are based of assumptions like emphasis on general representation but not physical properties of MRF, only selected sets of uncertainties are studied, and variations in the operating conditions can affect estimated quality of RDF.

4.2 Methodology

4.2.1 Description of input feedstock and mechanical treatment plant

The composition of the pre-sorted municipal waste, which is further blended to the RDF-3 fraction from 2 to 5 centimeters, is based on nine major waste categories as defined by Ali et al.[169]. For this study, the composition includes paper (6.48%), rigid plastics (5.72%), film plastics (20.98%), food waste (organics-30%), yard waste (1.30%), diapers and napkins (14.68%), and other combustibles (15.85%). The remaining 5% composition is a mixture of glass and non-combustibles materials (see Appendix (A2)) for a complete detailed description of the waste composition). The waste characterization study presented by Ali et al.[169] provides the method to perform the sieve analysis and composition analysis for categorizing waste types. Such a MSW composition first passes through a mechanical sorting line to separate bulky waste, non-combustible material, and hazardous waste. Afterwards, further mechanical processing includes a shredder, a separator of metals and a drum screener. The output from a drum screener passes through a wind sifter where heavies fall, and fines pass through the eddy current separator to get rid of electromagnetic materials. Then the processed material is re-shredded to fraction size in the range of 2 cm to5 cm. The material type retrieved after the final stage is dried to achieve the desired moisture content in the final product and now referred as RDF-3. The RDF-3 samples collected at the final stage of the process are prepared for lab analysis using ASTM (E829). They are processed in the lab for carrying out ultimate analysis to explore the potential heat value, physical and chemical composition of those samples. The ultimate analysis is done in accordance with ASTM 5373 and ASTM D4239 – 18 methods, whereas the calorific value calculation is based on ASTM D5865 method, measured with a bomb calorimeter. The residual moisture in the RDF-3 sample is measured using ASTM(E949-88) method.

4.2.2 A simulation modeling for identifying best-operating conditions

Waste management activities are best planned once it's identified which quality standards are to be used and secondly, under which operational or technical conditions a plant produces high-quality RDF. Based on these two factors, a simulation modeling framework shown in Figure 4.1 is developed in this study for the sustainable production of RDF. The two important aspects in the proposed framework are the quality standards and the operating conditions. First, by adhering to standards RDF is produced according to a defined quality assurance procedure, thus it can further become a certified "solid recovered fuel" (SRF-quality trademark). Finally, operational or technical conditions represent the different treatments that are deployed to process incoming wastes, like a mechanical treatment or a mechanical-biological treatment [9], [113]. Only mechanical treatments are within the scope of this study.

A generic form of decision-making in the biomass to RDF workflow is presented in Table 4.1, showing the interdependence of the biomass supply chain operations. The decisions taken in the upstream, like the selection of biomass for converting it into RDF, the choice of biomass conversion technology, or the facility's capacity among others, affect the downstream operations massively. Thus, the biomass supply chain should be robust enough to mitigate uncertainties and adapt to varied operational conditions. This is achieved by modeling uncertainties in the decision-making process and selecting only those residual fractions from municipal solid waste, providing high-quality RDF fuel with stable physical, chemical, and environmental specifications. Based on the conventional framework of waste management activities, the proposed method constitutes an extension to facilitate the integration of an assessment of selected set of uncertainties for adding value in biomass to the RDF supply chain. The new approach demonstrates the addition of the above factors using the simulation modeling technique. However, the RDF distribution and transport related decisions are out of scope in this study.

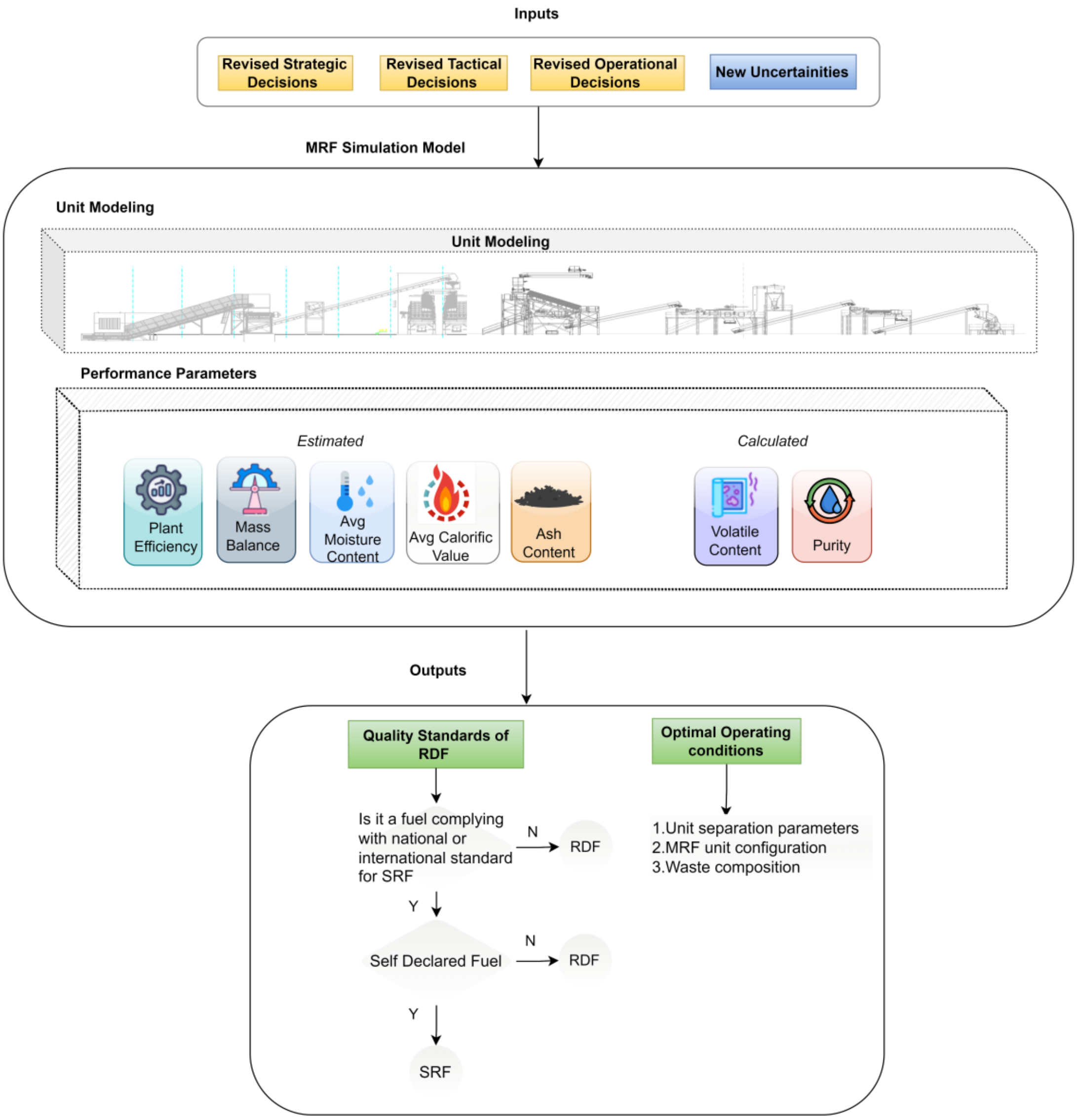

Figure 4.1: A simulation modeling framework for identifying best-operating conditions and quality standards for RDF

Table 4.1: In scope decisions making hierarchies of supply chain planning and design for producing RDF, after [17].

<table>
<tr><th rowspan="2">Biomass Supply Chain Components</th><th rowspan="2">Related Source of Uncertainty</th><th colspan="3">Decisions</th></tr>
<tr><th>Strategic</th><th>Tactical</th><th>Operational</th></tr>
<tr><td>Biomass Supply</td><td>Network</td><td>Selection of waste composition for producing RDF</td><td>-</td><td>-</td></tr>
<tr><td>Biomass Preprocessing</td><td>Internal</td><td>Technology upgrades</td><td>Technology performance</td><td>-</td></tr>
<tr><td rowspan="2">RDF Production</td><td rowspan="2">Internal</td><td rowspan="2">-</td><td rowspan="2">-</td><td>Biomass yield</td></tr>
<tr><td>RDF Quality</td></tr>
<tr><td>RDF Sales</td><td>Network</td><td>RDF market selection</td><td>-</td><td>-</td></tr>
</table>

The five major parameters for measuring the performance of the MRF are outlined in Figure 4.1 identifying plant efficiency, mass balance, moisture content, calorific value, and ash content, as estimated while volatile content and purity are tagged as calculated parameters. The calculated parameters are derived from the estimated parameters of the simulation model.

Material separation of municipal waste in a materials recovery facility is carried out using a sequence of mechanical units. In this context, a network flow modeling technique by Testa et al. can be applied in designing a simulation model for modeling the RDF production in a general material recovery facility (MRF) to evaluate its performance [17]. A basic representation of this system modeling technique consisting of individual processing units is shown in Figure 4.2, where square boxes denote processes of the MRF connected in a sequence, and the circles represent the input and final outputs of the system. This approach serves to organize operating units of an MRF into four types: mixing units, sorting units, splitting units, and comminution. A list of general operating units in MRF includes a primary shredder, ferrous separator, eddy current, wind sifters, waste screens, secondary shredder, dryer, and surge bin [9], [17], [18], [80].

These units separate out our desired target and undesired non-target material concentrations based on the following: 1) probabilistic modeling, which can describe units in the form of mass balance equations and are considered in the scope of this study; 2) deterministic modeling, which focuses on physical characteristics of the materials and considered out of the scope for this study.

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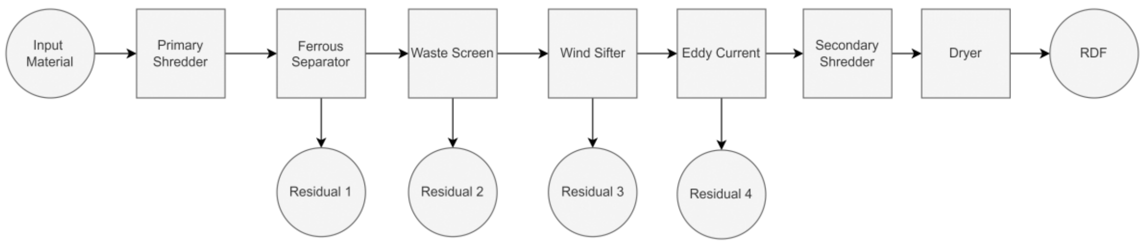


Figure 4.2:Building blocks of multi-output units represented by network flow modeling technique, adapted from after [17]

Karine et al. modeled a material separation process of MRF using the network flow modeling technique [80]. The separation process was modeled on a per-material basis with an empirically derived separation parameter. Based on that, it presented the performance evaluation of MRF depending on three parameters: 1) assembly line configuration, 2) parameters of separation, and 3) input material stream composition. Using this technique, it was illustrated how to measure the performance of an MRF by calculating the plant efficiency, recovery, grade (concentration of desired material), and associated business costs. It also studied the impact of uncertainty to account for variations in input stream waste composition on the performance. However, this study had a limited number of data points (nine samples) defining the uncertainty distribution for each material component feeding into the model. Adding more observations with outlined operating conditions can support the further refinement of the performed sensitivity analysis in the study. The inclusion of uncertainty in such type of modeling is present in the literature where stochastics and probabilistic tools are implemented for creating simulation scenarios like the Monte Carlo method for sampling from probability distributions [42].

Similarly, a similar network flow modeling technique was deployed to assess the limits of partition coefficients previously published in the literature for modeling the sorting efficiency of unit operations [18]. By using the simulation modeling approach in the study, the purity and recovery of the recovered materials were calculated as the MRF sorting efficiency parameters to evaluate the overall performance for each unit under consideration in the research. Units like air classifiers and ballistic separators have an influence on the recovery and purity measures for the RDF stream. The intensity of this influence variates by the choice of material separation configuration of the trommel unit used upstream. However, the trommel is out of scope in the context of this study.

4.3 Mathematical Modeling

In this study, the network flow modeling technique is used to design and compute the material flow in the system [17]. A waste processing system comprised of various multi-output units where each node can be represented as a unit (x), and (x,y) is a directed flow of material (M) from unit (x) to unit (y). The multi-output streams of each unit are considered two in this study. The flow of material can be represented as ε, expressing set of all nodes for all input and output units in the system. The following are the derived mathematical models for the four types of operating units considered in the scope of the study for modeling an MRF.

4.3.1 Sorting Units

A simple representation for modeling sorting units is shown in Figure 4.3, where for any mixture of material (M), a mass flow rate of (P_x^M), in the input stream (tons per hour) going to unit (x) is defined. Unit (x) processes the input material stream and afterward separates the material into two streams. These two streams could be tagged as the target unit (y) stream (having the desired material concentration) and the non-target unit (k) stream (having the undesired material concentration). The mass flow of material in the target unit is equal to $(s_{x,y}^T * P_x^T)$ where $(s_{x,y}^T)$ is called the separation coefficient or separation parameter. So, a unit (x) diverts a fraction $(s_{x,y}^T)$ of its flow to target unit (y) and diverts a fraction $(s_{x,k}^N)$ of its flow to non-target unit (k). The separation parameter value should be between 0 and 1. Each input node feeds a stream to the initial sorting unit. The inputs to each sorting unit comprise an input stream from an input node and an output stream from other sorting units. Every sorting unit can generate multiple output streams, as described before. There is no output flow from an output node as it is designated as a collection node.

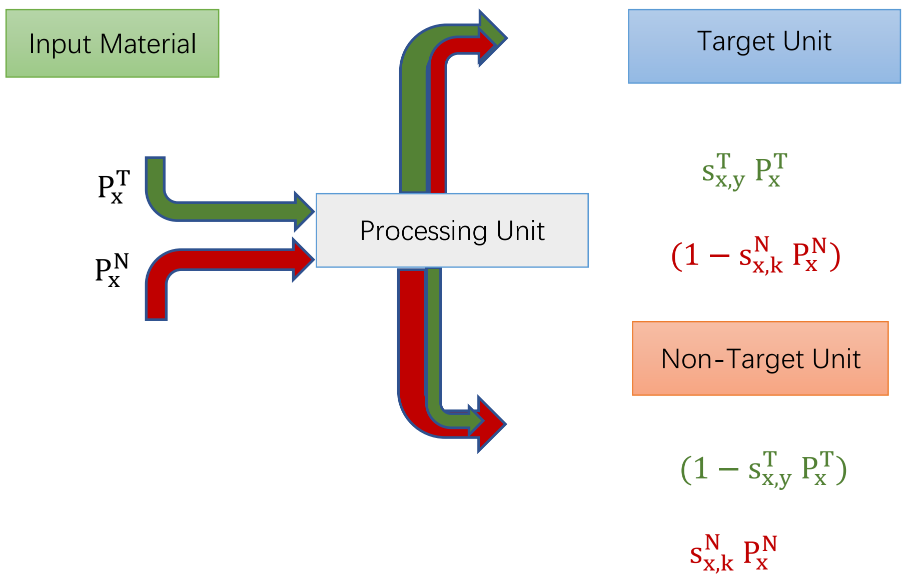


Figure 4.3:Scheme of a multi-sorting unit: sorting an input stream mixture of target and non-target materials into two streams.

(P_x^T) is the mass flow rate to unit (x) for target input material (m), (P_x^N) is the mass flow rate to unit (x) for a non-target input material (m), $s_{x,y}^T\ P_x^T$ is mass flow in the output stream to target unit (y), $s_{x,k}^N\ P_x^N$ is mass flow in the output stream to non-target unit.

For any given MRF, a steady-state flow rates of each material through each unit can be computed, provided if the quantity of input material, the sorting efficiency of each unit and the assembly line configuration are known. To compute the flow of materials though each sorting unit, the mass balance equation with external flow rate of material can be represented as:

$$P_x^m = \mu_y^m + \sum_i s_{x,y}^m P_y^m \quad \ldots\ldots \text{ Eq.(4.1)}$$

Where $s_{x,y}^m = 0$ if there is no connection between (x) and (y). Similarly, $\mu_y^m \neq 0$, only if an input unit feeds a sorting unit. For steady-state flow of each material through each unit, the system of linear equations for all units in a system can be presented in matrix notations as shown in the equation below.

$$\overline{P}^m = \overline{\mu}^m + (S^m)^T \overline{P}^m \quad \ldots\ldots\ldots \text{Eq.(4.2)}$$

Where ($\overline{P}^m$) is the flow vector of material (m), $(S^m)^T$ is the sorting matrix, which is system-level sorting matrix of material (m) that unit (x) receives in input and sends to unit (y), and ($\overline{\mu}^m$) is the input vector. Solving the system of linear equations one can derive the final steady-state equation of the sorting unit from obtaining the flow rate at each unit for each material (m) as:

$\overline{\mathrm{P}}^{\mathrm{m}} = (\mathrm{I} - (\mathrm{S}^{\mathrm{m}})^{\mathrm{T}})^{-1}\overline{\mu}^{\mathrm{m}}$ ……..Eq.(4.3)

4.3.2 Mixing Units

These units combine the input material flow to a single flow.

$\mathrm{P}_{\mathrm{x}}^{\mathrm{out}} = \sum_{(\mathrm{x,y})\in\,\varepsilon} P_y$ ……..Eq.(4.4)

4.3.3 Splitting Units

This type of units divides the input flow of material into output stream having same material composition based on the separation parameter.

$\mathrm{P}_{\mathrm{x,y}}^{\mathrm{out}} = \mathrm{s}_{\mathrm{x,y}}\, \mathrm{P}_{\mathrm{x}}$ …….. Eq.(4.5)

4.3.4 Communication Units

These units modify the size of inflow of material by shredding its components, thus mass balance is unchanged.

$\mathrm{P}_{\mathrm{x,}}^{\mathrm{out}} = \mathrm{P}_{\mathrm{x}}$ …….. Eq.4.6)

4.3.5 Final Mass Balance

Flow of each material type through all types of output unit (x) as follows,

$\mathrm{P}_{\mathrm{x}} = \sum_{(\mathrm{x,y})\in\,\varepsilon}^{\mathrm{Mix}} (\mathrm{P}_{\mathrm{y}}) + \sum_{(\mathrm{x,y})\in\,\varepsilon}^{\mathrm{Sort}} \mathrm{s}_{\mathrm{x,y}}^{\mathrm{m}} (\mathrm{P}_{\mathrm{y}}^{\mathrm{m}}) + \sum_{(\mathrm{x,y})\in\,\varepsilon}^{\mathrm{Split}} \mathrm{s}_{\mathrm{x,y}} (\mathrm{P}_{\mathrm{y}})$ …….. Eq.(4.7)

4.3.6 Dryer Unit Modeling

A dryer unit is required to ultimately increase the caloric value and decrease the moisture content of the RDF feedstock. The use of dryer is highly dependent on the demand requirements of the final RDF fluff and the selected market for its sale. Various types of dryers can be categorized generally into continuous or batch dryers at a high level. The drying methods used by the dryers include bio-drying, thermal drying, and dewatering. In this study the scope is limited to the Belt conveyor type of the dryer using the thermal drying method which consist of some sections with circulating or static fans and heating coils in continuous processes. Establishing an experimental test for reaching the feasible level of RDF drying was not possible due to operational restriction in this study. For this reason, a vendor is consulted for captivating guidelines regarding optimal RDF final moisture content, and they recommended the moisture content of 14%wt. The mass balance of the dryer unit is shown in Figure 4.4.

$$M_{Wet} \,.\, N_{Wet} = M_{dry} \,.\, N_{dry} + M_{evp} \,.\, N_{moist} \qquad \text{........ Eq.(4.8)}$$

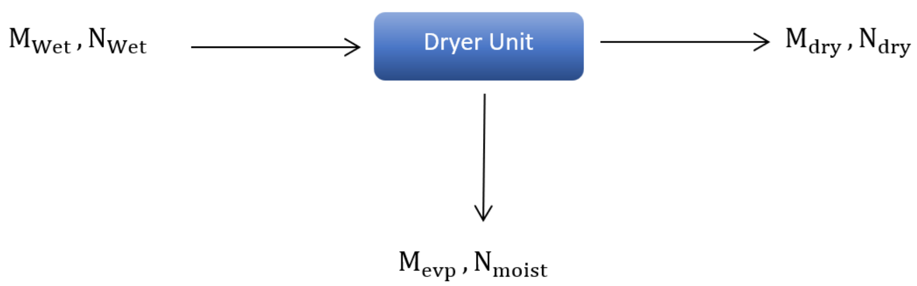


Figure 4.4: General mass balance model for the dryer (drying process).

Where (M_Wet) is the mass of wet RDF coming into the dryer, (N_Wet) is the moisture content of the wet RDF (wet basis), (M_evp) is the mass of evaporated moisture, (N_moist) is the moisture content of the evaporated moisture, (M_dry) is the mass of dry RDF leaving the dryer, and (N_dry) is the moisture content of the dried RDF mass (wet basis).

The heating value of the refuse-derived fuel can be used to quantify the energy generated by combustion with air following standard temperature and pressure conditions (STP-250C and 101.3 kPa). In this context, the state or phase of water in feedstocks defines the quantity of heat released during the combustion of RDF fuel. The first stage of combustion exhausts the RDF into gas and water vapors. The value of the total heat release during this stage is termed as low heating value. In the second stage, if the water vapors are condensed to a liquid state, then extra energy can also be extracted, and the total heat release is termed as high heating value. The high eating value will be estimated using the simulation model and from the collected observed samples for HHV of the RDF. The low heating value of the RDF can be estimated using the following equation [179].

$$\mathrm{LHV} = \mathrm{HHV_D}(1-\mathrm{M}) - 2.44\mathrm{M} \quad \text{........ Eq.(4.9)}$$

$$\mathrm{HHV_D} = \mathrm{HHV}/(1-\mathrm{M}) \quad \text{........ Eq.(4.10)}$$

Where (M) is the moisture content of the RDF on wet basis and (HHV_D) is the high heating value on dry basis. The constant of 2.44 is the latent heat for water at STP measured in MJ/Kg [180].

4.4 Simulation Model and Implementation

This study applies the material separation coefficient modeling technique to a novel material recovery line configuration shown in Figure 4.5. The modeling of this configuration is novel in a sense as it provides deep insights on conversion of RDF-3 to energy applications besides providing an extension to the research conducted by [18], [80]. Both modeled MRF configurations, which had different functions and didn't put emphasis explicitly on energy from waste applications.

The RDF facility used as a case study in this research planned to commission a dryer unit to be complacent with the required final product specifications. Therefore, the inclusion of dryer unit in the material recovery line configuration adds more value to understand its impact on the quality parameters of produced RDF-3 or SRF product. In this context, analytically estimating performance parameters of the RDF plant like (plant efficiency, mass balance, average moisture content, gross calorific value, ash, volatile content and purity) using data originating from such configurations is unique and, to authors best knowledge, not used for quality estimation of RDF-3 material. The simulation of this model is developed in Simphony.net, and the model results are validated with the actual laboratory results within the MRF, where the samples of the RDF are analyzed.

4.4.1 Model Inputs

The model's schema comprises units shown in Figure 4.5, where the inputs to the model are the probability distributions of in-feed waste compositions, moisture content and calorific values of individual waste components. The waste components include paper, rigid plastics, film plastics, food waste, yard waste, diapers and napkins, other combustibles, glass, and other non-combustible materials. The characteristics of such waste stream changes every season due to its heterogeneous nature, that is why a four-season dataset (containing 30 observations) is collected to record variability in waste composition, moisture content and calorific values as presented in Appendix (A1). The Monte Carlo method is used in the simulation for sampling from probability distributions to provide values of the performance parameters of MRF.

Besides introducing uncertainties in the waste composition and its associated characteristics as inputs in the simulation model, a combination of relevant strategic, tactical, and operational level decisions are also introduced in the model, as shown in Table 4.2. In the supply chain context, uncertainty is modeled depending on data availability. Generally, the nature of uncertainty can be distinguished as randomness, epistemic uncertainty, and deep uncertainty [114]. Deployment for each type of these uncertainties depends on the quality of information present, and this study guides on a further selection of suitable optimization approaches and uncertainty representation. Table 2 demonstrates the taxonomy of uncertainty sources and the selected decisions to measure their effect on the performance parameters of MRF using a scenario-based stochastic simulation modeling technique.

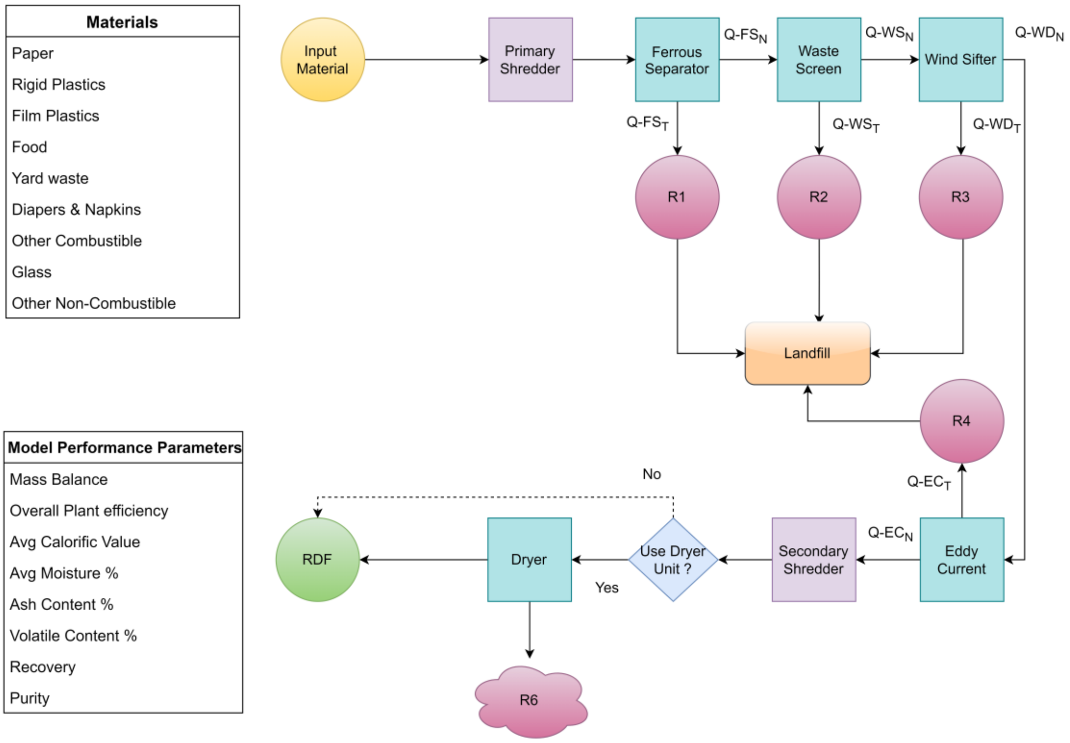


Figure 4.5: MRF assembly line configuration used in the simulation showing selected material composition as model input and performance evaluation parameters as model output

Table 4.2: In scope decisions making hierarchies with descriptions.

#	Decision Type	Decision	Description
1	Strategic	Selection of waste composition for producing RDF	Utilize various physical composition, moisture content and calorific value ranges of MSW as input to the model
2	Strategic	Technology upgrades	Adding new units in the RDF production line e.g. dryer
3	Strategic	RDF market selection	Consider various market value potential for the sale of RDF /SRF
4	Tactical	Technology performance	Utilize various ranges of unit separation coefficients as input to the model
5	Operational	Biomass yield/ Quality	Utilize various quality standards as evaluation criteria to measure the quality of RDF produced

4.4.2 Model Process Flow

The mass flow from each of the units in the MRF configuration shown in Figure 4.5, is diverted to target and non-target units based on the separation parameter values Q-FS, Q-WS, Q-WD, Q-ECT for each material. The targeted material stream falls into landfill bins whereas the non-target material stream moves on to the next processing stage and so forth until the final RDF fluff is produced. In the model, a dryer is one of the important components of the model because of its capability to reduce the moisture of the final RDF fluff and its use in the configuration depends on the predefined quality standards of the RDF to be produced. A sample run of the simulation is presented in Figure 4.6, showing the mass balance of the individual waste components flowing through each unit in the process. The sample run shows that a mixed waste stream with a mass flow rate of 39 tons per hour passes through the units. The concentration of individual waste components would separate out at the end of each process in a unit till they reach the final stage of processing in the drying unit. The partition coefficient information was available from an RDF plant about few streams (waste components) passing through sorting units and provided a range of sorting coefficients. However, it was not possible to assess the internal sorting coefficients for all the operating units. To address this, sorting efficiencies from literature were adapted for building the simulation model. Table 4.3 shows the selected design separation coefficients of the units found in the literature and the adjusted coefficients (highlighted in yellow color). For units with available information from the RDF plant, a few of the coefficients were adjusted within provided range in the model based on a basic optimization problem solved to realize the mass balance helping identifying partition coefficients for all waste streams of the units. These partition coefficients can be updated based on experience (historical data) or experimental tests on each unit in future to study its effect on the quality parameters.

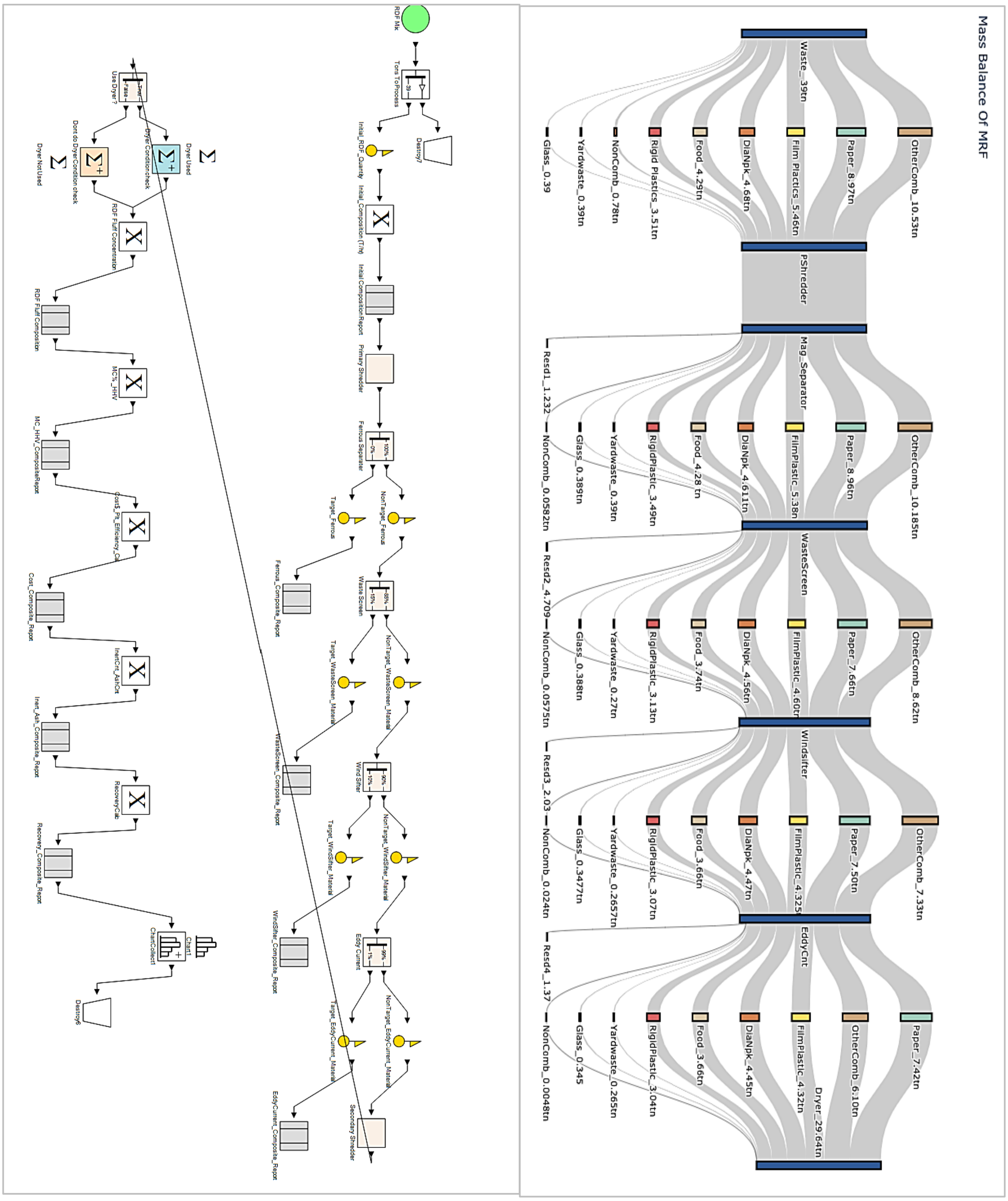


Figure 4.6: Simulation model of a MRF developed in Simphony.net and simulated mass balance with material recovery rates representing mass flow of individual waste components (in direction left to right) at each unit.

Table 4.3: Unit separation co-efficient for waste components, after [30], [80], [181], [182]

Units	Paper	Rigid Plastic	Film Plastic	Yard Waste	Food	Diapers & Napkins	Other Combustible	Glass	Non-Combustible
Shredder	1	1	1	1	1	1	1	1	1
Magnetic separator									
Target	0.0007	0.0031	0.0144	0	0.0002	0.0147	0.0327	0.0022	0.9253
Non-Target	0.9993	0.9969	0.9856	1	0.9998	0.9853	0.9673	0.9978	0.0747
Waste Screen									
Target	0.1453	0.1037	0.1439	0.3048	0.1272	0.0095	0.1532	0.0014	0.011
Non-Target	0.8547	0.8963	0.8561	0.6952	0.8728	0.9905	0.8468	0.9986	0.989
Wind Sifter									
Target	0.02	0.02	0.061	0.02	0.02	0.02	0.15	0.105	0.582
Non-Target	0.98	0.98	0.939	0.98	0.98	0.98	0.85	0.895	0.418
Eddy Current									
Target	0.011	0.008	0.001	0.002	0.001	0.004	0.167	0.006	0.8
Non-Target	0.989	0.992	0.999	0.998	0.999	0.996	0.833	0.994	0.2

4.4.3 Model Performance Metrics

Following are the parameters calculated by the model to measure the performance of the MRF:

4.4.3.1 Overall Plant Efficiency

It is the measure of how much infeed is properly sorted on mass basis, as described by [18].

$$\in = \frac{\sum_m f^m_{y(m)}}{u_m} \quad \text{.....Eq.(4.11)}$$

Where the single target output unit denoted by (y) for material (m), $(f^m_{y(m)})$ is the mass sorted correctly for material (m), and (u_m) is the total input flow of material (m).

4.4.3.2 Gross Calorific Value

It is the amount of heat created when moisture in feedstock is converted into water vapor and back to the liquid state. This study uses the estimation equation presented by Roshni et al. [72] as shown in the equation below,

$$CV = \frac{\sum_{j=1}^{n} W_{rj}\, CV_{rj}}{\sum_{j=1}^{n} W_{rj}} \ldots\ldots\text{Eq.}(4.12)$$

Where (n) is the number of individual material components, (CV_{rj}) is the calorific value of each individual waste component (j) on an as-received basis, (W_{rj}) is the raw weight of the individual waste component (j).

4.4.3.3 Moisture Content

It represents the weighted average (in percentage) of the moisture content of the total waste available.

$$MC(\%) = \frac{\sum_{j=1}^{n} (W_{rj})MC_{ij}}{\sum_{j=1}^{n} W_{rj}} \ldots\ldots\text{Eq.}(4.13)$$

Where $(\mathrm{MC}_{i,j})$ is the moisture content of the individual waste components (j) on a wet basis, and $(\mathrm{W}_{r,j})$ is the weight of the raw individual waste component (j).

4.4.3.4 Ash Content

Roshni et al. presented a way to easily estimate ash content in mixed MSW using the following expression [72].

$$ASH\ (\%) = \frac{\sum_{j=1}^{n} W_{(dry)j}\, IC_j}{W_{(wet)j}} \ldots\ldots\text{Eq.}(4.14)$$

Where (IC_j) is the inert content (in percentage) and is determined by separating the inert content of individual waste components from the sum of the total weight of the components, $(W_{(dry)j})$ is the dry weight of the corresponding component (j), and ($W_{(wet)j}$) is the total wet weight of the component (j).

4.4.3.5 Volatile Content

It is the material which could be transformed into vapors and the overall volatile content of the final product can be calculated as,

$VC(\%) = 100 - (MC - IC)$……Eq.(4.15)

4.4.3.6 Recovery

It measures the quantity of material (m) collected at the target (desired) unit.

$R_m = \frac{f^m_{y(m)}}{u_m}$ …….Eq.(4.16)

4.4.3.7 Purity

It measures the concentration of target material (m) in output stream (y),

$G_m = \frac{f^m_{y(m)}}{\sum_m f^m_{y(m)}}$………Eq.(4.17)

4.4.4 Model Outputs

The yield of the produced RDF is determined in terms of material and energy recovery. Material and energy recovery are calculated based on mass and energy balances from input to output streams of the MRF. Mass balance is established and calculated based on the mass of input waste feedstocks and by weighing the output streams produced. The energy content of the RDF is calculated by multiplying the individual waste components heating values by their respective total mass. The output of the model is a compiled report showing values of the performance parameters for measuring the efficiency of MRF. In other words, it provides evidence under which operational or technical conditions a plant produces high-quality RDF. The performance parameters included in this study are also shown in Table 4.4. The mass balance equation is derived previously as represented by Eq(4.7).

4.4.5 Model Limitations and Scope

The developed model is a simplification of the RDF production planning for supporting biomass supply chain planning. A series of assumptions have been made to simulate the RDF production in a MRF and as a result some of the processes in the developed model may not capture features of the real world. The modeling of units operating in a MRF focuses on its general representation but not physical properties. Similarly, the estimated quality of the produced RDF may be impacted by other processes of the MRF due to variations in operating conditions. Current assumptions and limitations of the model are listed below:

a) The model computes the steady-state flow rates for each material going through each unit.
b) The flows entering the system are assumed to be stationary.
c) The units to have no storage capacity or build-up.
d) The processes must operate under steady operating conditions.
e) The value of the separation parameters is constant and independent of the input composition.
f) No physical modeling of the units is considered.
g) Each separation process is modeled on a per-material basis with separation coefficients available from the literature and identified from an RDF plant.
h) Only selected set of the uncertainties affecting RDF production as shown in Table 1 are incorporated in the model due to limited data availability.
i) Cost relevant to logistics, plant operations, or inventory holding, and environmental impacts of the RDF production are not covered in the model.

4.5 Model validation and evaluation

The material separation simulation modeling technique is applied to a novel material recovery line configuration to model the RDF production and validated the results of the model with an RDF production plant in Edmonton. The output values from the model for five of the key quality parameters, calorific value, moisture content, ash content, mass balance and plant efficiency have been validated from the observed values. The comparison reveals that the simulation model results are representative of the observed results, inferring this model is a viable tool for estimating quality parameters for the RDFs. A data set that is normally distributed is crucial for the application of statistical analysis. In various applications, the collected quantitative dataset from an experiment is evaluated with a most suitable hypothesis test and a major assumption for this requires the data to be normally distributed [183]. This study tests the distribution of the output data sets from the model (experimental results) and observed samples for normality using both analytical and graphical methods. The check for normal distribution is being tested analytically using Kolmogorov-Smirnov Test or Shapiro-Wilk Test. However, Q-Q (quantile -quantile) plots and frequency histogram plots are the graphical methods used to validate normality of datasets [184]. Following are the two null hypothesis tests conducted in the study to discover whether two data samples are statically equal. The first null hypothesis (H0A) is, that both the data samples have similar probability distribution. The second null hypothesis (H0B) determines if there is no significant difference between the observed and experiment samples. To test the second null hypothesis (H0B), parametric test such as the T-test or Z-test or Levene test and non-parametric test such Mann-Whitney U test are used, as both the samples are unpaired, unequal, and independent in this study. The following Figure 4.7 describes the workflow for model validation process,

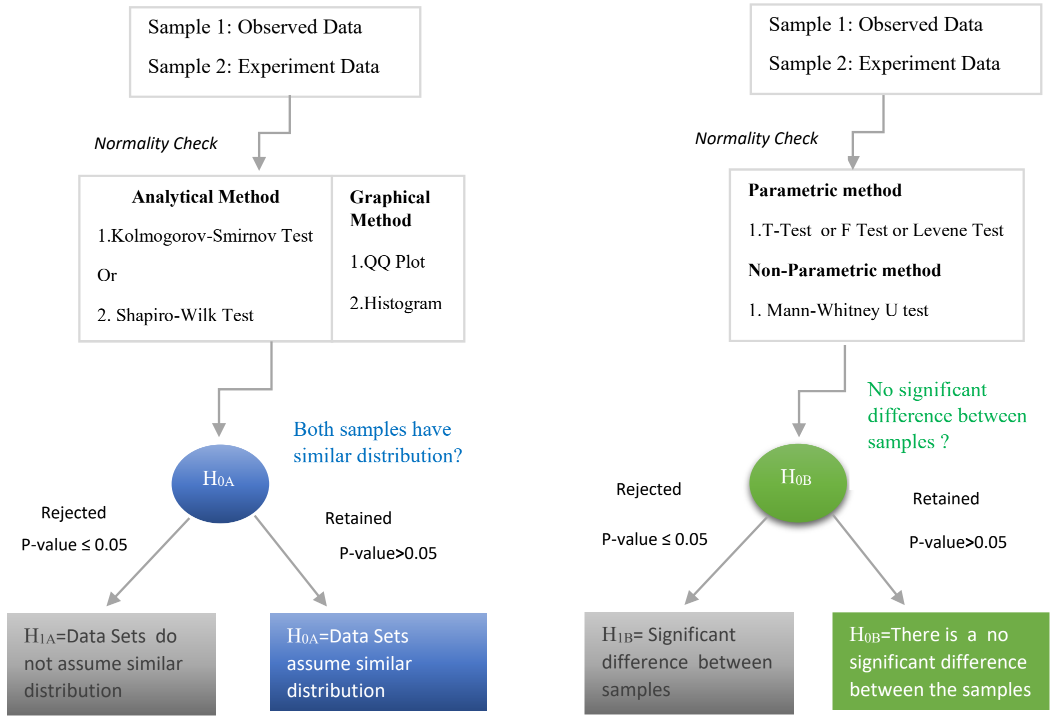


Figure 4.7: Hypothesis testing for validating (observed vs. model output samples) performance parameters of RDF production.

4.6 Results and Validation

In this study, the quality-related results of RDF production holding paramount standing are estimated using a simulation model and compared with an operating MRF. The conducted comparison highlights the effect of the varying input waste composition, moisture content and calorific value on the performance parameters of an MRF. These parameters (calorific value, moisture content, ash content, mass balance, and plant efficiency) cover the production yield and physical and chemical properties of the RDF, which can support classifying an RDF as an SRF quality fuel based on EN-5539 and ISO-21640. However, the quality of the collected data from the MRF could be undermined by factors like, 1) the collected samples are small in mass and compared to total material mass flow of system, 2) the plant operations should be close to typical and sustainable without disruptions, and 3) the collected samples should incorporate seasonal variations in waste compositions as innumerable feedstock components could be entering the MRF. The validation of the model is conducted for mass flow until the secondary shredder unit, as the performance data collection for the dryer unit is restricted due to MRF operations. Thus, the outputs of the dryer unit are estimated using analytical techniques.

4.6.1 Plant Efficiency Estimation Results

The first performance parameter of the simulation model evaluated is the plant efficiency, which focuses on the ratio of the correctly sorted material. The simulation model runs 100 times and the plant efficiency data collected from MRF and the estimated values from the model are represented in the histogram & Q-Q plot shown in Figure 4.8. Graphical techniques are used to assess how closely two samples agree to be normal, in a way that data points form a straight line in the Q-Q plot when samples are normally distributed. Most of the data points in both samples lie close to the center line and inside the 95% confidence interval suggesting both data samples are approximate to one another and can be considered statistically equal. Further, the analytical "Kolmogorov-Smirnov" method is used to validate what was perceived in the graphical method.

The probability value (p) is greater than the 5% significance level suggesting that both samples can be assumed to be normally distributed. A two-tailed t-test for independent samples (equal variances not assumed) showed that the difference between experimental values and observed values was not statistically significant, $p = 0.246 > 0.05$ with a 95% confidence interval. Thus, the null hypothesis is retained as both samples have approximately the same distributions and there is no significant difference found between the samples. The determination coefficient, R2, measures the goodness-of-fit in the regression analysis and the R2 value close to 1 indicates that the regression has explained a large proportion of the variability in the response. Whereas a number close to 0 indicates that the regression did not explain much of the variability in the response. Therefore, in our study R2 is 0.916 and 0.983, reflecting a good fit for the model.

In general, it was found that assembly lines in an MRF should start with shredding to achieve high efficiency in the latter stages of the material recovery process but on the downside, it can result in frequent jamming of the shredding unit. Similarly, the use of a drying unit brings in the limitations of slow feed rates and can become a bottle neck in MRF system. This is because drying of solid wastes is challenging due to its varying heterogeneity, biological , physical, and chemical properties. A conveyor belt dryer system could remove the moisture efficiently to meet RDF specifications but its costly to operate and generally reduces plant efficiency. Another important factor affecting the overall plant efficiency is the sorting coefficients for each type of waste component getting sorted in ratios at each unit in an MRF. However, the scope of this study considers static separation coefficients for designing the simulation model.

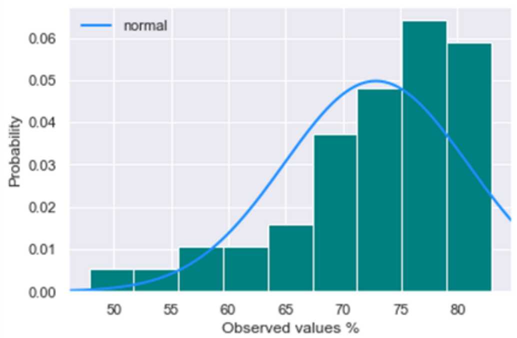
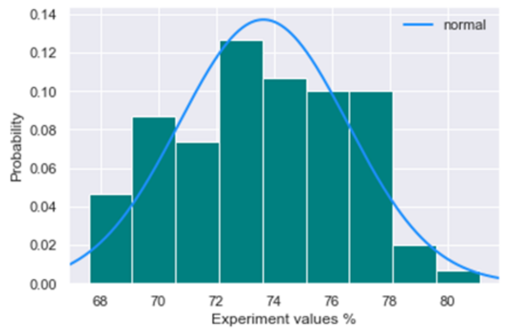
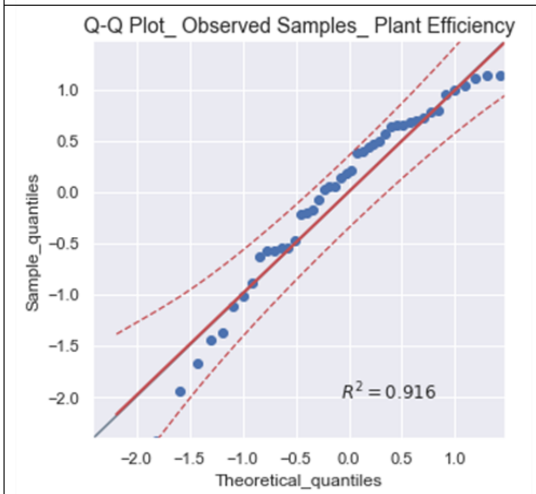
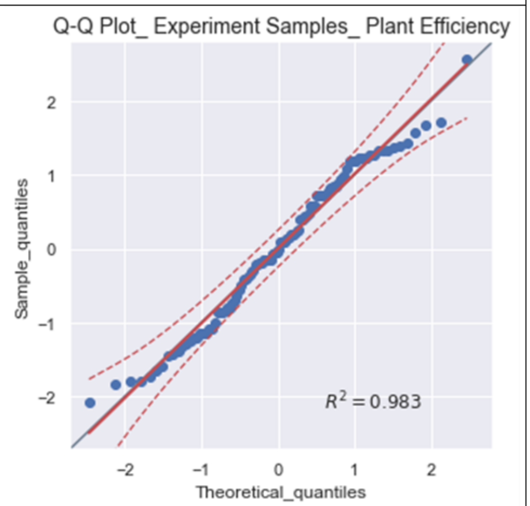
Graphical Method	
	
	
Analytical Method	
Kolmogorov-Smirnov p value = 0.361, p>0.05	Kolmogorov-Smirnov p value =0.765, p>0.05

Figure 4.8: Comparison of graphical and analytical methods for plant efficiency parameter.

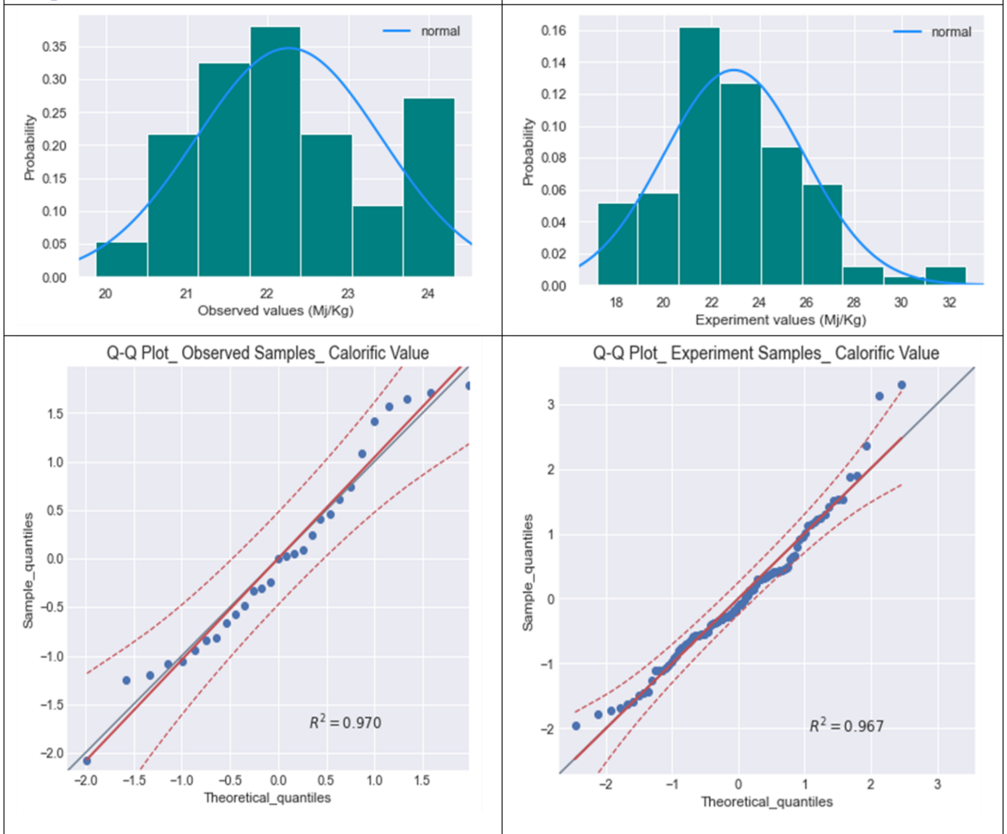
4.6.2 Calorific Value Estimation Results

The estimated energy content from the model once graphically compared to the observed value suggests that both samples are approximately normally distributed as shown in Figure 4.9. The (p) value resulting from the Kolmogorov-Smirnov method for both samples are greater than 0.05, which provides analytical evidence for both samples to be statistically equal. A two-tailed t-test for independent samples (with equal and not equal variances assumed) is conducted reflecting $p = 0.235$ and $p = 0.065 > 0.05$, showing that the difference between experimental and observed values was not statistically significant. The null hypothesis could be retained. The majority of the points in both cases reside inside a 95% confidence interval showing strong evidence for data samples to be normally distributed. The determination coefficient, R2 is 0.97 (observed data) and 0.967(experiment data), showing a good fit for the model. Only a few empirical models in the literature are suitable for predicting the calorific value of RDF-3 material. However, this study presents a practical way of testing various scenarios affecting the calorific value estimation. The developed model improves the prediction of calorific value for RDF-3 based on the physical and chemical characteristics of the infeed waste components. The calorific value of RDF increases as the RDF moisture content decreases, this influence will be discussed further in section 4.7.

4.6.3 Moisture Content Estimation Results

While conducting the normality checks of the moisture content parameter, it was discovered that both samples are approximately normally distributed. The observed data comprises monthly averaged moisture content collected during the normal operations of the MRF. As shown in Figure 4.10 ,the P-value for both the Kolmogorov-Smirnov test and the Shapiro-Wilk test are greater than 0.05 making it evident that both samples are normally distributed. Similarly, the Levene test of equality of variance provides a p-value of 0.091, which is greater than the 5% significance level. The Levene test is therefore not significant and the null hypothesis that all variances of the samples are equal is retained and there is variance equality in the samples. Moisture content is an important quality parameter as it directly impacts the use of the RDF in wide range of applications. Depending on the target application like the cement industry or other coal-powered plants, the use of a dryer unit significantly aids in lowering the moisture content to meet RDF specifications.

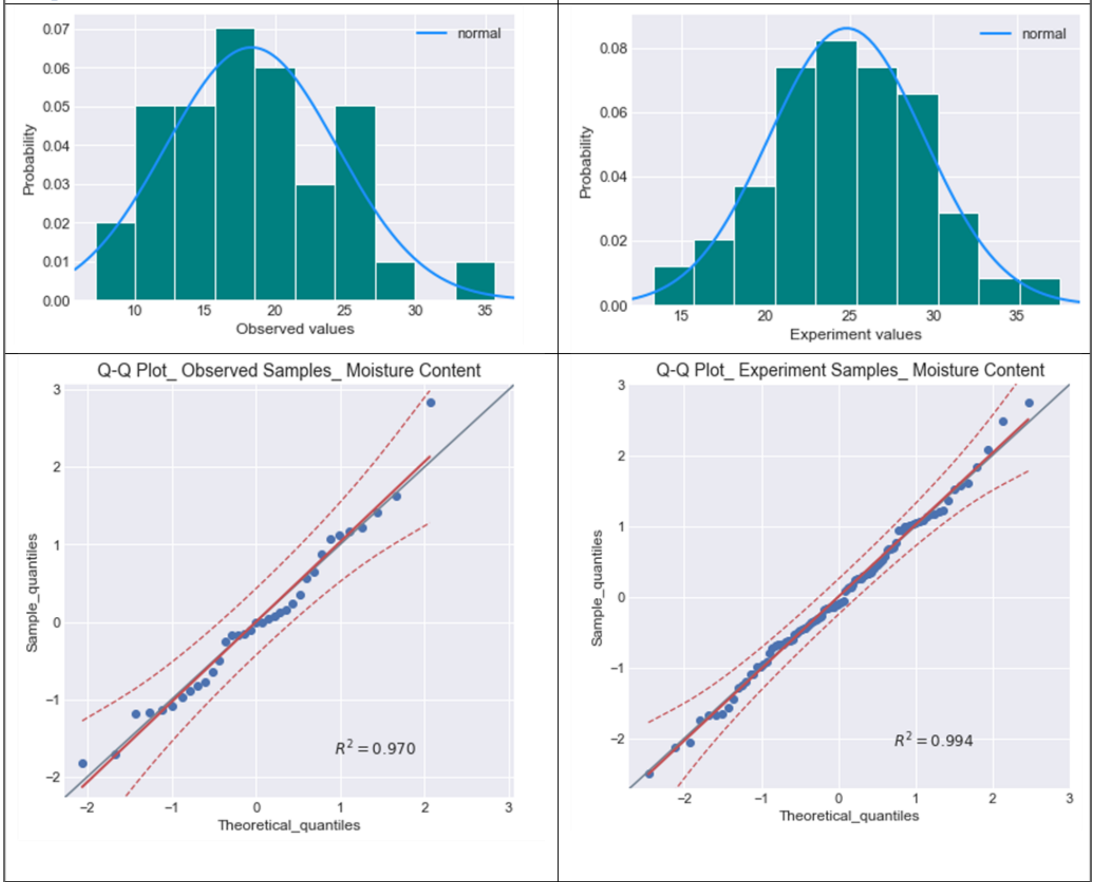
Graphical Method



Analytical Method	
Kolmogorov-Smirnov p value = 0.954, $p>0.05$	Kolmogorov-Smirnov p value =0.323, $p>0.05$

Figure 4.9: Comparison of graphical and analytical methods for the calorific value.

Graphical Method



Analytical Method

Kolmogorov-Smirnov: p value =0.866 , p>0.05 Shapiro-Wilk: p value=0.541 , p>0.05	Kolmogorov-Smirnov: p value = 0.941, p>0.05 Shapiro-Wilk: p value= 0.961 , p>0.05

Figure 4.10: Comparison of graphical and analytical methods for moisture content parameter

4.6.4 Ash Content Estimation Results

The samples under observation also assume normal distribution. However, the added investigation further elaborated the fact that both samples are more closely following lognormal distribution as shown in Figure 4.11. Considering a random variable T has a normal distribution, then (V=exp(T)) has a lognormal distribution. An F test is conducted to check whether the two samples have their variance differ significantly and the test showed the p-value (P=0.867), P >5% indicating that the variances of the two samples are equal. Thus, the null hypothesis is retained. The Figure 4.11 shows the histogram and Q-Q plot for both the samples with lognormal distribution in consideration

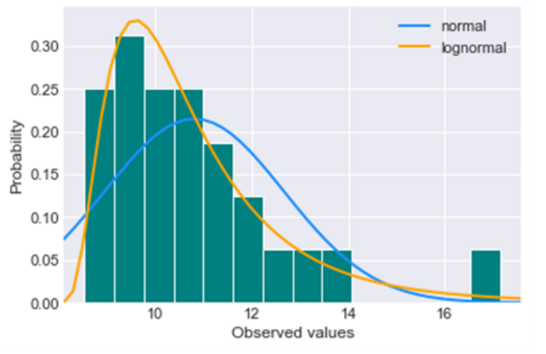
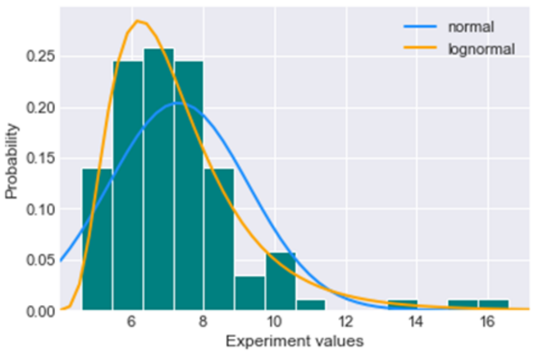
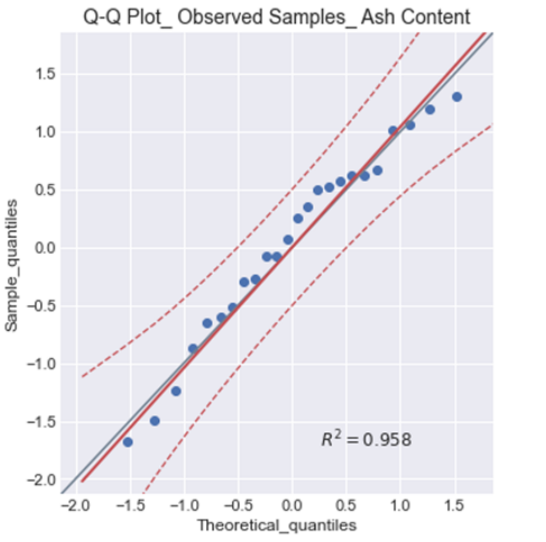
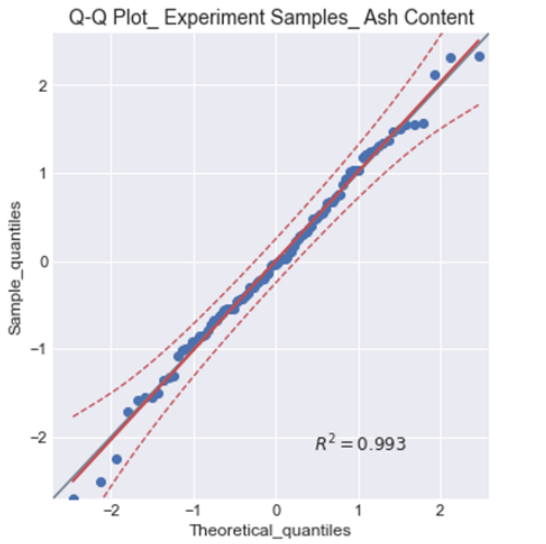
Graphical Method	
	
	
Analytical Method	
Kolmogorov-Smirnov p value =0.568 , $p>0.05$	Kolmogorov-Smirnov p value =0.061, $p>0.05$

Figure 4.11:Comparison of graphical and analytical methods for Ash content parameter

4.7 Optimal RDF Production Conditions

The final results of the two-line configurations modeled in this study are shown in Table 4.4. The difference between the two lines is just the placement of the dryer unit. The line configuration-1 without a dryer unit provides 73.1% plant efficiency, 24.8% average moisture content, 22.93 MJ/Kg gross calorific value and 7.33% ash content. The dryer units are added in an MRF to drop the moisture content of RDF to improve its heating value and to avoid more steam generation in the combustor. Thus, the drying unit is added to the system supplement the quality and meet the overall target specifications set for RDF fluff.

4.7.1 Impact of Dryer Unit

In our study the known observed average calorific value of RDF is 22.26 MJ/Kg and experimented average calorific value of RDF is 22.94 MJ/Kg. So, the values of the LHV can be estimated. As shown in Figure 4.12, by plugging in various values of moisture (M) and experimental conditions in Equations 4.9 and 4.10, it can be observed that the heating value ultimately increases as the moisture content of the RDF feedstock decreases.

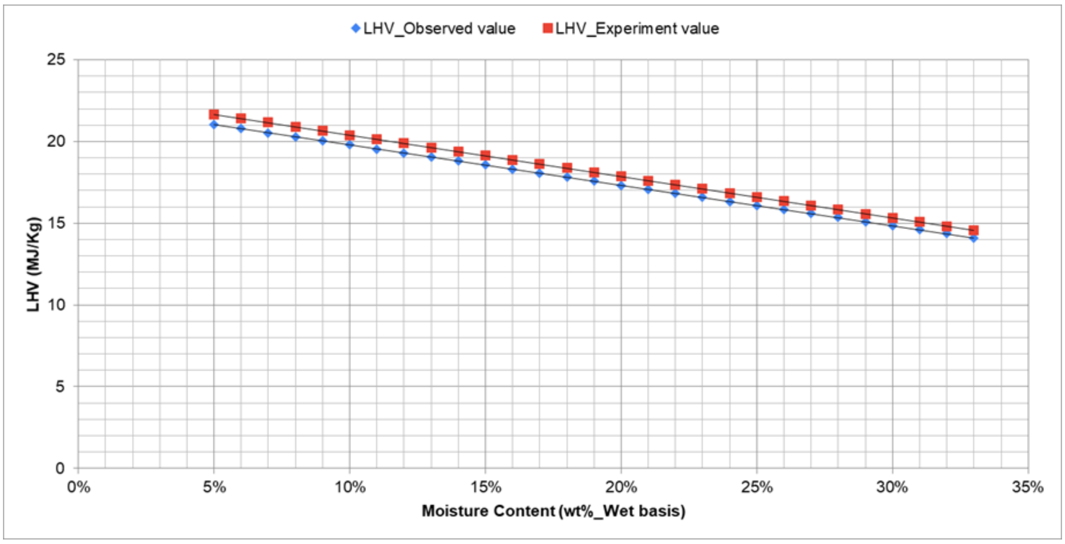


Figure 4.12: Moisture content vs. RDF heating value variation.

The moisture in feed material is lost in form of steam or depending on the drying method and dryer type used. This drying process increases the heating value of the RDF material. The heating value increases with decreasing of RDF moisture content. This fact can be observed by using dryer unit in line configuration 2 where it increases the heating value of RDF from 22.93MJ/Kg to various higher heating value thresholds depending on moisture settings on the dryer. Figure 4.13 provides evidence generated based on the model results to demonstrate this variation between the two. If the infeed material is high in moisture, then the dryer would take more time to reduce the moisture level of the outfeed, thus creating a bottle neck for having an efficient throughput in the system. Besides reducing moisture content, drying also results in mass reduction which improves storage and handling capabilities of the RDF fluff.

Table 4.4:Computation results of two-line configurations as model output

Line #	**Line configuration**	**Material produced**	**Efficiency (%)**	**Moisture (%)**	**Ash (%)**	**HHV(Mj/Kg)**	**LHV(Mj/Kg)**	**Volatile Content (%)**
			Avg, Std	Avg, Std	Avg, Std	Avg, Std	Avg, Std	Avg, Std
1	PS,FS,WS,WDS,EC,SS	RDF	73.1 2.94	24.8, 4.66	7.33 1.96	22.93, 2.97	22.33, 2.97	49.92, 0.046
2	PS,FS,WS,WDS,EC,SS,Dr	RDF	63, 3.4 62.19, 2.94 60.6, 3.189 59.3, 2.78 58.26, 3.4	12% 13% 14% 15% 16%	7.85, 2.5 7.78, 1.39 7.88, 1.883 7.32, 1.45 7.26, 1.40	25.44, 4.06 25.29, 4 24.6, 3.35 23.86, 3.3 23.813, 3.78	25.14, 0.93 24.97, 0.9 24.32, 0.9 23.49, 0.9 23.42, 0.9	49.99, 0.035 49.98, 0.023 49.98, 0.039 49.97, 0.021 49.96, 0.032

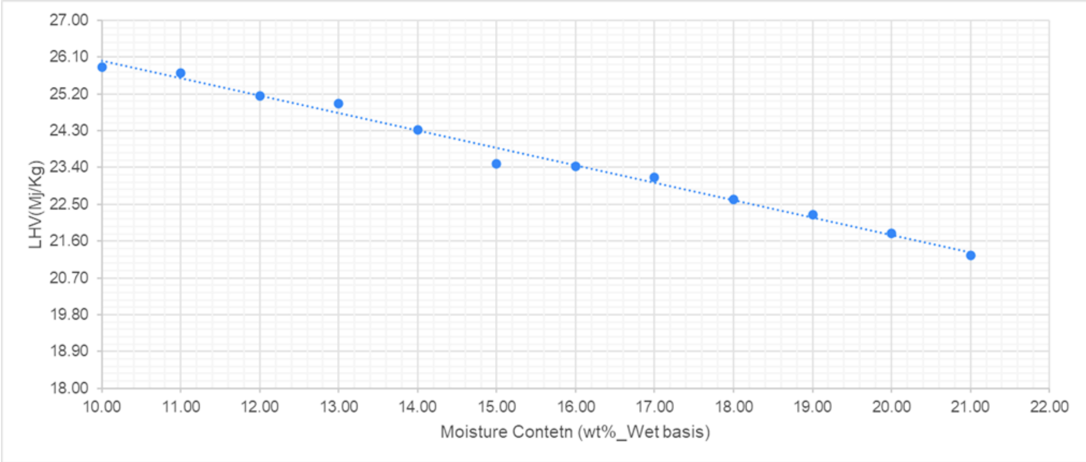


Figure 4.13: Simulation results of RDF moisture content Vs RDF LHV variation

4.7.2 Waste Composition at Target Units

One of the important parameters that are derived based on partition coefficients is the purity of the target materials. Table 4.5 represents the calculated purity measure of the rejects from all processing units in the assembly line. The non-combustibles, metals, and glass are highly undesirable for combustion purposes and the removal of these components can be effectively monitored using the developed simulation model. Though, the purity of the targeted material is affected by the material recovery measure dependent on the unit's material partition coefficients. These partition coefficients can be updated based on experience (historical data) or experimental tests on each unit. The effect of partition coefficients on purity and recovery can be studied using the developed simulation model. However, the scope of this study does not realize the sensitivity of these coefficients on the quality parameters in current edition of the simulation model.

Table 4.5: Rejects waste composition at target units (R1, R2, R3, R4, and final fluff)

Target Units	**R1**	**R2**	**R3**	**R4**	**RDF**
Waste Components	**Ferrous Separator**	**Waste Screen**	**Wind Sifter**	**Eddy current**	**Final Product Composition**
Contamination	6.8%				-
Ferrous Metal	93.2%	-	-	-	-
Glass	-	0.1%	11.0%	0.7%	0.9%
Noncombustible	-	1.1%	58.0%	80.1%	0.0%
Other Combustibles	-	14.7%	15.0%	16.6%	20.1%
Paper	-	13.9%	2.0%	1.2%	25.4%
Rigid Plastics	-	9.9%	2.0%	0.7%	8.2%
Yard waste	-	33.4%	2.0%	0.2%	9.7%
Food	-	12.2%	2.0%	0.0%	6.3%
Film Plastics	-	13.8%	6.0%	0.0%	15.9%
Diapers/Napkins	-	0.9%	2.0%	0.5%	10.2%

4.8 Discussion

4.8.1 Comparison with other methods

There are several approaches for network flow modeling techniques that can be used for waste flow modeling. Some of these approaches include linear programing, mixed-integer programming (MILP), agent-based modeling, system dynamics and discrete event simulation [17,21]. Each of these modeling approaches has its own strengths and weaknesses, and the choice of approach depends on the specific problem and available data. In the past various empirical models were developed to estimate the quality parameters of RDF. The previously developed empirical models used for estimating the quality parameters of RDF like high heating value (HHV) suffered massive deviations because of complexities in its physical and chemical characteristics. Table 4.6 below shows the other approaches used for estimating the HHV of RDF. The performance metrics used to evaluate the effectiveness of the modeling techniques generally include the coefficient of determination, average absolute error and average biased error.

Table 4.6: Comparison between quality measure from RDF plant and international standard (EN15539) for RDF classification

Author	Waste Residue	Year	Method	Performance Metric (AAE%)	Estimated-HHV(Mj/kg)
Shi H [41]	MSW	2016	MLR,SLR	6.73	27.633
Rui Galhano dos Santos [40]	RDF	2017	LR	3.90 - 4.65	20.22 - 21.53
This Study	RDF	2022	DES-NFM	2.3	22.93 - 25.44

Linear Regression(LR), Multiple Linear regression (MLR), Stepwise Linear Regression(SLR), Discrete event simulation-network flow modeling(DES-NFM)

The approach developed in this study caters to this gap by providing a framework for understanding the influence of input feed stock, technology and other MRF performance parameters on RDF/SRF production in a mechanical treatment plant. Aspects like various line configurations in a MRF, separation coefficients of material recovery units and municipal waste composition used for producing targeted material can have a considerable influence on the quality of RDF produced. The rationale for using the discrete event simulation model in this study was its applicability to explore the operational performance of a waste processing facility and only a few references are available using the network-flow modeling simulation method for these purposes [42]. In general, discrete event simulation is used to explore the effects of changes in processing capacity and time on the efficiency of the facility, as well as the effects of different arrival rates of waste on the processing time and facility utilization. The accuracy, computational efficiency, and robustness in the applicability of the developed network flow-based simulation model justify its use in comparison to other approaches presented in Table 4.6.

Therefore, the more powerful and not expensive approach to understand various physical systems for RDF production can be seen through the developed simulation procedure in this study. However, the discrete-event simulation models for large scale applications are incapable of capturing simultaneous events at independent facilities in waste processing centers, due to their limitation of having only one event executing per clock tick, globally.

4.8.2 RDF Market Selection

SRF differs from generic RDF as it is a fuel which follows international standards, and its quality features are known. Thus, these specifications vary globally depending on the various factors deciding the fate of the RDF fuel consumption in either cement industry or other power plants. The cement industry is an existing market where significant investment for alternatives fuels consumption have been made in recent times [185]. So, for assuring a sustainable and consistent supply and demand of RDF ,any term contract with cement plants for RDF supply would be beneficial.

Compared with international standards, the results from the model shown in Table 4.4 follow the specification that is reasonably acceptable for endorsing an RDF to SRF. An assessment of SRF quality standards (EN 15539) for European countries is presented by Giovanna Pinuccia [23]. The study provides reference values for physic-chemical properties of an SRF produced from municipal solid wastes. Hence, the result of this study can be compared with the reference values of [23] to evaluate the quality measures of the produced RDF. Table 4.7 shows the comparison of results between this study and the values from the reference. The scope of this study is limited to just the three fuel properties.

Table 4.7: Comparison between quality measure from RDF plant and international standard (EN15539) for RDF classification

Fuel Property	**Line #**	**EN 15539 Specification**	**This Study**	**Data Measure**	**Fuel Quality Standard (SRF or RDF)**
Net Calorific Value (Mj/Kg),ar	Line 1	Class-2, Class -3,Class-4 ,Class -5	22.33	Average	SRF
	Line 2	Class-1,Class-2, Class -3,Class-4 ,Class -5	>21	Average	SRF
Moisture,wt%,ar	Line 1	15.29	24.8	Average	RDF
	Line 2	15.29	≤15	Average	SRF
Ash % ,d	Line 1	13.83	7.33	Average	SRF
	Line 2	13.83	≤7.8	Average	SRF

The estimated quality standards of the RDF from simulated model for Line 2 provide reasonable evidence for endorsing it as an SRF. This endorsement is dependent on the use of dryer in the MRF as it provides the capability to increase the calorific value and reduce moisture content of the produced fluff. The RDF produced using Line 1 on the other end may not be tagged as an SRF quality product as the average moisture content property of the fuel does not comply with the international standards. But the specifications collected in the EN 15539 standard are collected from seven European countries whereas the final specification demand of the RDF/SRF could vary depending on the end-user's requirements of the product. The reported standard EN15539 does not apply to solid biofuels and to untreated municipal solid waste. It also does not account for variances in origin or end-usage of the examined solid recovered fuels. Thus, the comparison reveals that the simulation model results are precise in providing prediction for the fuel classification, deeming this model a viable tool for estimating HHV for the RDFs.

4.9 Comparison With Previous Studies

The waste treatment system, which transforms municipal solid waste to refuse-derived fuel (RDF), faces limitations in maintaining consistent production and quality controls standards of RDF. The profound cause is the unwary biofuel supply chain decision making in discovering the best waste diversion options. In the literature, various researchers tackled several sources of uncertainty affecting decision making in the design and planning of the biomass to biofuel supply chain. In this context, many publications focus on measuring the effect of uncertainties in strategic and tactical level decisions, whereas less emphasis is placed on operational decisions and combined strategic or tactical levels with operational decisions. The proposed method in this study constitutes an extension to facilitate the integration of an assessment of a selected set of uncertainties for adding value in biomass to the RDF supply chain. A network flow modeling technique is used to design a stochastic simulation model for a material recovery facility to estimate quality parameters of refused-derived fuel. The units of the MRF are modelled based on the study of Karine et al. and Testa et al. and the separation parameters of the units available in the literature are utilized for designing the infeed separation process on a per-material basis.

In this chapter, the authors have extended the application of work from Karine et al by incorporating more uncertainties as inputs to the model like new probability distributions of in-feed waste compositions, moisture content, calorific value of individual waste components (all with higher number of data samples) and technology upgrades affecting the performance of RDF production in an MRF. These uncertainties are related to strategic decision levels. Further the insertion of technology performance uncertainty in the simulation modeling assists the model in utilizing various ranges of unit separation coefficients as input to the model and applies to tactical level decisions. Similarly, the uncertainty in the identification of quality standards as evaluation criteria to measure the quality of RDF produced and the final yield are in relevance to operational decisions. The inclusion of dryer as part of the technology upgrade, justifies how the calorific value of the produced RDF can be improved while removing moisture content from the final product. The other major improvement is the application of advanced statistical analysis (like Q-Q plots and analytical methods) to evaluate the model results with a most suitable hypothesis test. Two null hypotheses considered in the study support establishing the fact the results of the model and observed data samples have similar normal probability distribution and there is no significant difference between the two samples. This concludes the achievement of the objectives in this study and that the established model can be used as a viable tool for estimating quality measures for the RDF. The outputs of the model provide resulting probability distribution of performance metrics and inform about the quality of the RDF or whether RDF could become SRF or not. The projected quality standards can be used by facility management for long term planning to increase productivity and RDF sales revenues which will be part of the future work of this study. This study also fills the gap where simulation method is not explored enough for modeling sources of uncertainties like biomass supply, technology, and quality in the RDF to biofuels supply network. Future work, depending on the application requirements ,could focus refining the model to incorporate more uncertainties listed in the model limitations section. During the design phase of unit configurations in a MRF, its manager can run several scenarios for each possible configuration to determine robustness configurations against variability of input uncertainties.

4.10 Conclusion

In this chapter, the material separation coefficient modeling technique was employed within a practical material recovery line configuration which produced RDF-3. This endeavor led to the development of a simulation model designed to identify the most effective operating conditions and predict the quality standards for RDF. Attending to the physical, chemical, and thermal properties, an RDF can be endorsed as a standardized SRF. The SRF produced can be used as an alternative fuel in cement kilns, power generation plants, or heat demanding processes, especially those from the material recovery stages. All the decisions type incorporated in the model provide insight into MRF management to improve the quality of the RDF product. The developed model can test the strategic, tactical, and operational decisions to evaluate their impact on the RDF quality. This study provides results that can support revisions in the strategic, tactical, and operational level decisions integrating different waste treatment technologies considering varied uncertainties. The model results are useful and can be used by public or private sectors to conduct the technical feasibility of replacing current fossil fuels with the SRF derived from MSW. Using these fuels as an alternative would reduce the municipal solid waste sent to landfills.

In the following chapter, the study reveals calorific value estimation methods and models for the produced RDF in an MRF. As part of the third objective of this study, new models are introduced to predict the calorific value of RDF. This highlights the need for more advanced studies focused on a distinct group of RDFs to validate the robustness of the models in the existing literature.

Chapter 5: Calorific Value Modeling Of RDF-3

5.1 Overview

In this chapter, new models are introduced to predict the calorific value of RDF, as more advanced studies are required to be conducted with a focus on a distinct group of RDFs for validating the robustness of the models in the existing literature. The calorific value based on ultimate (elemental) analysis considers the contents of C, H, N, S, and O elements in RDF. Using empirical and machine learning methods, the newly established models accurately predicted the calorific value of the samples provided by a local municipality situated in Edmonton, Alberta, Canada. Furthermore, these new models demonstrated a lower bias and average absolute error than the other twelve previously published models pertinent to RDF material. Based on the established workflow the ultimate analysis-based models gave a higher coefficient of determination (R^2) value in the range 0.78 -0.80, indicating that the developed model improves the prediction of calorific value for RDF. The newly developed machine-learning models showed better results than the empirical models developed in this study implying that complex correlations can be dealt with effectively while predicting calorific values for RDF.

5.2 Methodology

5.2.1 Experimental Procedure

In this study, a workflow is established which demonstrates steps starting from collection of wastes samples in a facility, method for processing of waste samples, and formation of models using the retrieved ultimate analysis data for making HHV predictions. The physical composition of the pre-sorted MSW, which is further blended to the RDF-3 fraction (2cm-5cm), is based on eight major waste categories. Figure 5.1

shows the complete experimental procedure and highlights the composition of samples included in the experiments like Paper (6.48%), Rigid Plastics (5.72%), Single-use plastics (0.04%), Film plastics (20.98%), Food waste (organics-30%), Yard waste (1.30%), Diapers/ Napkins (14.68%) and Woodchips (15.85%). The remaining 5% composition was a mixture of glass and non-combustibles materials.

Such MSW composition first passes through a mechanical sorting line comprising of trommel screens to separate bulky waste, non-combustible material, and hazardous waste. The described waste composition is pre-mixed in defined proportions to achieve a homogenous blend and it provides flexibility in keeping the final fluff specification meet client requirements. Afterwards, further mechanical processing includes a shredder, a separator of metals, and a drum screener. The output from a drum screener passes through a wind sifter where heavies fall, and fines pass through the eddy current separator to get rid of electromagnetic materials. Then the processed material is re-shredded to a fraction size in the range of (2cm-5cm). The material type retrieved after the final stage is called RDF-3.

The RDF-3 samples collected at the final stage of the process were sent to the lab for carrying out ultimate analysis to explore the potential heat value and chemical composition of those samples. The composition of the RDF in terms of its basic elements except for its moisture content and ash content is important for its utilization as a fuel. In this study, the ultimate analysis provides mass percentages of carbon, hydrogen, oxygen, nitrogen, and sulfur, respectively on an ash-free and dry basis (C+H+O+N+S=100%). Ultimate analysis was done in accordance with ASTM 5373, which provides instrumental determination of carbon, hydrogen & nitrogen contents, while ASTM D4239-18 was used for determining the sulfur content utilizing high-temperature tube furnace combustion. Using elemental analyzer, the ultimate analysis was performed by burning of weighted RDF sample in a controlled environment and analyzing the gas products like CO2, H20, NOY and SO2. The contents of C, H and N are determined automatically by the analyzer unit by following model, Eq(1),

$$\% \ of \ the \ Analyte \ = \frac{Detector \ response \ of \ analyte \ \text{x} \ Unit \ mass \ per \ detector \ during \ calibration}{Mass \ of \ the \ sample} \ \text{x} \ 100 \quad \text{.......Eq.5.1)}$$

Whereas the oxygen content is determined by the difference between the weights of the elements that are already been determined and the ash free-dry weights. The heating value is determined using ASTM D5865 method. The procedure involved operating a calorimeter in adiabatic mode and burning samples ranging from 1g to 1.5 g in size inside a metal vessel. The vessel is placed within in water-filled bucket to strictly control the temperature. Once the samples are completely burned in the vessel, consequently, there is a rise in the temperature of the water inside the bucket. The heat value produced is calculated by multiplying the temperature rise by the heat capacity of the calorimeter, which is a previously determined value obtained by burning a specific mass of the standard material (used benzoic acid as an assumption). This measurement is automatically completed by the calorimeter and the process is repeated completely if the samples are not entirely combusted.

For research purposes twenty-five waste samples were collected and processed at the waste management facility in Edmonton. The data collected is presented in the Appendix (A3). The chemical composition (independent variables) and HHV (dependent variable) data are used for creating models augmented with historical information for making HHV predictions. The estimated values of HHV from the developed models are compared with historical values to measure the accuracy of the models and provide operational support in data-driven decision-making. In this study, the defined framework and the composition of waste streams used for retrieving RDF-3 from MSW are shown Figure 5.1, which creates a sense of refinement in creating prediction models of RDF-3. The previously developed models in the literature didn't clearly state the experimental workflow, waste sorting units and composition of waste used for predicting the calorific value for RDF-3. Factors like waste composition, processing equipment, residual particle size and elemental analysis methods play a vital role in HHV prediction modelling [110], [111], [112].

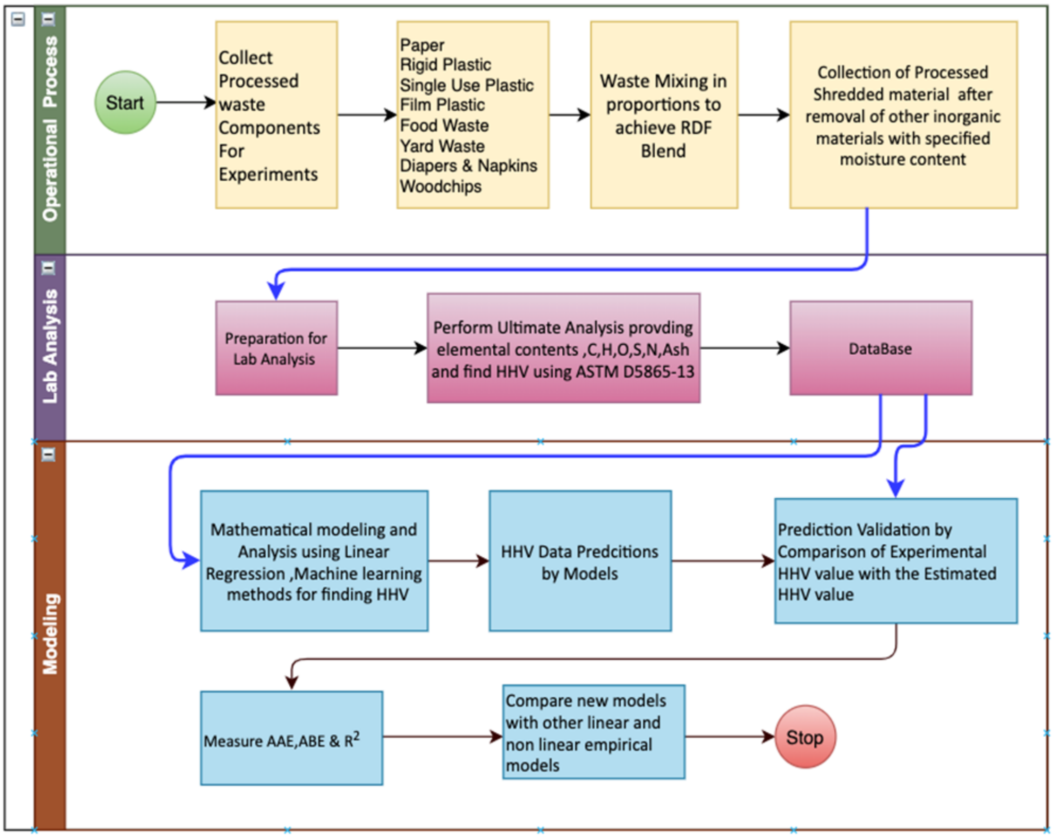


Figure 5.1: Experimental workflow from collection of processed waste to final HHV prediction modelling

5.2.2 Model Accuracy Indicators

The data collected in the database is used to drive linear models and machine learning models to estimate heat values. For comparison purposes, the previously established models for predicting HHV based on the ultimate analysis of Biomass were selected from the literature Table 2.1(Chapter 2). The accuracy of the models is compared based on the AAE known as average absolute error (1), ABE known as average Biased error % (2), RMSE known as Root means squared error (3) (for only machine learning model), and the best model is selected based on the lowest values observed in terms of % error calculated between the predicted values and the experimental values.

$AAE(\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{HHV_{\mathrm{est}}-HHV_{\mathrm{exp}}}{HHV_{\mathrm{exp}}}\right| \text{ x } 100$ ……Eq.5.2)

$ABE(\%) = \sum_{i=1}^{n}(\frac{HHV_{\mathrm{est}}-HHV_{\mathrm{exp}}}{HHV_{\mathrm{exp}}}) \text{ x } 100$ ……Eq.5.3)

$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\ (HHV_{\mathrm{exp}}-HHV_{est})^{2}}{n}}$ ……Eq.(5.4)

5.3 Mathematical Modeling

5.3.1 Linear Models

The selection of any method for conducting data analysis depends on its flexibility or restrictiveness (interpretability), in a sense that it can produce just a relatively small range of shapes to estimate any function (y) . Linear regression is one of the inflexible methods. The most common approach is the least square criterion, which involves estimating the coefficients in linear regression which is one of the methods selected for fitting regression models in this chapter. Mathematically, the linear relationship is expressed as ,Y= R_0 + R_1X where, R_0 and R_1 represent the intercept and slope terms in the linear model. Together, R_0 and R_1 are known as model coefficients. Once we have used our coefficient parameter training data to produce estimates ˆR_0 and ˆR_1 for the model coefficients, we can predict the future HHV value of Biomass based on the chemical composition of RDF samples by computing, ˆy = ˆ R_0 + ˆ R_1X. For multiple linear regressions the following expression describes the relation between 'p' distinct predicators.

$Y = R0 + R1X1 + R2X2 + \cdots.. + RpXp + Er$.…….Eq.5.5)

For meaningful interpretation of the results in multiple linear regression analysis, there are certain conditions which must be satisfied. These conditions are 1) Linearity, which instigates the requirement for existence of linear relationship among the dependent and independent variables. In this context, Figure 5.2 shows the scatter plot with individual independent variables on the x-axis and dependent variable (HHV) on the y-axis. The plots demonstrate that concentrations (%) of carbon, hydrogen, and oxygen directly impact the high heat value (Mj/Kg). This is concluded on the basis that in linear regression, the straight line is laid through the data, and the linearity exists where the majority of data points are positioned around the straight line. 2) Normality of errors, which is determined either analytically or graphically. The check for normality is being tested using analytical methods like Kolmogorov-Smirnov and Anderson-Darling. The p-value resulting from both methods are 0.771 and 0.093. This provides analytical evidence that the errors are normally distributed as both p values are greater than 0.05 with 95% confidence interval. Figure 5.2 also shows the graphical method where a histogram plot between the residuum and their probability provides an compelling evidence for satisfying the condition of normality of errors. 3) Multicollinearity, it is tested whether two or more independent variables correlate strongly with each other. The developed correlation matrix is shown in Figure 5.3. It is observed that none of the independent variables had a strong correlation with each other as the Tolerance (1-R2j) and VIF (variance inflation factor, 1/Tolerance) values of all independent variables remain under threshold values (Tolerance >0.10 and VIF <10) as shown in Table 5.1. Though, oxygen content barely makes it across the Tolerance threshold. This would further be discussed in the next section for deciding on important variables using the backward selection method.4) Homoscedasticity, an assumption for linear regression, is that the residuals have a constant variance. If this condition is not met, heteroscedasticity is present among the residuals, and this makes the results of the regression unreliable. To meet this condition, there are multiple ways to validate a data samples, though in this study, the Breusch-Pagan Test and White Test methods are used. Both methods include first fitting a regression model, calculating the squared residuals, a new regression model is fitted using squared residuals as response values and compiling chi-square test statistics. The corresponding p-value to this chi-square test statistic is compared with the significance level (0.05). Using Breusch-Pagan Test, a p-value (0.62, 0.68) was observed, and similarly, using the White Test method a p-value (0.128,0.139) was observed. Since both the p-values are greater than 0.05, thus it is assumed that homoscedasticity is present.

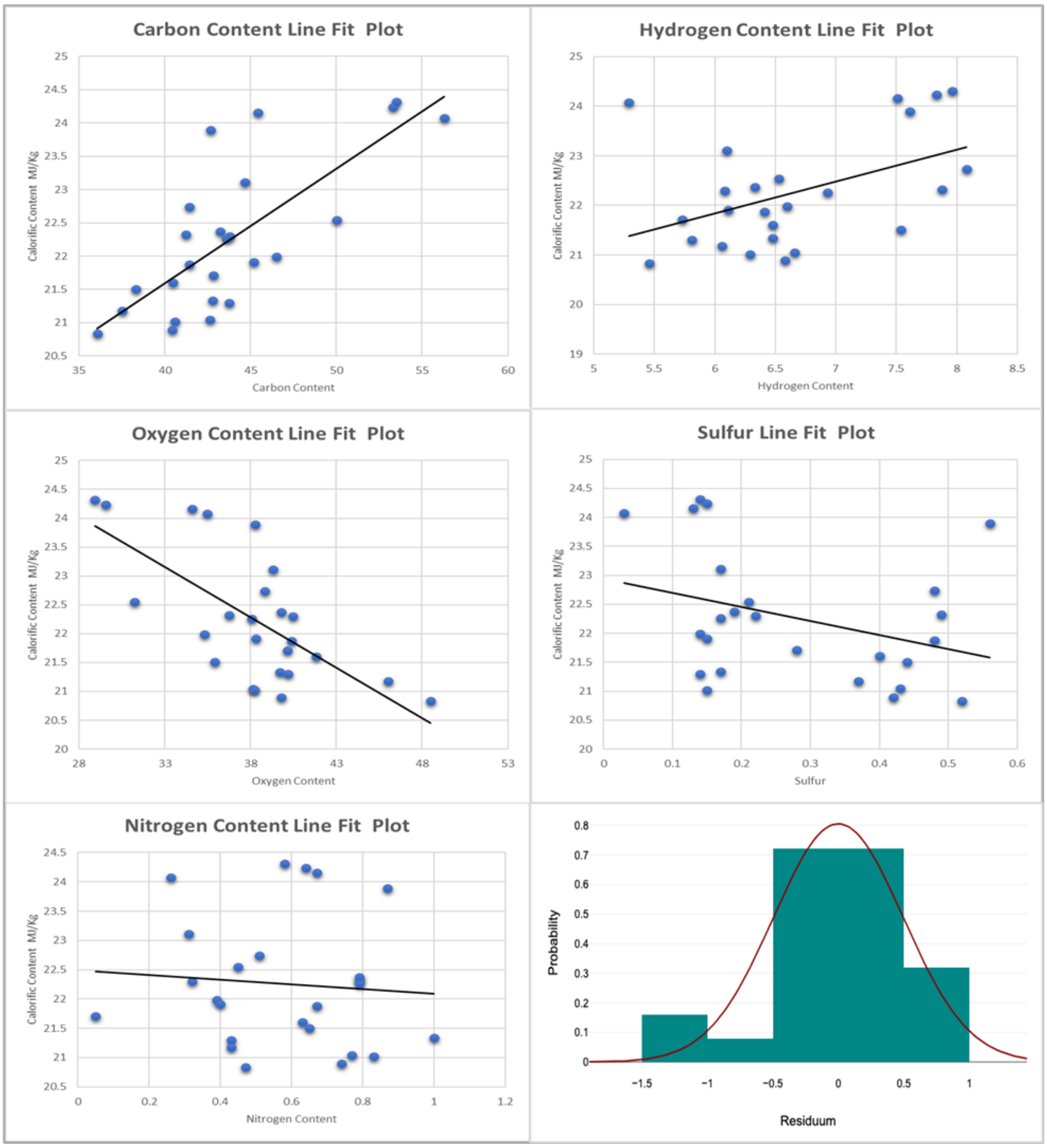


Figure 5.2:Scatter plot of independent variables vs dependent variable for identifying linearity; Histogram plot represents normality check for the errors

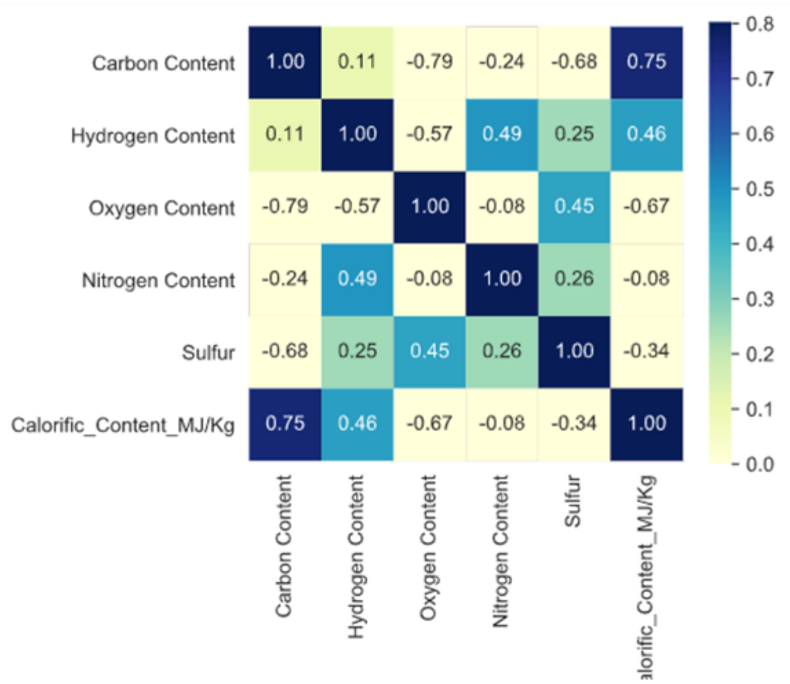


Figure 5.3: Correlation matrix: Carbon, Hydrogen and Oxygen contents directly impact Calorific value (Mj/Kg)

Table 5.1: Multicollinearity check to identify predictors correlating with each other

Independent Variables	**Tolerance**	**VIF**
Carbon Content	0.18	5.48
Hydrogen Content	0.25	4.07
Oxygen Content	0.13	7.92
Nitrogen Content	0.66	1.51
Sulphur Content	0.38	2.61

5.3.1.1 Observations

In this study, multiple linear regression is conducted after meeting the basic requirements for improving the interpretability of regression analysis. The obtained Pearson's values clearly indicated that C (0.75), H(0.46), and O(-0.67) are the most significant variables to estimate HHV values due to their Pearson's coefficient, which for higher correlation, R, should be as close as possible to 1 or −1. The determination coefficient, R2, measures the goodness-of-fit in the regression analysis and the R2 value close to 1 indicates that a large proportion of the variability in the response has been explained by the regression. Whereas a number close to 0 indicates that the regression did not explain much of the variability in the response. Therefore, in our study R2 is 0.9994, reflecting a good fit for the model. The F- statistic value is 7883, which is far larger than 1, providing compelling evidence that there are one or more predictors directly affecting the HHV of Biomass. The P-value of 8.133E-31 is well below the alpha value of 5%. It should be mentioned here that the constant was considered to be zero, which led to better linear regressions. Following is the first model for predicting HHV,

$$(0.2388\ \mathrm{C} + 1.01\ \mathrm{H} + 0.144306\ \mathrm{O} - 0.6506\ \mathrm{N} - 0.26927\ \mathrm{S}) \quad \cdots\cdots\cdots \text{Eq.5.6)}$$

5.3.1.2 Deciding on Important variables Using Backward Selection Method

The process commenced with a comprehensive inclusion of all variables within the model, followed by stepwise elimination of the variable exhibiting the largest P-value, indicating lesser statistical significance. This iterative procedure involved fitting a new model with (p − 1) variables, persisting until a halting criterion was met—signifying that all remaining variables possessed P-values below the threshold of significance (<0.05).

In this case, Carbon, Hydrogen, and Oxygen content are the selected predictors that impact the HHV value for biomass samples because each one of them has a p-value less than <0.05. Performing regression analysis again provides a better estimation of coefficients based on selected predictors.

$(0.25099C + 0.8856H + 0.1401O)$.......Eq.5.7)

5.3.1.3 Results

The developed correlations have presented a low bias error as well as a lower absolute mean error when compared with other established equations mentioned in Table 5.2. Figures 5.4 and 5.5 show the Estimated vs Experimental HHV plots of the Linear Regression Models eq 5.6 and eq 5.7. Thus, the developed equations represent a tool that can be applied to estimate the higher heat values of RDFs by using the simple numerical procedures models.

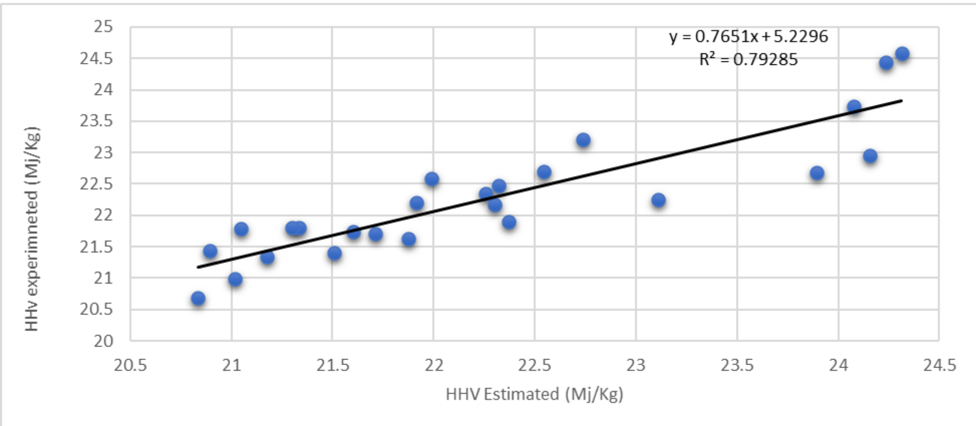


Figure 5.4: Graphical plots of estimated HHV (HHVest) vs. experimental HHV (HHVexp) for Linear Regression Model-Eq.5.6

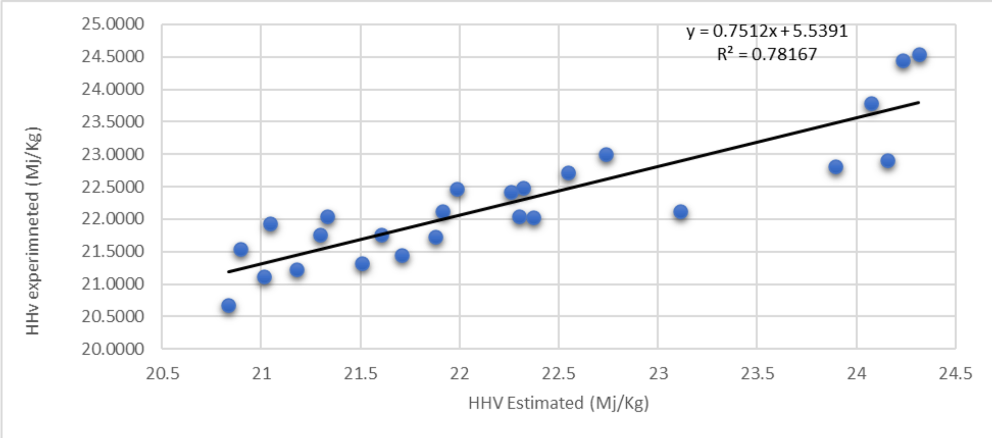


Figure 5.5:Graphical plots of estimated HHV (HHVest) vs. experimental HHV (HHVexp) for Linear Regression Model-Eq5.7

The average absolute errors and average bias errors of the newly established model are compared to those from 12 models to estimate the HHV of Biomass available in the literature. Table 5.2 shows the AAE %and ABE% of each model and its respective errors. It is observed from the ultimate analysis data, the carbon and hydrogen fractions are most significant as they have a significant impact on the HHV of RDF. The oxygen fraction has limited effects on the RDF HHV. For validation, the collected quantitative dataset from the model is evaluated with the most suitable hypothesis test. In this case, the Null hypothesis H0 is to determine if there is no significant difference between the experimental values and estimated values of HHV. A two-tailed t -test for independent samples (with equal variances assumed) was conducted, which showed that the difference between the estimated and the experiment HHV values was not statistically significant, with $p=0.996$, 95% confidence interval. Thus, the null hypothesis is retained. Besides, it is also observed that both data samples have a similar probability distribution. As shown in Figure 5.6, a graphical technique is used to assess how closely two samples agree to be normal, in a way that data points form a straight line in Q-Q plot when samples are normally distributed. Most of the data points in both samples lie close to the center line and inside the 95% confidence interval suggesting both data samples are approximate to one another and can be considered statistically equal.

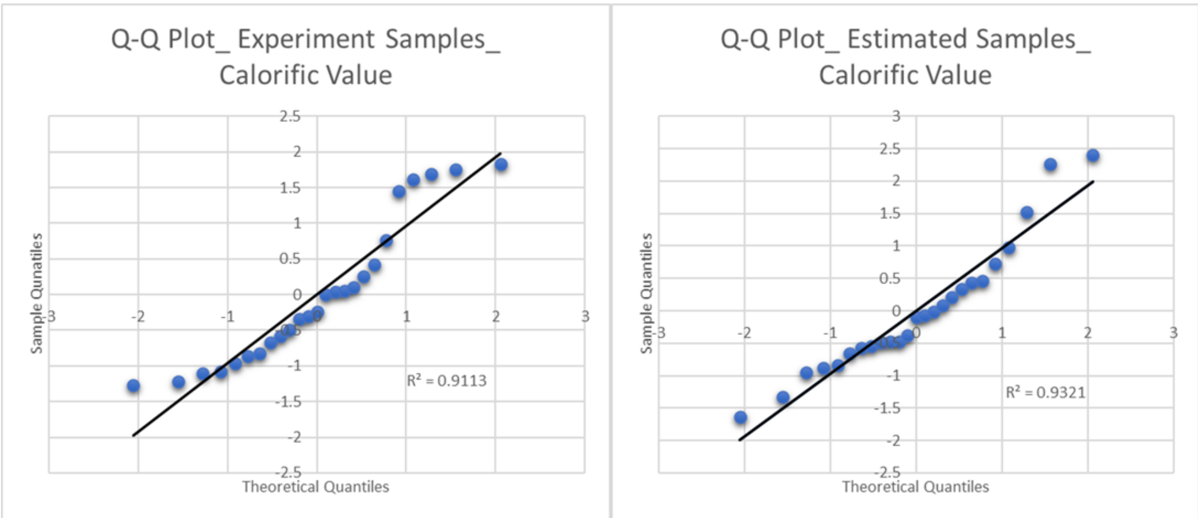


Figure 5.6: : Q-Q plot represent how estimated and experimented HHV values are closely related and assume similar normal distribution.

Table 5.2: Comparison between existing models and established correlation in this study presenting computed % error.

Model	Author	Waste Residue	Year	AAE%	ABE%
Eq 1	Wilson DL.	MSW	1972	12.879	-11.726
Eq 2	Channiwala SA	MSW	2002	7.677	7.123
Eq 3	Channiwala SA	MSW	2002	15.326	-15.248
Eq 4	Meraz L	MSW	2003	17.001	-16.703
Eq 5	Kathiravale S.	MSW	2003	37.493	37.493
Eq 6	Reza B	RDF	2013	9.368	9.128
Eq 7	Shi H	MSW	2016	15.144	-15.124
Eq 8	Rui Galhano dos Santos	RDF	2017	10.981	-10.860
Eq 9	Rui Galhano dos Santos	RDF	2017	11.281	-10.760
Eq 10	Octávio Alvesa	MSW	2018	11.969	11.490
Eq 11	Imane Boumanchar	MSW	2019	20.159	-20.159
Eq 12	Imane Boumanchar	MSW	2019	27.300	-23.391
Eq 13	This Study	RDF	2022	1.691	0.052
Eq 14	This Study	RDF	2022	1.761	0.067

5.3.2 Machine Learning Models

So far ,linear models were developed based on the chemical composition of the RDF, and moving on in this part ; it would be discussed how to use a supervised learning algorithm to train the model to get a better prediction of HHV by feeding unfamiliar test data set to the trained model. A reasonable way to achieve this goal is to implement an ordinary least squares linear regression model. Such a model is formulated as shown in eq 5.8,

$y_n = \sum_{i=0}^{n} C_i\, x_{ni} + e_n$ ………Eq.(5.8)

Where *xi* is the explanatory variables, Y is the dependent variable, *n* is the number of samples, and the coefficient *C* is found by minimizing the error of prediction. Training such a model means setting its parameters so that model best fits the training set. While training such a model, it is vital to not over fit or under fit the training data and to achieve this most used practice is to monitor performance measures like Root mean squared error (RMSE) and determination coefficient (R^2). Literature review showed that only a few studies had used different techniques to split up the training dataset relevant to RDF material and created useful estimates of performance for the least-squares linear regression models. The techniques incorporated in this study are the least computationally expensive and provide reasonable performance in the estimate of accuracy. Our study evaluates the predictions accuracy on the RDF-3 dataset using the following techniques such as,

5.3.2.1 Train and Test Sets

It is one the fastest algorithm evaluation techniques. This technique trained the linear regression model in a short duration with 70-30 splits for training and test datasets. In addition to specifying the volume of the split, the random seed is also declared to ensure that the same random numbers are obtained each time when the model runs. The model showed an accuracy score of approximately 70% on the test dataset and the RMSE value of train and test datasets is shown below in Table 5.3. As shown in Figure 5.7, the perfect linear line is plotted between the predicted and the observed HHV values.

Table 5.3:Train and Test set algorithm performance measure

Measure	**Training Dataset**	**Test Dataset**
MAE	0.3186	0.537
MSE	0.1955	0.4060
RMSE	0.442	0.637
R^2	0.830	0.699

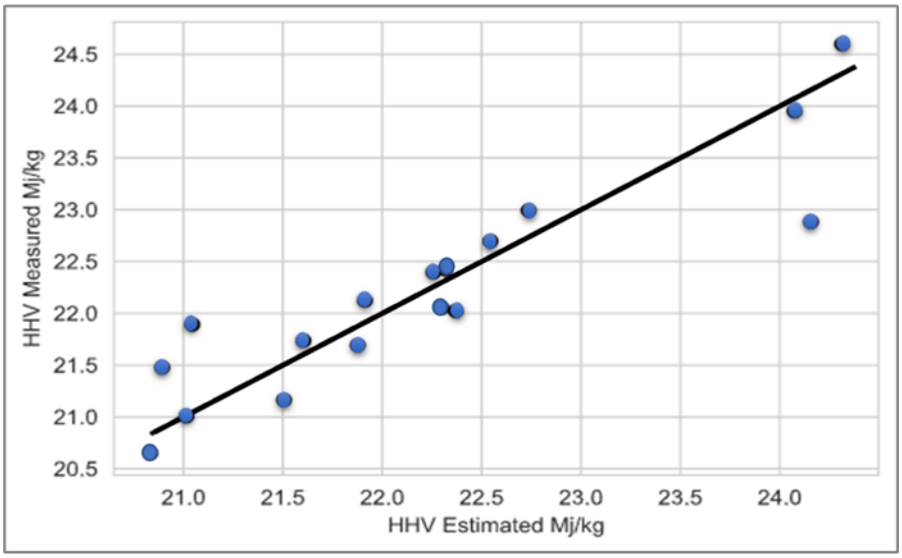


Figure 5.7:HHV Observed response vs HHV predicted response using Train and test set technique.

5.3.2.2 K-fold Cross Validation

In this study, the number of RDF samples available for analysis is not large, which is why we have employed the K-fold cross-validation technique, where every observation in the dataset has the chance of appearing in the training and test data set. The scikit learn library is used for implementing such a linear regression model in tandem with the cross-validation technique to split datasets for training and validation purposes. This approach provides a better estimate for the performance of a machine-learning algorithm with less variance as compared to a single-use train /test set split. Cross validation is expressed as,

$cv_k = \frac{1}{K}\sum_{j=1}^{k} e_j$.......Eq.(5.9)

Here k is the number of times the process repeats to obtain Mean square Error *e_(j)*. The random seed is specified to 1 and the shuffle is set true in order to change the selection of samples at every run of the model. The k folds for cross-validation were selected in the range from 5 to 10. As shown in Figure 8, the perfect linear line is plotted between the predicted and the observed HHV values and with trial and error the best results were obtained at k=10 where the RMSE = 0.558 and the other performance measure are shown in the Table 5.4.

Table 5.4: K-fold Cross Validation performance measure

Measure	Value
MAE	0.445
MSE	0.311
RMSE	0.558
R2	0.733

5.3.2.3 Results

It is observed that machine learning modelling further improves the performance of the HHV model by training them with high accuracy. In both the techniques, the mean absolute error is well below 1, indicating that machine learning models could predict the HHV value more accurately as compared to the earlier presented empirical models in this study (Eq 5.6-Eq 5.7) as well as other models presented in the Table 5.2.

However, the higher R^2 value of 0.733 for the test set and the greater number of points near the curve of HHV estimated vs. HHV experimental (Figure 5.8) demonstrate that the K-fold Cross-Validation technique for training the datasets is more suitable for this analysis and more desirable as compared to the Train and Test sets technique. Generally, lower values of RMSE indicate a better fit of the model. The RMSE value derived from the test train evaluation technique is 0.558, which is better and since errors are averaged after being squared, RMSE is very useful when large errors are specifically not desired where the number of samples is limited.

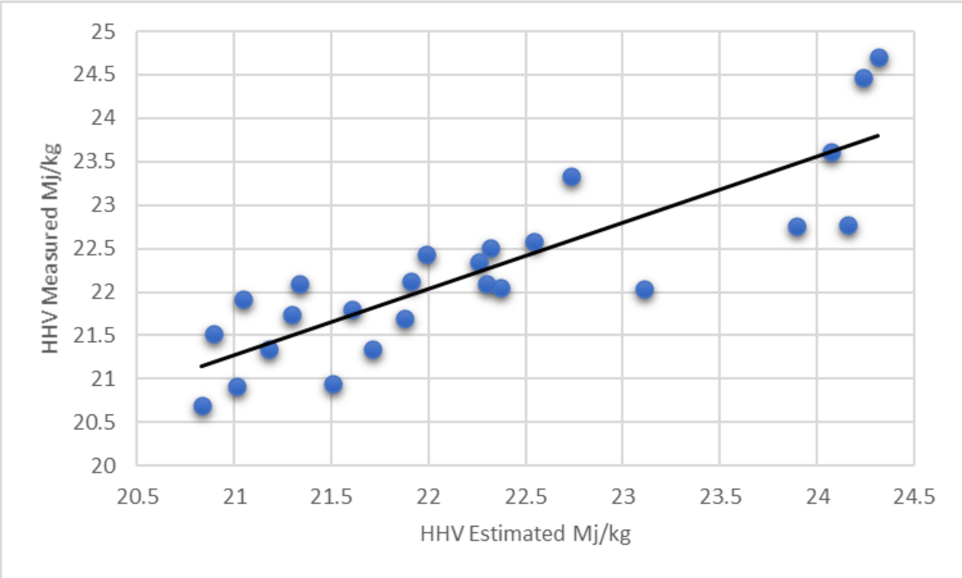


Figure 5.8: HHV Observed response vs HHV predicted response using K-fold Cross Validation technique

Calorific value prediction based on ultimate analysis data can minimize laborious effort, cost and time because most of the steps involved in ultimate analysis are very time-consuming. Besides, this is a major attempt to utilize Waste-to energy processing plant data for developing a predictive model for RDF-3 material using a Machine Learning-based approach. One of the other benefits of using this study is its practical application in optimizing the operations of a waste processing facility for supporting informed data-driven decision-making. The model developed is tested at the Edmonton waste management plant and provides an efficient medium to forecast the calorific value predictions for the operational planning and process integration tasks at the facility like providing RDF-3 to different waste processing vendors.

5.4 Discussion

During this study it was observed that the calorific value of the RDF depends on the performance of the material recovery facility. Running the plant in various configurations and fluctuations in the efficiency of waste processing units had an impact on the composition of the RDF produced. This finding is also highlighted in a study by [18]. Factors like various material recovery line configurations, parameter of separation of material recovery units and municipal waste composition used for producing targeted material can have a significant impact on the quality of RDF produced. This uncertainty in the identification of quality standards of RDF are in relevance to operational decisions of the plant. The chemical characteristics of refuse-derived fuels can be modified by mechanical operations to reach and assure quality targets. However, methods to analyze the performance of material recovery facilities will be studied in the future for improving the quality of produced RDF. Future studies could also focus on investigating how separation parameters of a facility depend on both the input composition of municipal solid waste and the overall feed rate in a plant.

5.5 Conclusion

This Chapter considers an extensive investigation into estimating the calorific value of processed RDF-3, which is a very uniquely characterized biomass fuel. Only a few models in the literature are suitable for predicting the calorific value of RDF-3 material and validation of the prediction accuracy for these models have to be conducted, which was the goal of this study. Using previously developed empirical models sometimes provides massive deviations in estimations because of the complex chemical and physical characteristics of RDF-3. To achieve the goal of this study, authors established a workflow (shown in Figure 5.1) explaining from the collection of processed waste to the final HHV prediction modelling for RDF-3. The developed mathematical models are based on the processed MSW to RDF-3 conversion technology, which involves mechanical processing of the feedstock. These new models help in reducing the dependency on the laborious and time-consuming efforts required to conduct the ultimate analysis of RDF-3 material for improved decision-making at tactical and operational levels in the facility. This is accomplished by collecting historical HHV data from experiments using ASTM 5373 and ASTM D5865 methods comprising unique procedures in their implementations. Therefore, analytically estimating HHV by using data originating from these standards is unique and, to authors best knowledge, not used for HHV estimation of RDF-3 material. Judging by the higher number of points near the curve of HHV estimated vs. HHV experimental, models presented in this study for RDF-3 type material are better, in fact, more accurate than the model proposed in the past, as verified by the ABE and AAE indicated in the Table 3. This comparison reveals that the HHV prediction performance of the linear regression and machine learning model is consistently better than that of their existing linear and/or nonlinear counterparts. The implementation of other machine learning approaches will be studied in the future study of HHV estimation for RDF-3.

In the next chapter, as part of the fourth objective of this study, a comparative analysis of Public-Private Partnership (PPP) models in Energy from Waste (EfW) projects in the UK and Canada will be presented. This analysis introduces a novel quantitative probabilistic model that simulates EfW feasibility while considering risks in Operations and Maintenance (O&M) contracts. The model is specifically designed to accurately capture the multifaceted impact of variables, emphasizing the importance of modeling these variables for financial viability. Additionally, the study highlights the inherent risks in EfW technologies and advocates for the superiority of PPP models over traditional models in the EfW sector.

Chapter 6: Risk Modeling In Waste to Energy Project Partnerships

6.1 Overview

This chapter bridges a critical gap by conducting a comparative analysis of the prevalent PPP or PFI (Private Finance Initiative) models operational in EfW projects within the UK and Canada. The PPP, and some of its specific types such as the PFI, have been significantly adopted over the last three decades as a mechanism for the financing and delivery of projects. It had been adopted to procure various infrastructure projects across communication, energy, transport, waste, and water sectors. Its adoption is driven by the proposition that it provides good value for money and increases accountability and efficiency of public spending where the private sector assumes a major share of responsibility in terms of risks associated with such partnerships. These attributes that promoted its adoption are now subjected to increased scrutiny and review by both policy makers and researchers. Concerns about the value for money of PFI to taxpayers in the energy from waste (EfW) sector are increasingly raised by both governments and investors in the UK and Canada. Despite these concerns, studies on the value of money of PFI in EfW are missing.

This chapter introduces a novel quantitative probabilistic model, aiming to simulate EfW feasibility during the operation phase. This unique model adeptly navigates the intricate landscape of operational phase costs and profitability, encompassing a spectrum of lifecycle risks. By capturing the multifaceted impact of variables—ranging from contractual service quality standards, typically passed on to the Operation and Maintenance (O&M) contractor, to the fluctuating dynamics of technical, payment, and incentive structures—the quantitative probabilistic model emerges as a pivotal predictive tool. Its role is crucial in accounting for and predicting the potential ripple effects these variables can have on the financial viability of EfW projects. This study underscores the criticality of accurately modeling the impact of these variables. Failure to do so could lead to significant losses for the O&M contractor, ultimately undermining the entire viability of the EfW project. The latter employs psychometric methodology to delve into the primary concerns of professionals involved in EfW projects regarding associated risks. The thorough analysis highlights key risks inherent in EfW technologies, focusing on areas such as unplanned maintenance, reduced waste inflow, market price fluctuations, unsustainable debts, and policy dynamics. Ultimately, the study strongly supports the idea that Public-Private Partnership (PPP) models outshine traditional delivery models in the UK and Canada when it comes to EfW applications.

6.2 Methodology:

The concept of risk is used in various disciplines, and the methods deployed for modeling them are usually explained against the background of their epistemological foundation [186]. When calculability limits arrive, the risk is studied using different approaches. The implications of such diverse perspectives in theorizing on risk and uncertainty can be real and objective, subjectively biased, socially mediated, and socially constructed or transformed. In that context, this study aims to model risks from two perspectives: 1) real and objective and 2) subjectively biased. The methodology applied in this paper uses a case study within Canada and SITA UK (SUK), one of the largest EfW providers in the UK and Europe. It analyses the feasibility of PFI for procuring waste management facilities.

Considering risk as real and objective, a technical risk assessment of the operations and maintenance contract is conducted, shown in Figure 6.1 (left branch in the tree). Several components contribute to the fee for the O&M contract. These components include base payment, waste transfer payment, waste diversion performance, performance KPI deduction, electricity production incentive, mileage deduction, non-acceptance fee, and annual major maintenance fee. The developed expressions for calculating the fee associated with each of these components are summarized in Table 6.1. This involves analyzing various factors, such as the scope of work, duration of the contract, required resources, and associated risks, to establish a reasonable fee mechanism. The detailed calculation of each of these contract components and their relationship with the inherent risks is included in the next section 6.3 . A probabilistic model is developed on top of contract components to calculate and predict payment outcomes at the O&M phase. The model employs the Monte Carlo simulation method to explore the possible payment mechanism outcomes while considering the sensitivity of inputs and the likely risk associated with each. This kind of methodology allows an analysis of risk factors under variable sensitivity settings during contract negotiation and therefore aids the formation of an accurate contract cost and provides a forecasting tool during the contract term to predict possible outcomes in the following contract period to aid budgeting purposes.

Figure 6.2 shows the simulation modeling, incorporating eight risk factors outlined in Table 6.2 and the O&M contract fee data from Appendix (A8) as inputs. These elements influence the payment mechanisms and are included in this probability model based on the South Tyne & Wear waste management partnership PFI project final business case [187] and [152]. Table 6.3 subsequently identifies the risk factors considered within the contract components, influencing the payment mechanism analysis alongside a designated sensitivity value for the examined parameter. The methodology for calculating each risk's impact involves multiplying the applied sensitivity value by the difference between the risk factor outcome and a neutral threshold of 0.5. Subtracting 0.5 from the risk factor result transforms the scale so that it centers around zero. This adjustment allows the formula to account for both positive and negative deviations from this midpoint. The simulation model provides outcomes in the form of net cashflows. After running hundred simulations, a set of cash flow outcomes $CF_{t,s}$ are generated for each time period t for simulation s. CF is the average cash flow at time t across all simulations. The results of the simulation model are explained in section 6.3. This methodical simulation approach provides insights into the net cash flows, utilizing Net Present Value (NPV) and Internal Rate of Return (IRR) analyses to determine the profitability of the case studies under consideration. Specifically designed for private stakeholders in EfW PPPs, this model is instrumental in evaluating profitability and pinpointing the uncertainties that affect the financial outcomes of the O&M contracts. Furthermore, it delves into identifying which sources of uncertainty influence the financial return of the O&M contract and how the relationship between NPV and discount rates influences the project acceptance or rejection decision. The discount rate here refers to the interest rate, and due to lack of available data, it has been taken as a certain parameter in the study. The results generated by the simulation highlight the impact of various risks, as detailed in Table 6.3, on the calculations related to the O&M fees. This underscores the importance of risk selection by users, tailoring the analysis to the unique aspects of each project.

Considering risk as subjectively biased shown in Figure 6.1 (right branch in the tree), a psychometric approach is deployed within case framework to explore the concerns of professionals regarding various risks in EfW applications. A standardized questionnaire shown in Appendix (A17), psychological scaling, and multivariable analysis aid in constructing cognitive maps to discover general patterns. Using such an approach, this second branch in the tree considers the perspectives of the different stakeholders qualitatively on the value of money, transfer of risk, or influence shifts and quantitively based on cost, time, and quality. The stakeholders are involved in the Special Purpose Vehicle (SPV), with representatives from the PFI bid group, the project management group, and the Operation and Maintenance (O&M) contractor.

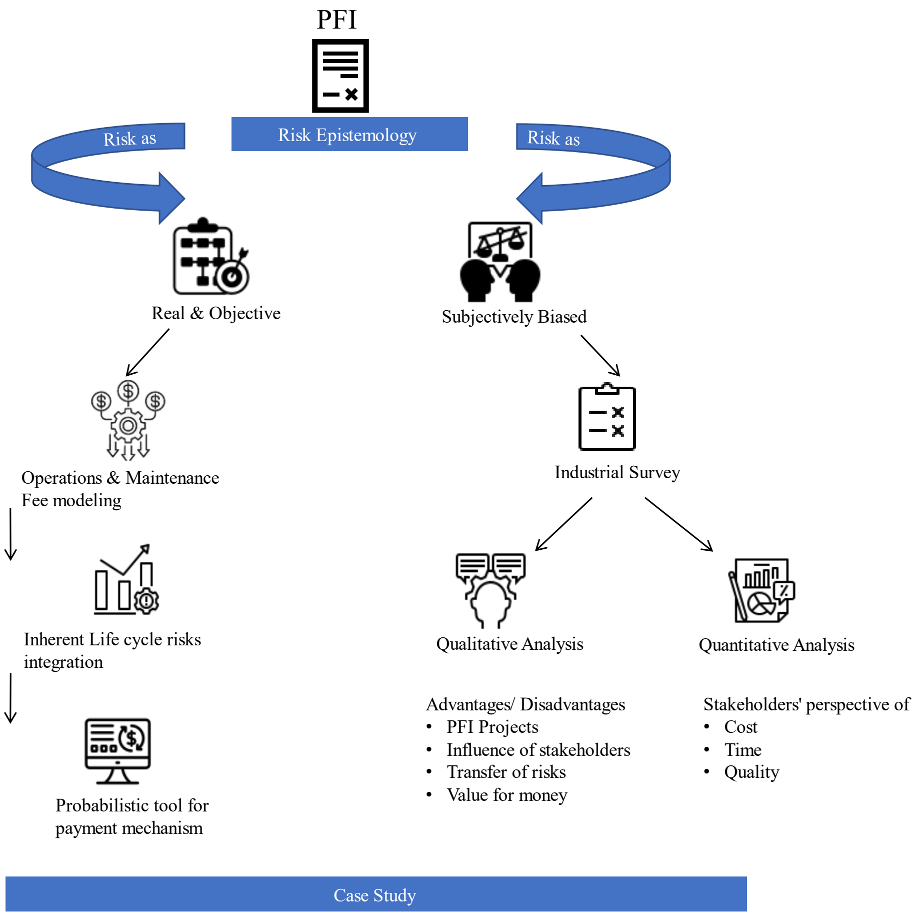


Figure 6.1: Methods used for modeling and identifying risks in EfW PFI project (UK)

The case study considered is the EfW plant STV 4 & 5 operated by SUK a large recycling and resource management company and provider of services to local authorities and businesses under an O&M contract. Mixed quantitative and qualitative methods are applied in the case study. Individuals pertinent to PFI in the case study were selected to receive a questionnaire based on the nature of their position within the PFI project structure Appendix (A11). That stakeholder structure includes members from the SUK PFI bid team, the SUK project management team, the Suez Environment Project management team, the SUK plant operations management team, SUK technical support team, and the PFI SPV management consortium. The questionnaire included both quantitative and qualitative components. The questionnaire is formulated to draw out key project stakeholders' opinions of the advantages and disadvantages of PFI projects when considered against facilities procured through internal corporate finance.

Each candidate has been sectioned into a group based on their role and employer, allowing a summary for each group to be formulated for each question. Quantitative questions are asked concerning cost, time, and quality. Each question is scored 1 to 5 as a priority to the statement regarding the question. The response rate to the questionnaire is approximately 60% (n=24), which can be considered adequate. The response may reflect a possible sensitivity of the PFI topic within the Waste Management Industry or a lack of general knowledge of what PFI represents as a scheme and, therefore, an unwillingness to participate in this study. The candidates are asked to consider two situations for the construction of an EfW project, one being a PFI project funded under the PFI scheme finance from the private sector that of STV EfW lines 4,5 and the other an internally funded project by SUK for Suffolk EfW.

Additionally, a case study of the Canadian P3 model for procuring EfW infrastructure projects is included Section 6.4. Incorporating the Canadian P3 model, this study examines the high-level dynamics of risk allocation and the modeling of contract fees. This analysis sheds light on the strategic distribution of risks among stakeholders and outlines the methodologies used to calculate fees within the framework of Public-Private Partnerships in Canada. Lastly, the study also involves a theoretical implications and comparison of PPP models of EfW-procured project using P3 in Canada and UK. The comparison provides further insights into successful P3 implementation in Section 6.5

Table 6.1 Operations & Maintenance contractor fee modeling, abbreviations are attached in Appendix (A7)

Eq	Component	Equation
1	Annual O&M Contract Fee	$\sum_{i=0}^{n} BP_i + WTS_i - DPD_i + PD_i + EII_i - MD_i - NAD_i + AMM_i$
2	Base Payment (BP)	$\sum_{i=0}^{n} (FFrpix_i * I) + (FFawe_i * Iawe) + (VF_i * Ttn * I)$
3	Waste Transfer Station Fee (WTS)	$\sum_{i=0}^{n} (TST_{ij} * TSR_j) * I + (TSF_{ij} * I)$
4	Diversion Performance Deduction (DPD	$\sum_{i=0}^{n} (AULT_i - TULT_i) * ULAR_i * I + (APLT_i - TPLT_i) * PLAR_i * I)$
5	Performance Deduction(PD)	$\sum_{i=0}^{n} APFD_i * I$
6	Electricity Income Incentive (EII)	$\sum_{i=0}^{n} EPAG_i * EPS_i$
7	Mileage Deduction(MD)	$\sum_{i=0}^{n} CWAD_i * MTD_i * HR_i * I$
8	Non-Acceptance Deduction (NAD)	$\sum_{i=0}^{n} NADR_i * CWNA_i$
9	Annual Major Maintenance Fee(AMM)	$\sum_{i=0}^{n} LM_i$
10	Target Unprocessed Waste to landfill (TULT)	$\sum_{i=0}^{n} (CWA_i + CWNA_i) * ULPT_i\%$
11	Target Processed Landfill Tonnage(TPLT)	$\sum_{i=0}^{n} CWP_i * PLPT_i\,\%$
12	Electricity Production Above Guaranteed Electricity Production (EPAG)	$\sum_{i=0}^{n} (Mwha_i - Mwhg_i) * Pe * I$
13	Electricity Production Shortfall(EPS)	$\sum_{i=0}^{n} ((Mwhg_i + WVF_i) - Mwha_i) * Pd + ETA$
14	Monthly Lifecycle Maintenance Fee	$\sum_{i=0}^{n} LM_i * M * I$

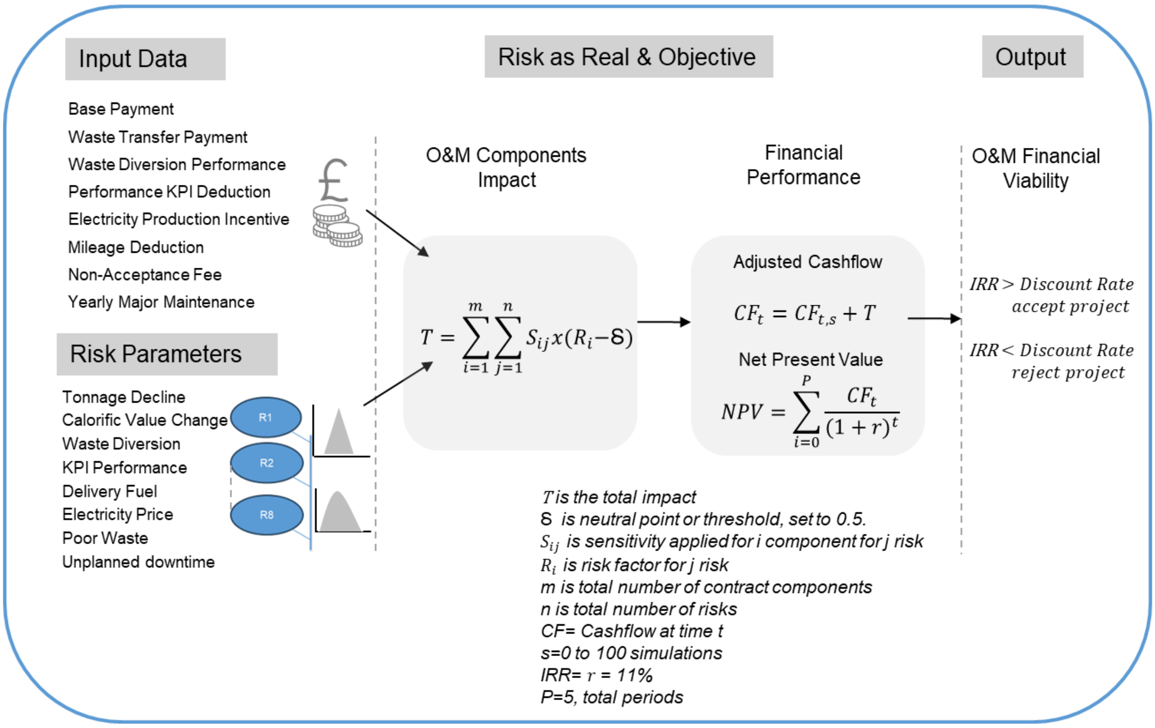


Figure 6.2: Proposed payment mechanism assessment simulation modeling

Table 6.2: Risk factors selected for uncertainty analysis in O&M contractor fee [152], [187]

Risk Factors			
Risk No	Description	Probability Distribution	Result (μ,σ)
1	Tonnage Decline	Triangle (0,0.4,1.0)	0.59,0.34
2	Calorific Value Change	Triangle (0,0.4,1.0)	0.52,0.37
3	Waste Diversion	Triangle (0,0.8,1.0)	0.38,0.35
4	KPI Performance	Normal (0,0.5,1.0)	0.47,0.23
5	Delivery Fuel	Triangle (0,0.7,1.0)	0.44,0.35
6	Electricity Price	Triangle (0,0.6,1.0)	0.45,0.35
7	Poor Waste	Triangle (0,0.8,1.0)	0.42,0.36
8	Unplanned downtime	Triangle (0,0.5,1.0)	0.47,0.37

Table 6.3: Selected risk factors in contract components

Contract Components	Risk1	Risk2	Risk3	Risk4	Risk5	Risk6	Risk7	Risk8
Base Payment	☑	-	☑	-	-	-	-	☑
Waste Transfer Payment	☑	-	☑	-	-	-	-	☑
Waste Diversion Performance	-	-	☑	-	-	-	☑	☑
Performance KPI Deduction	-	-		☑	-	-	☑	☑
Electricity Production Incentive	☑	☑	☑	-		☑	☑	☑
Mileage Deduction	☑	-	-	-	☑	-	-	☑
Non-Acceptance Fee	-	-	-	-	-	-	☑	-
Yearly Major Maintenance	-	-	-	-	-	-	-	-

6.3 Results

In this section, the methodology outlined in previous section are employed to conduct a comprehensive case study analysis of the PFI's in UK and Canada. This involves a thorough assessment of the O&M contracts in place and a detailed survey analysis. The section further delves into intricate calculations that consider various performance indicators providing an in-depth view of the effectiveness and efficiency of the O&M contracts within these PFI implemented WtE projects. The results of these calculations highlight the significance in evaluating the success of the PPP models.

6.3.1 Energy from Waste PFI:UK Case Study

The South Tyne and Wear Waste Management partnership in UK was established to jointly procure solutions for treating and disposing of residual municipal waste [188]. It comprises the Borough Council of Gateshead (local authority 1), the Council of the Borough of South Tyneside (local authority 2) and the City of Sunderland (local authority 3). The framework for the PFI contract administration and network is shown in Figure 6.3 which shows makeup of the SPV is presented as 45% being owned by SUK, 20% by banks, and 35% by the authority. The Authorities in partnership have a contract agreement with the SPV, and the SPV is responsible for managing the different contracts and subcontracts, as shown in the lower part of Figure 6.3. The case study discussion will focus on the operation and maintenance contract and phase. Published in the Official Journal of the European Union on 16 September 2008 (reference 2008/S 179-239146), expressions of interest were invited from appropriately qualified organizations for services relating to the design, installation, operation, and maintenance of residual waste treatment facilities for the specified contract period. The facility began treating residual waste at its 256 thousand tons per year capacity energy-from-waste incineration plant in 2014.

The consortium attempted the adoption of an optimum risk allocation approach. Design and build procurement for STV lines 4 and 5 with penalty payments for late project hand was adopted. The risk to the SPV is partly transferred to the EPC contractor to provide facilities within budget, within time, and to an agreed specification and performance. As returns on their financial investment, they are entitled to a guaranteed payment mechanism regardless of plant performance. The risk or any shortfall in the business case that results from the operation lies with STV, the O&M contractor, and ultimately SUK. This approach of transferring risk to the SPV formed the basis of a sound business case for the local authorities.

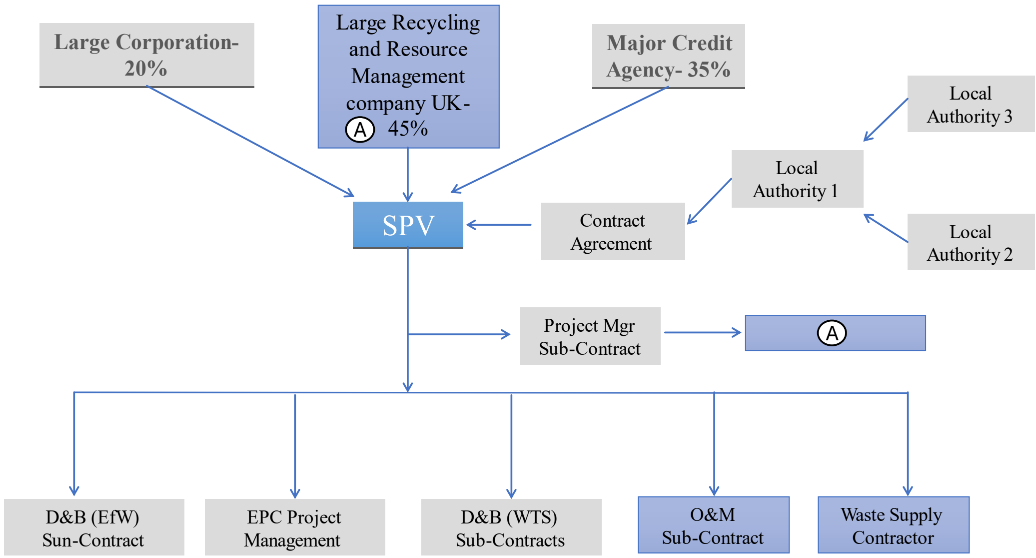


Figure 6.3: SUK PFI Contract Administration. Source: SUK.

6.3.2 Operation and Maintenance Contract

An EfW provides a long-term relationship with the local communities for a disposal point for municipal wastes with a 25-year-long contract. For the SPV, this period represents an adequate opportunity to recover the capital cost and accrued interest on the project debt and achieve revenues. Revenues are assigned to an escrow account to cover the O&M costs of the facility according to a method of determining the deductions. The O&M contract is formed between the SPV (i.e., the employer) and the O&M contractor (i.e., SITA UK). The O&M contractor shall carry out major maintenance following a major maintenance schedule. The major maintenance schedule considers a unitary charge, which includes an annual capped maintenance fee. If the cost of major maintenance is higher than the annual maintenance fee in any one year, the risk is borne by the O&M contractor. This occurrence does not relieve the O&M contractor from performing the major maintenance. However, the O&M contractor can retain savings achieved after executing the major maintenance. Therefore, the accurate estimation of the annual major maintenance fee when preparing the contract fee for inclusion in the contract bid is crucial for the economic viability of not only the O&M contract but also the entire project. Indeed, the SPV is responsible for both the construction and operation of the asset, and the cost of both, including the cost of finance, is included in a single price making up the “unitary charge” provided to the local authority. PFI supporters argue this way of packaging the financial model encourages up-front investments that will drive down the cost of the project over the asset’s life cycle [128]. Spending more on construction might prove fruitful if this results in lower maintenance spending in the long term.

The O&M fee is a complex calculation considering key performance indicators that can be either positive or negative. The design of annual O&M fee includes eight major components shown in Table 6.4 which are calculated using equations developed in this study presented in Table 6.1. The gate fee (£18/tn), waste handling fee (£10.80/tn), landfill disposal charge (£60/tn), performance failure fee (£1M at 98%), non-acceptance fee (£15/tn) are selected from the data set available in Appendix (A8). The final annual fee for the O&M contract is estimated to be (£5,050,405) for processing 170,835 tonnage. The ongoing cost during the asset’s lifecycle, including the O&M contract, is usually high due to the required resources over a 25-year contract and the pressure to fulfill the KPIs associated with calculating and negotiating agreed variables [187]. These inherent risks are passed to the O&M contractor, who requires accurate calculation when forming the O&M contract. The accurate calculation is affected by the sensitivities to driving forces that, if not fully considered, could result in serious losses to the O&M contractor.

Table 6.4: Annual O&M fee calculation tool using Year1 data, Appendix (A8).

		Tonnage	Gate Fee		Result
1	**Base Payment**	170,835.00	£18.00		£3,075,030.00
		Tonnage	Handling Fee		Result
2	**Waste Transfer Payment**	170,835.00	£10.80		£1,845,018
		Tonnage	Landfill Charge		Result
3	**Waste Diversion Performance**	7,848.00	£60.00		-£470,880.00
		KPI%	Failure Fee		Result
4	**Performance KPI Deduction**	98	£1,000,000.00		-£20,000.00
		Extra MW	Incentive		Result
5	**Electricity Production Incentive**	6000	£13.15		£78,900.00
		Tonnage	Fee	Miles	Result
6	**Mileage Deduction**	170,835.00	£1.45	3.2	-£792,674.40
		Tonnage	Fee		Result
7	**Non-Acceptance Fee**	7000	£15.00		£105,000.00
		Tonnage	Fee		Result
8	**Yearly Major Maintenance**	170,835.00	£7.20		£1,230,012.0
	Indexation				**1**
	Final Annual Fee				**£5,050,405.60**
	Monthly Fee				**£420,867.13**

6.3.3 Prediction of O&M Payment Outcomes

A Monte Carlo analysis tool presented earlier, is developed to allow the decision makers to apply varying risk profiles to a set of predetermined risks that will influence each parameter of O&M fee calculation. The risks can be added in the contract bid stages as the decision makers require to integrate the inherent life cycle risks. An appropriate probability distribution can be selected to represent the risk shown in Table 6.2 and the reasonable number of iterations (default-100) to gain a result. Appendix (A10) provides a practical demonstration of the tool's application, showcasing its functionality and the step-by-step process involved in its utilization. As an example, this would mean for the task, Base Payment, and Risk 1, a sensitivity of 50,000t is applied and a Risk factor of 0.59, which results in 50,000 * (0.59-0.5) = 4757. This means that the resultant risk is 4,757 tons of waste lost from the base payment calculation, and as shown in table Appendix (A10), the result considering all associated risks for the task is a payment of £3,137,073. The resultant total taking all tasks and risks into account for the final annual O&M contract fee is changed to £4,974,802 from what was £5,050,405, demonstrating the possible losses to revenue to the O&M contractor. This change in revenue is imposed by inclusion of risks in O&M. Figure 6.4 shows a box plot highlighting the financial effect of risks on contract components. It depicts that inclusion of selected risks on contract components bring financial impacts on contract components like base payment (bringing an average change of £8,546), waste transfer payment (bringing an average change of £5,127), and waste diversion performance (bringing an average change of £126,050).

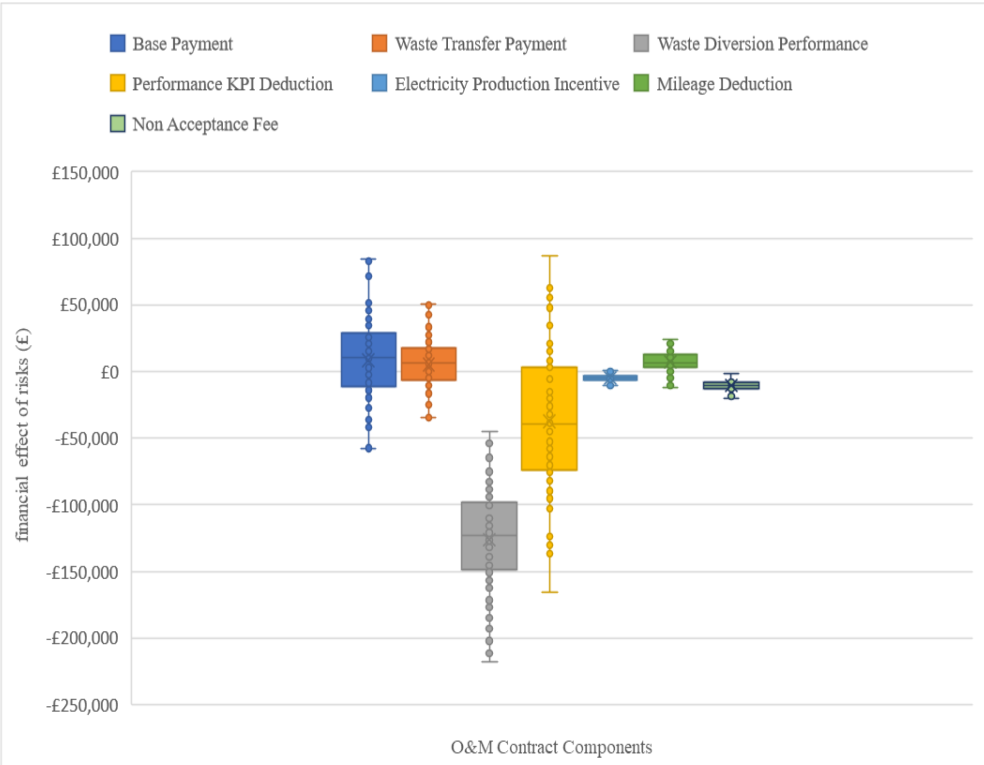


Figure 6.4: Financial impact of selected risks on O&M contract components

6.3.4 O&M Contract Financial Viability

For the private partners to measure the profitability of this project, the discounted cashflows are calculated for the first 5 years of the project. The discount rate is assumed to be set to 10%, and the initial capital investment is assumed to be £8M. This method for measuring productivity emphasizes the time value of money and determines the present value of upcoming and past cash flows. To achieve this, the net present values(NPV) can be calculated, and based on that, the calculated internal rate of return (IRR) can be compared with discount rates [189]. If IRR is smaller than the discount rate, it generally indicates that the project is not expected to generate higher returns than the cost of capital. In this case study, the project is not considered financially viable and acceptable for investment. The tool developed simulates the risks associated with contract components and provides calculated net present value plotted against a range of discount rates. Figure 6.5 shows that under current assumptions, the IRR (11%) is greater than the discount rate (10%), which is marginal evidence to consider this project financially viable. The net present values are positive until the discount rate is 10% but becomes zero and negative beyond that value. The tool can therefore be used to develop all sensitivities and measure the outcomes of all possible scenarios impacting the final O&M annual fee. The simplified calculation and risk analysis tool could aid the O&M contractor in obtaining a payment mechanism that is easier to administrate on an ongoing basis during the contract term, reducing costs

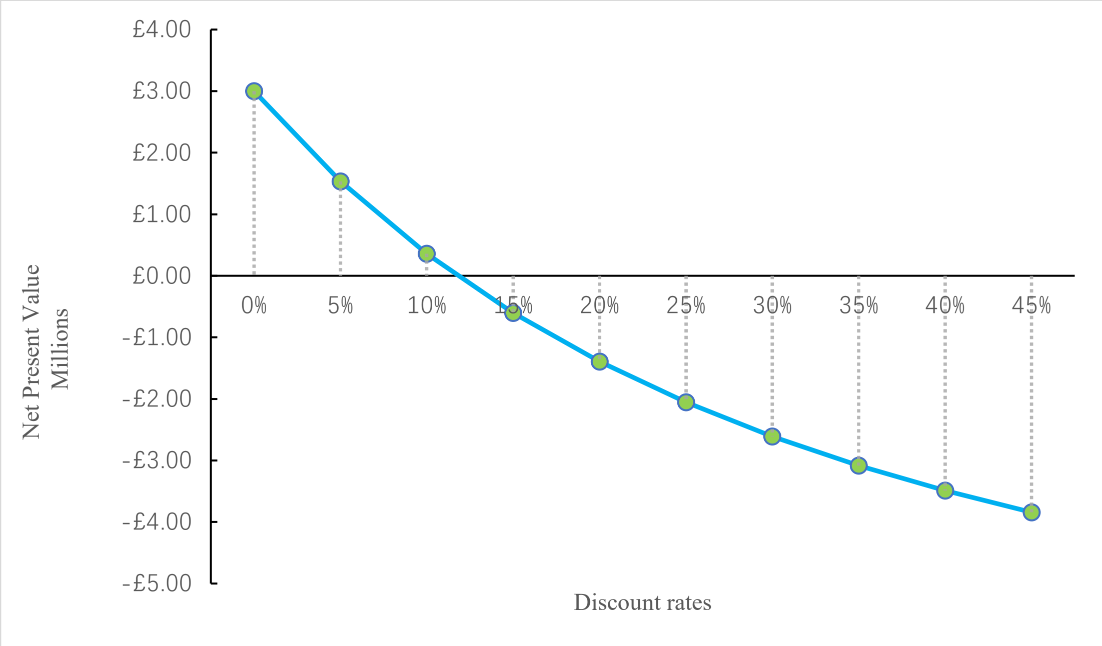


Figure 6.5: Discount rate vs simulated net present value

Two mechanisms play a role here in PFI and risk transfer; firstly, the fact that the contractual agreements entered into automatically transfer key risks from one party to another; in other words, they are in-built into the process of PFI. Examples are the securing and provision of funding being passed from Local Authority hands to that of the SPV, the securing of planning permissions being passed to SUK, and the construction contract being transferred to a construction contractor. This, in theory, is the best-placed entity to deal with the risk. Therefore, in the argument that risk transfer may not be sufficient, the PFI scheme is not correctly set out in how it operates in principle. Secondly, that agreement mechanisms built into those very contracts in the form of payment mechanisms, rewards, and penalties are designed to mitigate the risk that has transferred over to the particular body, thus the argument that costs naturally increase. The costs associated with risk transfer in the case of STV 4 and 5 are within the affordability model of "do minimum" costs, and arguably are comparable to that of a standalone facility in terms of building costs. This would suggest that the cost of the original services is high compared to the cost of STV 4 and 5 as a solution or that STV 4 and 5 is keenly priced as it is not higher than the "do minimum" cost. The overall cost associated with unitary payment mechanisms is complex and can be stated as providing a guaranteed income to the O&M contractor as long as KPIs are within parameters. There is scope for losses to the O&M contractor if the given solution of an EfW plant does not perform to its specification; hence the design is high quality with over-capacity in-built. Risk can be seen as in the hands best placed to manage that risk; there is likely an increased cost associated with that risk, which falls within a financial cost no greater than that already being experienced for existing services.

6.3.5 Industrial Survey: Integrated Assessment of PFI

The industrial survey is organized using a questionnaire designed as a mechanism to collect qualitative as well as quantitative information, (Appendix A17). This method assisted in truly protracting key project stakeholders' opinions of the advantages and disadvantages of PFI projects considered against EfW facilities bought through internal corporate finance. All groups included in the survey have had a strong knowledge of the PFI scheme. For comparison, SITA's Suffolk EfW project is considered in the survey questionnaire against the PFI of the South Tyne and Wear Waste Management partnership.

6.3.5.1 Qualitative View

The following are the findings from the qualitative section of the survey,

a) All groups of SUK do not support the idea of transfer of risk not only of the project build to the stakeholder best suited to address it but also risk transfer in the operation of the facilities over the 25-year O&M contract.
b) The majority group in the survey believes that there is an increased cost associated with risk transfer within a PFI contract and that the method of PFI is complex, leading to high pre-contract award costs, the end contract is inflexible to the local authority due to long 25-year contract term, but this also gives a

guaranteed waste management route of known costs. This shows clear gains for SUK in the author's opinion here due to long-term contracts at a fixed cost, a guaranteed income without the cost of the asset on the balance sheet, an increased company profile and security of the company because of an increase in size, and leading long-term relationships developed with local councils.

c) It was mutual consent among the groups that establishing a well-crafted PFI is a costly and time-consuming exercise for all parties involved in the contract. Suppose the intricacies in the engineering procurement & construction (EPC) and O&M contracts are not addressed with clear cost and time perspectives. In that case, the result can be disastrous, with high contractual penalties if things go wrong.

d) Some groups believed that project profits might be higher if it is funded internally by SUK, like an example quoted for the SITA Suffolk EfW project, but this is at increased risk to SUK. It was observed that a question on VFM has been achieved. Sufficient responders focused on VFM must be demonstrated in a specific calculation process, demonstrating the obligations of the local council under the PFI scheme before a PFI contract is awarded. This should ensure a degree of confidence. The questionnaire result states the asset was built on cost and on time and functions at full capacity, operated by an experienced company at a fixed cost to the client. Also, providing a guaranteed waste recycling point for the next 25 years, achieving the local council recycling targets set by the government. Effective transfer of risk plays a key role in obtaining these outcomes by allowing the appropriate stakeholder in the PFI project to manage that risk.

e) **In Local Authorities' perspective**: PFI projects can be seen as the infrastructure on credit and, therefore, have an associated increased cost to pay back that credit. Overall, this is seen as VFM for the public, based on the alternatives available, there is also the opinion that the public's perception would be that of a costly enterprise to deliver a waste management facility as they would not have the same level of knowledge of the cost of alternatives and the risks associated with unproven technologies. Risks for Local Authority include Legislation, Planning, Technology, Waste flow modeling, and attractiveness of the project.

f) **In facility's Operator Perspective**: A degree of lack of transparency may also contribute to a deficiency of public knowledge of PFI. All groups agree that internal funding will give the best financial return to SUK but is constrained by available funding and acceptance of risk, while PFI guarantees a known return with reduced financial risk and allows participation in many more projects. There is an emphasis on improving efficiency, reliability, and operational capability in order to service the O&M contract effectively. Effective use of known technologies (EfW) has been used as the risks associated with unproven technologies are too high to undertake in a PFI due to financial risk. Improvement in the facilities due to required higher specification has also driven up the service provided by the O&M contractor; this relates to the quality of assets provided and not necessarily by an increased drive to improve upon service delivery. Contractual frameworks for performance measurement and associated reward/penalty schemes drive requirements; again, an increase in cost is associated with providing this level of service. The risk for this category includes Utility prices, permitting/planning, Diversion targets, performance framework, schedules, and pollution residues market test.

g) **Strategic Insights on PFI:** Costs of the SUK project may have increased in later PFI schemes in proportion to risk transfer. The tendering process has to some extent, in the view of the SPV, maintained a degree of control of the cost of services due to the competitive nature of PFI bidding. The government has withdrawn the current version of PFI for the waste industry sector; all groups see that there should be a variant of the PFI scheme for the sector going forward. Alternate approaches may benefit from being tied to a long-term contract or the flexibility of shorter-term contracts. The SPV hold strong views of the benefit provided by the integration of the private sector specialisms into the management of EPC contracts and ongoing O&M contracts, even to the extent that Central Government should aid Local Authorities in their own procurement processes for large capital-intensive projects, further funding seen by the SPV as desirable

6.3.5.2 Quantitative View

The analysis was conducted about the cost, time, and quality associated with PFI EfW and traditional EfW projects. The main category is further sectioned into three sublevels, as shown in Table 6.5. Based on these sublevels, the importance of responses from all stakeholders is categorically highlighted in Figure 6.6. Regarding the actual cost of the project, there is a clear lean towards higher importance on keeping costs down if considering the position of SUK, whether it is internally funded or not. So an inference is that costs may not be the most important factor for Local Authority in the candidates' judgment. In all situations, cost certainty, and VFM are scored as desirable, with no desire for cost overruns in any of the situations posed. Time in relation to the project's earliest possible start contributes little to the study and reflects, in each case, a viewpoint of the individual and their role within the PFI structure or organization. Certainty over contract duration, as in costs, is a high consideration for the majority in each case, and acquiring the shortest possible contract duration is not a high priority for the majority. So, in each case, completing a project on time to a manageable program is a sensible viewpoint. Quality of product scoring high may reflect a desire to minimize life cycle costs and reflects in each case; this may also reflect a desire to increase long-term profit; a PFI contract itself will influence this in that the profit going to the SPV is a shared resource to that consortium, SUK, Local Authority, and Funding partners, for each case of STV 4,5 and Suffolk the profit-sharing mechanisms are similar. The desire to influence the design gets a mixed response which reflects the candidates' roles. Risk considerations appear to play a part in the answers given for quality for some candidates depending on where they sit in the PFI process and to which organization they belong is influencing their viewpoint. The EfW design may be viewed as a standard package, and therefore control over design may not be a top priority for the SPV or SUK, or PFI bid team, and in line with the appropriate PFI process of risk transfer to the private sector for the public sector, leave it in the hands of the constructor.

Table 6.5: Parameters selected for quantitative analysis of survey (Cost, Time, Quality)

	C1	Lowest possible capital expenditure
Cost	**C2**	Certainty over contract price, no fluctuation
	C3	Best value for money overall
	T1	Earliest possible start on site
Time	**T2**	Certainty over contract duration
	T3	Shortest possible contract period
	Q1	Top quality, minimum maintenance
Quality	**Q2**	Sensitive design, control by employer
	Q3	Detailed design not critical, leave to contractor

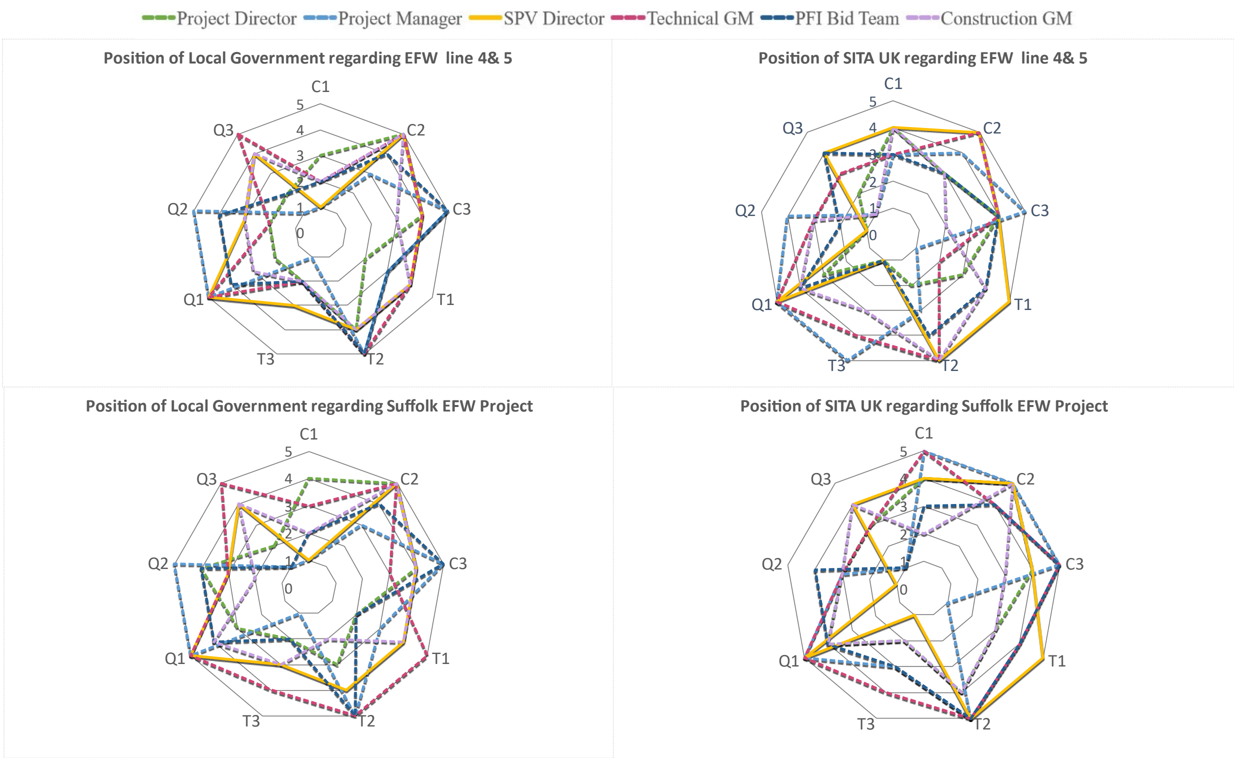


Figure 6.6: Response of Local Government Vs SUK for PFI and Traditional EfW projects

6.4 Energy from Waste P3: Canada Case Study

The Canadian P3 model for procuring infrastructure projects is one of the most successful in the world. However, Canada's EfW market and relevant infrastructure are not as developed as in Asia or Europe. This factor can be subjected to various factors like vast land available for landfills, limited policy support available for the EfW industry, or other economic concerns. Recent projects in Canada provide indicators that because of growing pressure to reduce the amount of waste going to landfills, the government at municipal and provincial levels is undergoing a change by adopting P3 in procuring EfW infrastructure. Provinces like Quebec, Ontario, Alberta, and British Columbia have EfW facilities, among which a few are procured under the P3 model. Appendix (A16) shows a comprehensive list of risks and their subcategories commonly considered in PPP projects in Canada. The procuring authority transfers the ownership of risk to private partners and retains certain risks as part of their project development strategy under the PPP model. These risks are specific to energy from the waste sector, like waste feedstock uncertainty, revenue, market trends, social and political issues, residual disposals, procurement process, etc.

One of the great cases is the successful delivery of the Surrey Biofuel processing facility project under P3 model for public services in BC, Canada, in 2018. A well-crafted business case determined that the capital costs of the biofuel facility will be approximately $68 million. It also examined the advantages of such an investment considering alternative strategies for handling the same organic waste stream by the City of Surrey (Procuring Authority/Owner). The business case recognized the most suitable project procurement and delivery model by evaluating qualitative and quantitative metrics and set out a preferred long-term transaction structure that allocated key project risks to the party most able to manage such risks cost-effectively. The business case also determined that the project should be procured using a design, build, finance, operate and maintain (DBFOM) delivery model. The project was put together at no cost to the ratepayers of Surrey, BC. Funding for the facility was made possible through the federal government's Public-Private Partnership program, and the project finished on time with no budget overruns. It also focused on analyzing proven and established technologies for processing organic waste streams. The facility is designed to process 115K tonnes of organic waste per year to produce 120K GJ of renewable natural gas through an anaerobic digestion process and approximately 45K tonnes of compost [190]. The Fortis BC (FEI) will consume a surplus portion of the biomethane produced. The funding source for this project includes 25% of capital cost support from PPP Canada, and a private group of companies for design, build, finance, operations & maintenance of the facility will invest 75% of the funds. Figure 6.7 shows schematics for the key stakeholders in the project. So private partners are responsible for producing and selling the product in the market [191]. The risk for the City of Surrey may seem low compared to a private group of companies and others, as it essentially provides land, tipping fees, and feedstock for 25 years. The risks in managing operations and maintenance contracts are there, as nobody knows where the RNG market will sit in the coming years.

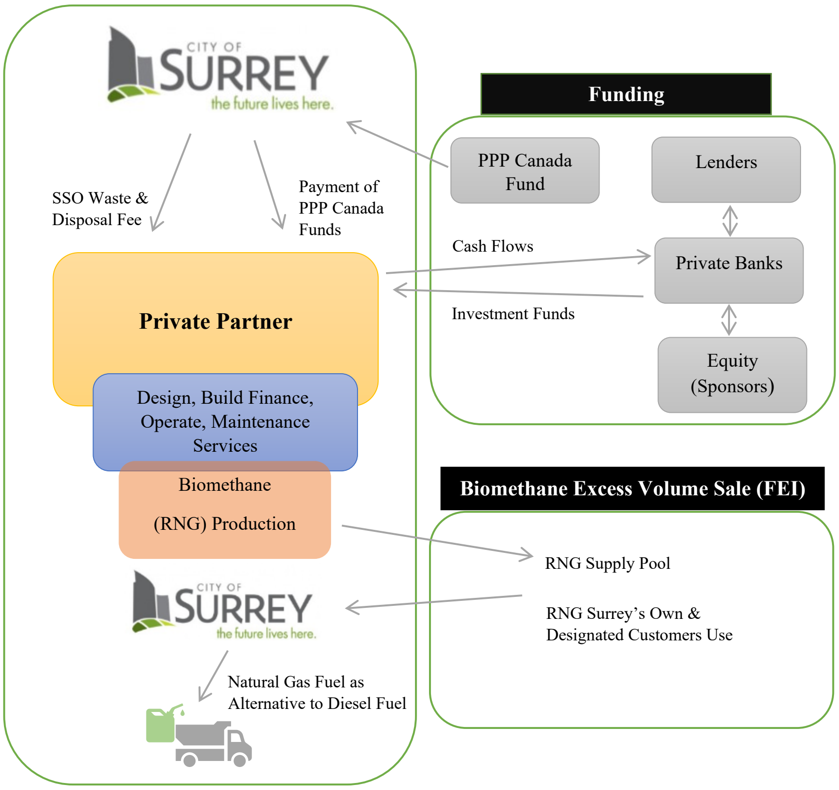


Figure 6.7:Surrey Biofuel facility development under DBFO agreement structure

6.4.1 Assessment Of O&M Contract and Risk-Canada

The Surrey biofuel facility is a 25-year partnership between the City of Surrey (COS) and its private partners. The FEI will store the produced renewable natural gas (RNG) from other contract partners in its grid at the biofuel facility. The City takes responsibility for selling biomethane and uses it for fueling garbage trucks used in residential collection [191]. The City will pay a tipping fee to the private partner based on a tiered pricing arrangement. The City will buy, sell and store the produced biomethane to FEI based on biomethane energy recovery charges like Net sales rate and Recovery rate depending on the volume of biomethane produced. The City will also pay FEI a facility fee between $10K and 14K per month to compensate for capital and operating costs for developing the interconnection facility that will store the biomethane supply [192]. The private project partner will share revenues for biomethane production in excess of a preset value. Suppose the production targets of biomethane are not met due to a shortfall or operational /maintenance failure. In that case, private partners must compensate the City of Surrey for the shortfall. Besides, they must ensure acceptable odor levels, manage the feedstock residuals and process other bioproducts. In this case study, risk probability and risk severity are used to determine risk ranking, and both are expressed as an integer from 1 to 5 [134]. Based on that, the risk significant index and risk impact are calculated to evaluate the significance of identified risks. In this context, Figure 6.8 shows the risk impact score for the eleven dominant risks and their allocations among the stakeholders, reflecting their focus on each risk component. This information is compiled based on the authors' interpretation of the available literature /contract details [134],[192],[191],[193] and presented in Appendix (A14).

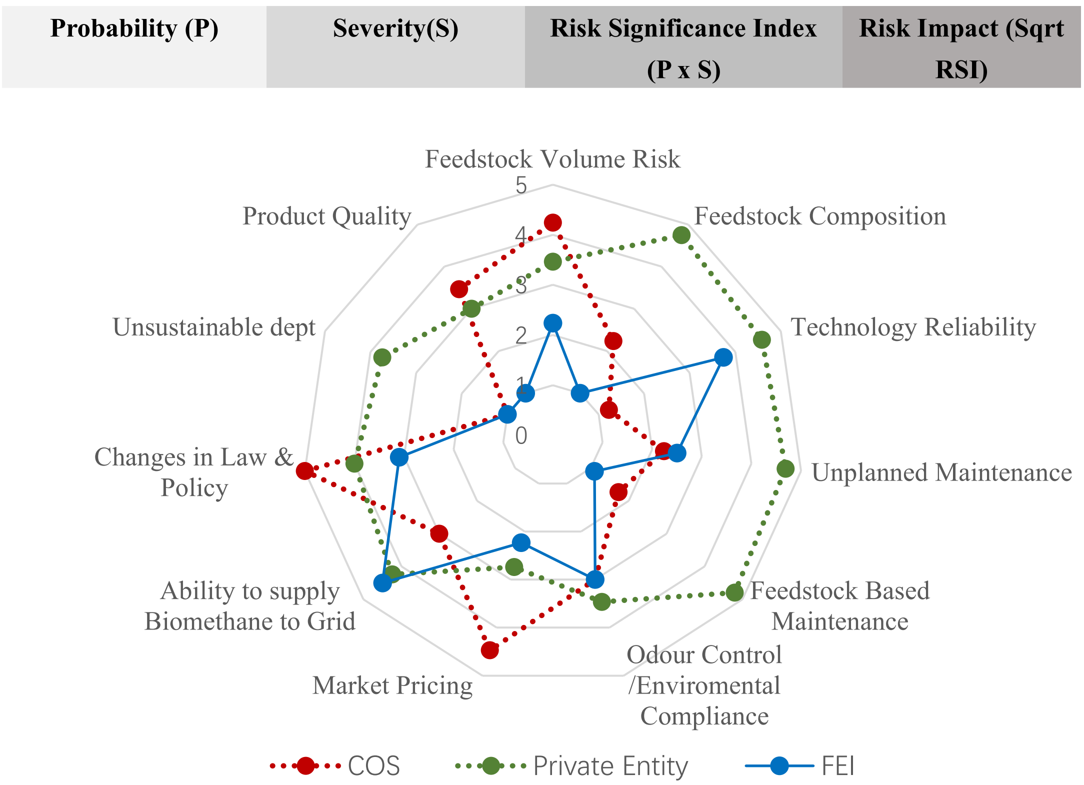
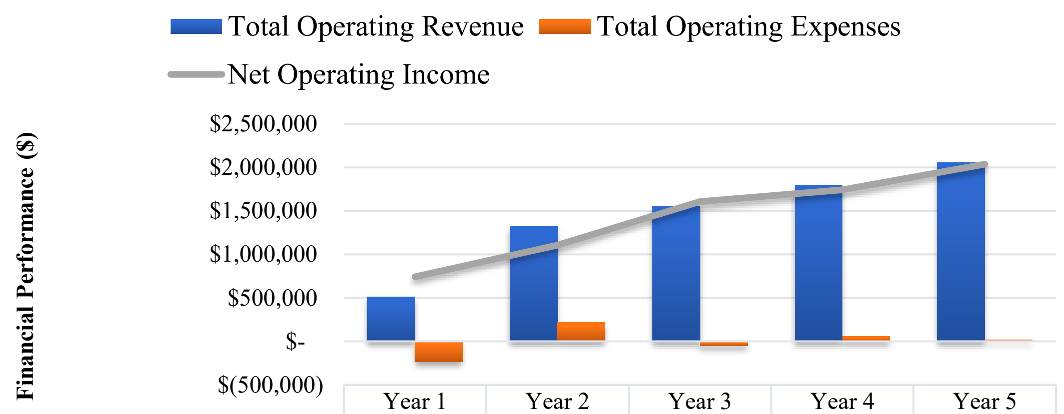


Figure 6.8: Risk allocation among stakeholders in the Surrey Biofuel facility project

However, not enough data points are available in the literature for the O&M contract of the Surrey biofuel facility. Based on the findings from the sample dataset of an AD facility operating in a waste management facility in Edmonton, a cost-benefit analysis can be developed for depicting an O&M contract. This project can contribute to private contractors achieving financial performance goals with a positive net annual operating position, as indicated in the cost-benefit analysis presented in Appendix (A12). Projecting the residential waste generation rate for the next eight to ten years, the proposed ADF(Anaerobic Digestion Facility) benefits from the extended capacity of 48,000 tonnes per year. The HSADF, while annually reducing the GHG footprint by 43,000 tCO2e, is anticipated to generate 12.1 million kWh of electrical and 45,800 GJ of thermal energy annually. In addition, it is expected to produce 24,400 tonnes of compost material annually. The assumed capital budget for this project is $36,944,000. The generated power will be utilized in the composting facility in Edmonton to offset fossil fuel-generated power, and the heat will be beneficially used at the same waste management facility for drying or heating purposes, replacing natural gas. The underlined assumptions for the analysis are presented in Appendix (A13).

Such a cost-benefit analysis from the AD facility in Edmonton can be implemented for measuring the financial performance of the O&M contractor at the Surrey AD facility. Figure 6.9 shows that the project in Edmonton has a positive net operating income indicating that operations are generating more revenue than its operating expenses, resulting in profitability. This is because the project significantly reduces GHG emissions from operations by generating renewable energy, avoiding hauling and landfilling activities, and associated GHG emissions. Thus, the Edmonton project represents a unique renewable energy project like Surrey with the ability to generate distributed “green” power and “renewable” heat from residential waste materials.



	Year 1	Year 2	Year 3	Year 4	Year 5
Total Operating Revenue	$509,155	$1,321,855	$1,554,325	$1,798,280	$2,054,150
Total Operating Expenses	$(232,667)	$216,032	$(51,228)	$56,962	$18,849
Net Operating Income	$741,822	$1,105,823	$1,605,553	$1,741,318	$2,035,301

Figure 6.9: Planned scenarios to evaluate financial feasibility of AD project

6.5 Discussion

6.5.1 O&M Contract and Risk

The process of risk management ensures the project itself is managed appropriately, delivering a quality project on time and within budget. The risk allocation register produced by the Local Authority highlights the key risks that they transfer to their contractor SUK and risks that SUK acknowledges as being born by themselves. As stated in the key stakeholder survey, a higher specification of the facility has been required to ensure SUK meets contractual requirements to mitigate their risk of operation shortfalls. This also reflects in the level of service provided; this, therefore, has been beneficial not only to the Local Authority in the facility provided but also to SUK as it has demanded that they raise their level of performance to match. The O&M contract and annual management fee that SUK has to manage and calculate, as stated above, is complex, as shown by the author, and thus has an associated level of management time and cost associated with its upkeep, employing financial managers to ensure contractual penalties are mitigated.

Analysis of the O&M contract and development of the sensitivity of risk analysis indicates the sensitivity to the risk associated with the contract and its direct relation to the annual fee chargeable. This risk is being transferred to the operator SUK. It can be considered that this drives VFM for the public purse for waste disposal by mitigating the possibility of failure by each party, the consequences of which would not be beneficial to any party. PFI in the waste industry has had its success stories and failings, as noted by Gyekye [194]. For the Local Authority STV 4&5 PFI has provided the required facilities as specified by the Local Authority to meet its obligations under the waste directive within a cost framework determined by the "do nothing" calculation thus can be considered VFM. The ongoing O&M service contract providing an income to SUK may be argued as high or low dependent on the fee to provide the same service to the Local Authority as a purely private enterprise.

The O&M contract annual cost evaluation tool provided by the author makes a simple calculation of a gate fee as the starting point for base calculation, equating to a gate fee of £18 per tonne of waste. This is a comparable figure to EfW gate fees within the SUK group. The O&M payment mechanism calculation tool is a simpler solution along with a risk sensitivity and analysis tool, allowing a saving over the lifetime of the contract due to ease of administration of the contractual obligations in the calculation of the ongoing annual payment mechanism. The risk analysis and risk sensitivity taken to individual tasks provide future O&M contact evaluation and ongoing forecast analysis of annual budget requirements; this will help reduce ongoing cost and reduce future contract formulation costs, should the government provide a future PFI or similar scheme. SUK for major EfW build limit their risk by using an EPC contract, whether it is as a PFI or internal funding mechanism. The return on a PFI is limited when compared to internal funding, the latter being an increased risk financially, as the capital outlay is large. Growth in the company is high because EfW build PFI is providing a secure method of finance without stretching the capital available from the parent company of SUK, Suez Environment. The parent company Suez Environment also controls contract selection and award; a greater stake should be undertaken by SUK stakeholders if diversification of the contract is desirable with associated retention of some risk. SUK should consider risk sharing of the project build in terms of desirable common key plant machinery, as this will increase cost savings in the longer term and possibly improve the reliability and quality of the product if the risk is managed well.

6.5.2 Key Differences of PFI-P3 Project in the UK and Canada

Public-Private Partnerships (PPPs) in energy from waste (EfW) projects have been implemented in both Canada and the UK. The key differences between PPPs for EfW in these two countries are quite contrasting. Drawing parallels between these two countries, it is evident that both are utilizing their versions of Public-Private Partnerships to address the growing deficits in EfW infrastructure. The UK's EfW PFI or PPP projects have shown higher procurement times and costs on average compared to Canada. However, a direct comparison between the two countries is not feasible due to limited information and differences in project sizes. The success of PPPs in each country depends on factors such as the governing framework, market size, financing structures, technology, and public perception. For both countries, the complexity of designing and managing long-term public-private arrangements presents some limitations and challenges in sustainable development goals for energy from the waste industry. In order to realize their social value beyond their economic value, PPPs need to be "fit for purpose." This is because, in the UK, O&M contracts of PPPs for EfW projects have typically been financed through a combination of equity and debt, with lenders willing to provide long-term debt financing. This prevents the emergence of critical risks for O&M contractors presented in Table 6.6. In Canada, the regulatory framework varies by province and municipality, and no national program is specifically focused on EfW PPPs. Canada has efficient procurement processes matured through experience, and a diverse market for project finance is the successful determinant.

The common risks prevailing for both countries also depend on the technologies deployed to extract energy from waste. The common risks in both technologies identified in this study prevail around five key areas, unplanned maintenance, infeed waste reduction, market price, unsustainable debts, and policy changes. The quantification of these risks in the public and private sectors requires a comprehensive risk analysis methodology encompassing risk identification, assessment, allocation, and mitigation. Conducting risk workshops with subject matter experts from all stakeholders, including financial advisors, can aid more in assigning probabilities to identified risks and assessing their impacts on various project phases.

Adding to this discussion, Figure 6.10 shows that the majority of Canadians support or somewhat support the delivery of infrastructure projects through PPP. The portion of the population which approves support for PPP out of the total sample size (S) is presented in percentages. The people from Prairie province are more likely to approve in favor of PPP's compared to Quebec and favor that PPP's are beneficial to indigenous communities as well as to environmentalists [195]. The UK has a higher adoption of advanced EfW technologies, such as gasification and pyrolysis, which have not yet been widely adopted in Canada. In both countries, there have been concerns about the environmental impact of EfW facilities and the potential for negative health effects. However, there is generally more public support for EfW projects in the UK than in Canada due to a long history of successful implementation and better education about the benefits of the technology. Overall, while there are some differences between PPPs for EfW projects in Canada and the UK, both countries offer opportunities for private-sector involvement in this sector. Integrating affordability of EfW projects to consumers in low- and middle-income groups. Providing training opportunities for communities to harness specific skills of local stakeholders.

Table 6.6: O&M risks identified in EfW PPP projects in UK and Canada

Risks Identified for UK(incineration technology	**Risk Identified in Canada (AD technology)**
Tonnage Decline	Feedstock Volume Risk
Calorific Value Change	Feedstock Composition
Waste Diversion	Technology Reliability
KPI Performance	Unplanned Maintenance
Delivery Fuel	Odor Control /Environmental Compliance
Electricity Price	Market Pricing
Poor Waste	Ability to supply Biomethane to Grid
Unplanned downtime	Changes in Law & Policy
	Unsustainable dept
	Product Quality

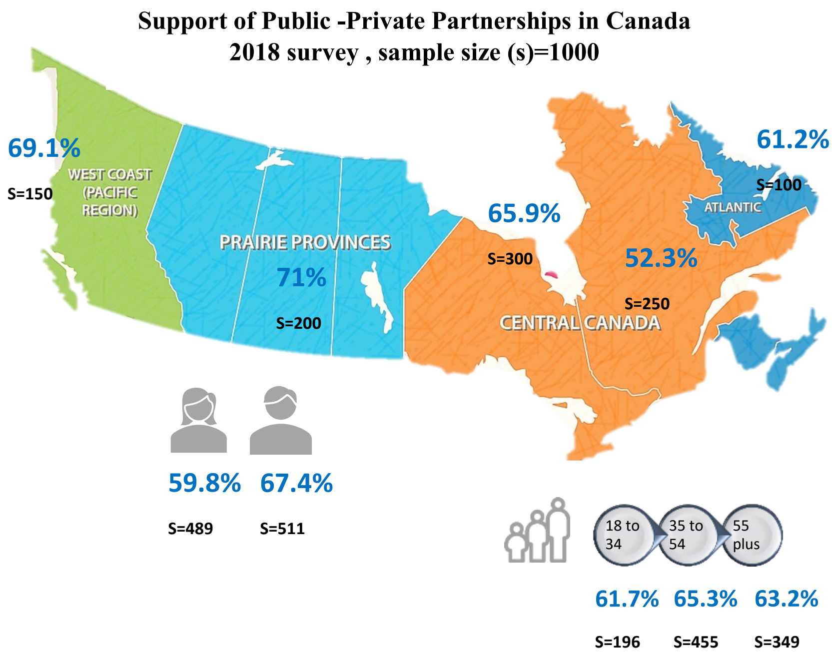


Figure 6.10: Canadian PPP support stats with gender and age demographics, adapted after [181]

6.5.3 Key Implications

In dissecting the dynamics of risk transfer within PFI, two mechanisms emerge as foundational: the intrinsic risk redistribution embedded in PFI contracts and the contractual mechanisms aimed at mitigating these risks. This bifurcation offers substantial implications for both theoretical understanding and practical application in the realm of PFI's.

6.5.3.1 Implications for Theory

The adoption of a mixed risk epistemology approach, coupled with the use of simulation for risk modeling, in this study has significant implications for theory in project management and public-private partnerships. It underscores the importance of integrating quantitative and qualitative methods, alongside simulation techniques, for a comprehensive evaluation of risks in infrastructure projects. This approach challenges traditional theoretical frameworks that often prioritize objective data, highlighting the value of incorporating subjective perceptions and experiences, as well as the dynamic nature of risks captured through simulation. Additionally, the study enriches the theoretical framework of PFI and risk transfer by acknowledging the dual mechanisms at play, the risk redistribution and the contractual mechanisms such as operations and maintenance payment schemes, rewards, and penalties as risk mitigators. This perspective encourages a reevaluation of risk management theories to incorporate the nuanced, structural components of PFIs that designate risk handling to the most apt entity, moving beyond simplistic models to a more integrated view of contractual risk management. Overall, this study contributes to a more nuanced understanding of project evaluation and risk assessment, encouraging a shift towards more holistic theoretical models in the field.

6.5.3.2 Implications for Practice

For practitioners, these insights translate into actionable strategies for optimizing PFI arrangements. The recognition that risks are not just transferred but strategically allocated within PFI contracts necessitates careful planning and drafting of agreements. Practitioners must ensure that contracts clearly define the roles and responsibilities of each party, matched with their capability to manage specific risks. This alignment minimizes misunderstandings and disputes over risk ownership, leading to smoother project execution. Furthermore, the understanding that contractual mechanisms are designed to mitigate transferred risks while potentially increasing costs highlights the importance of financial modeling in PFI projects. Practitioners should employ robust financial analysis to predict the impact of risk transfer on project costs and ensure that these costs are within the projected 'Do Minimum' affordability models. This approach ensures that PFI projects remain financially viable without compromising on quality or performance standards.

Moreover, the recognition of inherent cost implications associated with risk management mandates a proactive approach to cost control and value for money. Practitioners should negotiate contracts that balance risk mitigation with cost efficiency, ensuring that unitary payment mechanisms and performance incentives align with the project's financial objectives. This balance is critical in maintaining the financial sustainability of PFI projects, ensuring that they deliver public value without undue financial strain on public resources.

The exploration of risk transfer mechanisms within PFI contracts not only broadens the theoretical understanding of risk management in PFI but also provides practical guidance for structuring and managing PFI projects. By acknowledging and strategically addressing the complexities of risk transfer, both theorists and practitioners can contribute to the development of more effective and efficient PFI arrangements that meet the needs of all stakeholders involved.

6.6 Conclusion

This study has employed a unique methodology by incorporating mixed research methods, including subjective and objective epistemology concepts, to model the risks associated with operations and maintenance (O&M) contracts for EfW applications. This methodology, by bridging quantitative risk modeling including contract components modeling with qualitative insights using survey approach into stakeholder experiences, provides a unique contribution to the literature on PPPs in EfW applications. It not only addresses the gap identified in existing research but also offers practical recommendations for policymakers, project managers, and private sector partners involved in the planning and execution of PPP EfW projects.

Through this research, it has become evident that careful planning and execution are essential for the success of Private Finance Initiative (PFI) or Public-Private Partnership (PPP) projects. Success factors such as providing detailed technical information during the Request for Qualifications (RFQ) stage and aligning it with the Request for Proposal (RFP) are crucial for incorporating the right expertise within the private partner's team. To ensure cost and time efficiencies throughout the EfW project life cycle, public partners can draft project agreements and procurement documents based on the developed quantitative probabilistic model, which models and captures operational phase costs and profitability. Using mixed epistemology method our study has achieved several key objectives, including capturing the perspectives of key stakeholder groups on the use of PPP models in waste management projects, providing comparative data to determine VFM and the quality of products and services, analyzing the complex nature of O&M contracts in terms of risk quantification, examining the payment mechanism's costs and forecasts for the contract duration, and conducting a hypothetical comparison of lessons learned from EfW projects procured using P3 in Canada and UK. The objective based risk modeling for EfW incineration technology in this study helped estimate a decrease of £75.5K in the annual O&M cost as compared to the original designed cost. Also, its subjective biased risk modeling concludes that certainty over contract price with no fluctuation is ranked highly among stakeholders in EfW projects. The risks identified in this study like unplanned maintenance, infeed waste reduction, market price, unsustainable debts, and policy changes for both incineration and AD technology in EfW applications have a drastic impact on the financial performance of O&M contracts. These findings contribute to a better understanding of the challenges and opportunities associated with PFI and PPP models in EfW projects, providing valuable insights for industry practitioners and policymakers. Further research and analysis in this field can continue to enhance the O&M contract understanding and drive improvements in implementing PFI and PPP models in the waste management sector. Nonetheless, this research concludes that PPP or P3 models outperform traditional delivery models in both Canada and the UK.

The final chapter of this study emphasizes the significance of the integrated decision support system developed throughout the course of this research. This system plays a crucial role in mitigating challenges at both operational and management levels within an MRF. By integrating various modeling approaches and considering uncertainties, the decision support system enables a more informed and effective decision-making process. It serves as a valuable tool for optimizing operations, enhancing resource efficiency, and ultimately improving the overall performance of MRFs.

Chapter 7: Conclusion, Discussion & Future work

7.1 Conclusion

This study establishes a decision support system targeting managerial and operational challenges within MRFs. At the management level, it introduces an advanced quantitative probabilistic model. This model intricately analyzes lifecycle risks' impact on operational phase costs and profitability in WtE projects. It accurately depicts risk factors typically delegated to O&M contractors, considering technical, payment, and incentive variables' fluctuations. This approach identifies prevalent risks such as unplanned maintenance, waste reduction, market price volatility, debts, and policy changes associated with WtE technologies.

At operational level, this study addresses key concerns affecting sustainability and RDF production quality. Firstly, it enhances waste characterization by mass using computer vision, enabling accurate waste detection and early mitigation strategies for unsuitable compositions. Secondly, it extends waste management practices, incorporating uncertainties to enrich the biofuel supply chain. This approach enhances operational conditions, predicting RDF quality to meet set specifications.

Additionally, new empirical models predict RDF's calorific value, validating their reliability against established models. Systematic computational experiments and real-world case studies validate the effectiveness of these methods. The proposed framework delivers a robust decision support system comprising four intelligent solutions, offering comprehensive solutions for both managerial and operational challenges in MRFs.

This study makes significant theoretical, managerial, and global implications for sustaining RDF production. Following are the benefits of this research,

a) Intelligent Framework for RDF Production Plants:

This study contributes to theoretical advancements by introducing an innovative framework that combines technical assessment and economic feasibility analysis for RDF production plants. This framework offers a comprehensive approach, considering both technical aspects such as processing efficiency, waste sorting, and energy recovery, alongside economic factors like cost-effectiveness and profitability. It offers a comprehensive approach that advances understanding in waste management and resource recovery domains.

b) Simulation Environment for Decision Support:

From a managerial standpoint, this study's framework provides valuable decision-making tools. Within a simulation environment, this study empowers decision-makers at strategic, tactical, and operational levels. It provides a platform to simulate various scenarios, aiding in decision-making related to maintaining consistent production levels and ensuring high-quality control standards applicable to various types for RDF materials.

c) Robust Unit Configuration Design in MRFs:

The framework developed in this study allows managers in Material Recovery Facilities (MRFs) to conduct scenario analyses during the design phase. This enables the identification of robust configurations that can effectively handle uncertainties in input variables, ensuring efficient operations despite variability.

d) Enhancing Profits and RDF Material Quality:

Beyond theoretical and managerial impacts, the study holds global relevance. By improving RDF production efficiency and quality, it contributes to global waste management practices. For MRF operators aiming to improve profits and enhance the purity and quality of RDF material, this study offers valuable insights derived from the framework's assessments. It provides guidance on modeling processes and strategies to achieve higher-quality RDF outputs.

e) Efficiency Modeling for Waste Diversion:

Waste managers at local and regional levels benefit from the efficiency modeling provided by this study. The correlation of efficiency parameters with quality aids in redirecting waste streams to facilities where sorting processes are more efficient, optimizing the overall waste management system. Additionally, it aligns with global sustainability goals by offering insights into waste diversion and efficient resource utilization, impacting waste management practices internationally.

f) Informing Policy Decisions for Recycling:

Policymakers gain valuable insights into material sorting processes and recycling policies through this study. It bridges knowledge gaps, enabling the formulation of policies that align with desired environmental outcomes. This aspect makes it a valuable resource for shaping future waste management policies and regulations.

Each aspect contributes to a more holistic understanding and practical application of RDF production, waste management, and policy formulation, offering valuable tools and insights for various stakeholders involved in these domains.

7.2 Research Contributions

The main contributions of this research are summarized as follows:

a) Developed a waste characterization system that contributes by pioneering the assessment of waste composition estimation for RDF-3 production using computer vision techniques like frame differencing and motion compensation, filling an area devoid of prior evaluation with real material recovery facility data. This fills a crucial void in research, offering insight into the practical application of computer vision in optimizing RDF-3 production. processes.

b) Constructed methods based on statistical and heuristics modeling techniques for estimating calorific values and other important parameters of RDF production that significantly diminishes the need for labor-intensive and time-consuming processes involved in characterizing RDF material. It offers precise, instantaneous, and ongoing data on waste composition, alleviating the challenges posed by traditional characterization methods.

c) Designed and extended network flow modeling application for RDF-3 production that provides the best operating conditions and prediction for quality standards. It demonstrates that attending to the physical, chemical, and thermal properties, an RDF can be endorsed as a standardized SRF. The modeling of the application of the dryer unit and its impact on RDF-3 production in a real-world environment are uniquely explored in this study.

d) Proposed a decision support system that can test the strategic, tactical, and operational decisions to evaluate their impact on the RDF quality. This study provides results that can support revisions in the strategic, tactical, and operational level decisions integrating different waste treatment technologies considering varied uncertainties like waste composition technology performance and upgrades, yield and quality of RDF and RDF market selection. The combined effect of all types of decision was not explored enough in past research.

e) Established design of experiments which addressed the scarcity of detailed information regarding sorting efficiencies and output quality from MRFs producing RDF-3 material.

f) Developed a framework for modeling and identifying risks in energy from waste PPP projects using risk epistemology.

g) Developed an quantitative probabilistic model that is capable to model and capture how operational phase costs and profitability are affected by lifecycle risks (such as quality of service driven by contractual requirements that are usually passed on to the Operation and Maintenance (O&M) contractor).

h) Incorporated mixed research methods to include survey results from industry experts (local authorities and operator perspectives), on successful delivery and operation of WtE plants based on time, cost and quality parameters.

i) Explored the pivotal O&M risks within EfW PFI and PPP projects in the UK and Canada. This research bridges a literature gap by delving into the risks associated with O&M contracts using real-world examples, an area largely missing in existing studies on PPP or PFI in EfW applications.

7.2.1 Comprehensive Insights

Additionally, this study thoroughly examines various modeling approaches employed in related research within this domain. By offering a comprehensive exploration of diverse methodologies used in similar contexts, this comparative analysis enhances the broader understanding of modeling landscapes, serving as a valuable reference for both researchers and practitioners in this field. Moreover, this research employs a combination of statistical, survey, experimental, and heuristic methods to address decision-making challenges. It specifically addresses random and epistemic uncertainties, as highlighted in Table 7.1 below, providing comprehensive insights within this context.

Table 7.1: Comparison of frameworks from literature with underline study for strategic(S), tactical(T) and operational(O) decisions in scope of this study. Legend: ✓ indicates authors have used methodology and tackled the decisions in biomass supply chain in a bro

References	**Modeling approach**							**S**		**T**		**O**			**Type of Uncertainty**		
	Statistical Method	Mathematical Programming	Survey or Experimental Methods	Heuristic Methods	Stochastic Process	Theoretical Methods	GIS/Other	Technology Upgrade	Biomass market Selection	Waste Selection /Composition	Technology performance	Biomass yield	Biomass Quality	O&M Risks	Random	Epistemic	Deep Uncertainty
Bairamzadeh et al,2017[42]		☑									☑				☑	☑	☑
Castillo et al, 2017 [41]					☑						☑		☑		☑		
Nunes et al, 2023[164]		☑			☑								☑		☑		
Aboytes-ojeda et al, 2022[165]					☑								☑		☑		

Mohseni et al, 2016[166]		☑					☑					☑			☑		
Testa et al, 2015[17]		☑		☑				☑		☑	☑	☑	☑		☑		
Sebastian et al, 2022[72]						☑				☑			☑				
Ip et al, 2018[80]		☑			☑						☑	☑	☑		☑		
Arina et al, 2020[167]			☑									☑	☑				
Tanguay et al, 2021,[18]		☑			☑			☑			☑	☑	☑		☑		
Sharma et al, 2013[168]		☑					☑					☑			☑		
Dolla et al, 2021[151]			☑						☑		☑			☑		☑	
Nasrullah et al, 2017,			☑								☑	☑	☑				
This Research	☑		☑	☑	☑			☑	☑	☑	☑	☑	☑	☑	☑	☑	

7.3 Limitations and Future Work

Despite achieving its primary goal, the research presented in this study is confronted by several limitations that warrant further exploration in future work. These limitations can serve as opportunities for enhancing the study's impact and addressing unresolved questions. Figure 7.1 highlights these limitations and future research directions in detail, providing a roadmap for advancing the field.

The study successfully achieved its objectives of investigating RDF-3 production and relevant waste management processes selected in the scope of the study. It provided valuable insights into the impact of various factors on RDF quality, such as plant configurations and the study highlighted the importance of understanding the chemical characteristics of refuse-derived fuels and the need for improved methods to analyze the performance of MRF. Following are the limitations and research areas to enhance the current study in the future,

a) The current research primarily centers on RDF-3 production goals, yet it doesn't emphasize decisions concerning scheduling, maintenance, sorting unit reliability, energy consumption, and production schedules. To enhance production efficiency and reduce environmental impact, it's crucial to address these overlooked objectives. Future studies should explore aspects like carbon emissions, equipment reliability, service quality, and resource utilization to effectively resolve RDF production challenges.

b) The research problems in the current study are confined to static conditions, relying on predetermined operating and processing conditions, quality standards, intuitions from design of experiments and other constraints. Yet, the inherent unpredictability of waste composition, separation coefficients, biofuel supply chain planning require future investigations. That would focus on handling additional uncertain factors like processing times, sequence-dependent setups, fluctuating processing RDF yields and maintenance times, to better align with real-world complexities.

c) This study introduces computer vision techniques for waste characterization. While these algorithms effectively solve the identification of physical composition problem in terms of quality RDF production, the investment to obtain the optimized solution remains high. Hence, imperative algorithmic enhancements are needed to achieve high-quality solutions more efficiently, reducing computational costs. From the algorithm's perspective, the frame differencing technique brings some limitations. For example, it is only tailored for detecting moving objects in videos and may require a waiting period to establish background models, most likely not limiting its real-time capabilities. However, this technique works well with stationary cameras but is less practical for moving ones and close objects may be falsely identified as a single object, posing a challenge.

d) The PPP and PFI case studies in this work come from the UK and Canadian WtE industry, which is a relatively limited scope for risk modeling of O&M operations contract. The research in this study in confined, yet there are other countries where WtE projects are successfully delivered and operated under PPP. Therefore, more research on case studies needs to be conducted to verify the universality as well as application of the developed risk epistemology-based framework in this study.

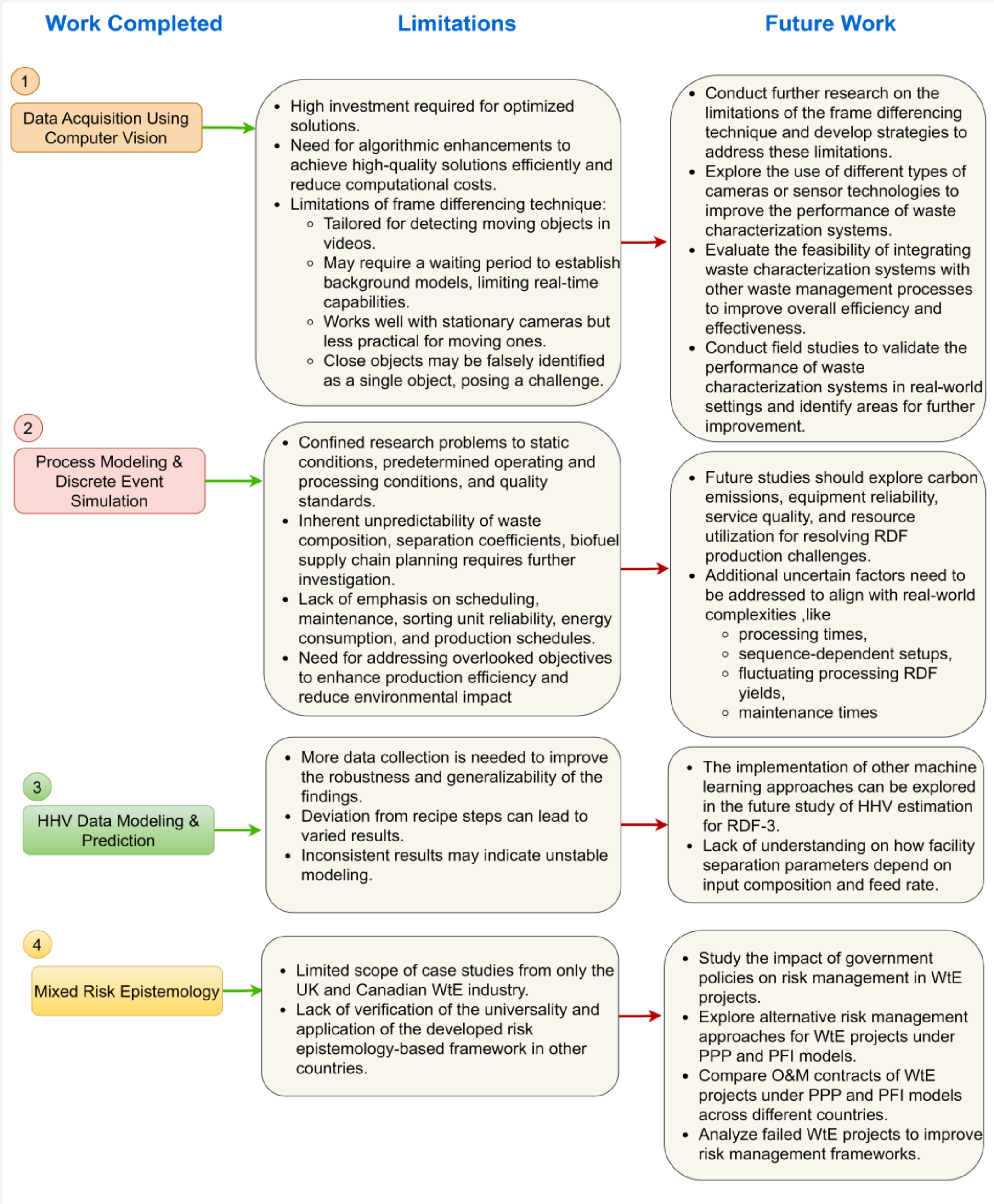


Figure 7.1: Limitations of the study and areas for future research

e) Maintaining a quality standard for RDF is challenging, and various interventions are required to mitigate inconsistent production in an MRF. A ZDM methodology integrated with a data mining approach can avoid failure to maintain a consistent RDF quality. Wang C.[196] applied such a datamining approach to manufacturing zero defect products by collecting process and product data and applying advanced machine learning techniques to predict the failure in the manufactured products. The simulation and modeling approaches developed in the previous sections of this study could be considered to be the key enabling technologies of ZDM as described by [197]. Similarly, ZDM aims to eliminate defects completely through defect prediction and prevention [198]. In a study, Powell et al.,(2022), presented a research framework for advancing ZDM strategies. One of the framework's vital components emphasized the extension of ZDM strategies to less explored manufacturing processes. For instance, continuous manufacturing processes involve thermal or chemical transformations or systems where its process parameters must adapt to the product characteristics obtained via thermal or chemical transformations acting on the material properties [198]. However, the integration of the ZDM framework with this study provides an opportunity for further research in this field.

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Appendix

A1: The probability distributions applied in the simulation for modeling uncertainty in material composition, moisture content and calorific value of the waste components.

Sources of uncertainty	Materials	Probability Distribution	Mean	Standard Dev	Shape	Scale	Low	High
Input Material Composition	Paper	Normal	0.22292	0.07412				
	Rigid Plastic	Weibull			1.874904	0.077246		
	Film Plastic	Weibull			4.052993	0.158514		
	Yard Waste	Normal	0.11106	0.11279				
	Food	Weibull			0.91315	0.062846		
	Diapers & Napkins	Normal	0.07885	0.04883				
	Other Combustible	Normal	0.25514	0.08449				
	Glass	Weibull			0.452483	0.002496		
	Non-Combustible	Gamma			1.134841	0.023413		
Moisture content	Paper	Normal	0.20158	0.06276				
	Rigid Plastic	Uniform					0.019087	0.102264
	Film Plastic	Normal	0.1756	0.06834				
	Yard Waste	Normal	0.47176	0.10938				
	Food	Weibull			6.172186	0.622246		
	Diapers & Napkins	Normal	0.41913	0.10813				
	Other Combustible	Weibull			2.644437	0.194076		
	Glass	Beta					0	0.084
	Non-Combustible	Weibull			1.174516	0.095154		
Calorific Value	Paper	Normal	17.56	2.86				
	Rigid Plastic	Normal	38.26	11.22				
	Film Plastic	Normal	38.12	5.321				
	Yard Waste	Normal	17.49	0.859				
	Food	Normal	19.31	3.43				
	Diapers & Napkins	Normal	22.544	4.3				
	Other Combustible	Normal	18.74	1.9				
	Glass	-					0	0.0001
	Non-Combustible	-					0	0.0001

A2: Waste composition categories, after [169].

	Waste Components	Description	Category
1	Paper and Cardboard	Writing and computer paper, newspaper, flyers, envelopes, magazines, egg cartons, corrugated cartons, packaging, and cardboard boxes, etc.	Combustibles
2	Rigid Plastic	Household bottles and containers* (shampoo, detergent, sauce, yogurt, etc.), food dishes, beverage bottles, lids, tubs, plastic utensils, etc.	Combustibles
3	Film Plastic	Mainly garbage, shopping, and grocery bags, etc.	Combustibles
4	Yard Waste	Trimmed grass, leaves, garden waste, thatch, tree limbs, or woody bush, etc.	Compostable
5	Food Waste	All types of food waste	Compostable

6	Sanitary	Diapers, napkins, and toilet papers	Compostable
7	Other Combustibles	Polystyrene foam, pellets, wood, textiles and fabrics, shoes, rubber, colorful wrapping plastics, etc.	Combustibles
8	Glass	All broken pieces of glass	Inert
9	Metals and Non-Combustibles	ferrous and non-ferrous metals (e.g., tin cans, aluminum foil, aluminum cans), wire (insulated or uninsulated), hangers, utensils, rock, drywalls, etc.	Inert

A3: The chemical composition data (concentration %) for RDF-3 produced in Edmonton

#	Carbon Content	Hydrogen Content	Oxygen Content	Nitrogen Content	Sulfur	Calorific Content Ash free-Dry Basis (Heating Value, MJ/Kg)
1	50.04	6.53	31.23	0.45	0.21	22.545
2	56.29	5.29	35.48	0.26	0.03	24.075
3	46.52	6.6	35.33	0.39	0.14	21.987
4	38.31	7.54	35.92	0.65	0.44	21.506
5	41.25	7.88	36.76	0.79	0.49	22.32
6	42.67	7.61	38.26	0.87	0.56	23.894
7	41.45	8.08	38.83	0.51	0.48	22.737
8	42.62	6.66	38.14	0.77	0.43	21.045
9	40.42	6.58	39.78	0.74	0.42	20.893
10	41.43	6.41	40.37	0.67	0.48	21.877
11	40.49	6.48	41.84	0.63	0.4	21.604
12	53.29	7.83	29.55	0.64	0.15	24.236
13	53.5	7.96	28.94	0.58	0.14	24.314
14	45.45	7.51	34.6	0.67	0.13	24.157
15	43.58	6.93	38.09	0.79	0.17	22.258
16	40.59	6.29	38.23	0.83	0.15	21.016
17	42.81	6.48	39.71	1	0.17	21.334
18	44.66	6.1	39.29	0.31	0.17	23.11
19	43.25	6.33	39.77	0.79	0.19	22.37
20	43.76	5.81	40.19	0.43	0.14	21.298
21	45.21	6.11	38.32	0.4	0.15	21.913
22	43.79	6.08	40.46	0.32	0.22	22.3
23	42.84	5.73	40.14	0.05	0.28	21.71
24	36.07	5.46	48.48	0.47	0.52	20.834
25	37.51	6.06	46.01	0.43	0.37	21.176

A4: Waste composition categories.

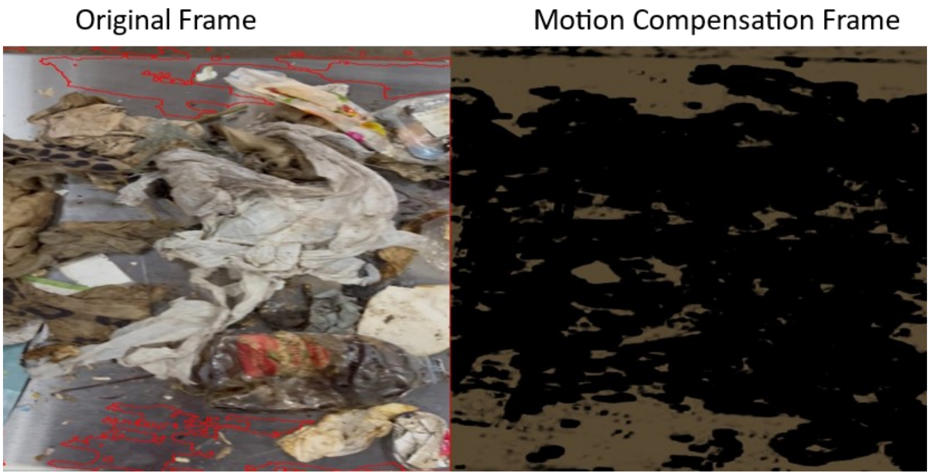
	Waste Components	Description	Category
1	Paper and Cardboard	Writing and computer paper, newspaper, flyers, envelopes, magazines, egg cartons, corrugated cartons, packaging, and cardboard boxes, etc.	Combustibles
2	Rigid Plastic	Household bottles and containers* (shampoo, detergent, sauce, yogurt, etc.), food dishes, beverage bottles, lids, tubs, plastic utensils, etc.	Combustibles
3	Film Plastic	Mainly garbage, shopping, and grocery bags, etc.	Combustibles
4	Yard Waste	Trimmed grass, leaves, garden waste, thatch, tree limbs, or woody bush, etc.	Compostable
5	Food Waste	All types of food waste	Compostable
6	Sanitary	Diapers, napkins, and toilet papers	Compostable
7	Other Combustibles	Polystyrene foam, pellets, wood, textiles and fabrics, shoes, rubber, colorful wrapping plastics, etc.	Combustibles
8	Glass	All broken pieces of glass	Inert
9	Metals and Non-Combustibles	ferrous and non-ferrous metals (e.g., tin cans, aluminum foil, aluminum cans), wire (insulated or uninsulated), hangers, utensils, rock, drywalls, etc.	Inert
10	Batteries	9v, C , D, CR123A, 23 A, AAAA, AAA, AA	Inert

A5: The distribution of waste composition for MF and SF, as assessed in the laboratory, is being compared with the predictions made by Smart-Sight.

		Multifamily Waste Composition				Single-family Waste Composition			
Waste Components	**Category**	**Lab Sample 1**	**Predict Sample 1**	**Lab Sample 2**	**Predict Sample 2**	**Lab Sample 3**	**Predict Sample 3**	**Lab Sample 4**	**Predict Sample 4**
Batteries	Inert	0.0%	0.00%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Cardboard	Combustibles	22.8%	24.33%	20.1 %	22.9%	5.3%	8.8%	4.6%	12.5%
Diapers/Napkins	Compostable	18.0%	10.56%	24.0 %	9.5%	0.3%	2.5%	14.1%	20.0%
Film Plastics	Combustibles	22.1%	18.76%	8.5%	14.9%	23.3%	52.1%	22.8%	26.8%
Food waste	Compostable	2.9%	1.91%	4.4%	0.0%	1.2%	0.0%	5.4%	0.0%
Glass	Inert	0.4%	0.00%	0.0%	0.0%	2.7%	0.0%	0.0%	0.0%
Metals	Inert	0.0%	0.00%	0.3%	0.0%	0.1%	0.0%	1.4%	0.0%
Other	Combust	0.0%	2.93%	0.0%	4.4%	0.0%	0.0%	0.0%	0.0%

Combustibles	ibles								
Other Noncombustible	Inert	0.0%	3.05%	0.0%	1.4%	0.0%	1.8%	0.0%	0.0%
Paper	Combustibles	18.3%	19.75%	19.4%	35.6%	34.6%	28.3%	27.1%	9.3%
Rigid Plastics	Combustibles	9.7%	17.73%	14.6%	9.6%	30.1%	6.4%	13.9%	31.4%
Wood	Combustibles	2.9%	0.96%	4.4%	1.7%	1.2%	0.0%	5.4%	0.0%
Yard waste	Compostable	2.9%	0.00%	4.4%	0.0%	1.2%	0.0%	5.4%	0.0%

A6: Sample frame demonstrating motion compensation which assists in stabilizing camera movement and object detection.



A7: O&M contract fee modelling abbreviations

I =Indexation, FFrpix =Fixed O&M fee, FFawe= Fixed O&M fee average weekly earnings, VF= variable fee , Ttn= Total Tonnage of waste processed, Iawe= Indexation average weekly, TST= (Number of tonnes waste accepted each transfer station earnings, TSF= Fixed waste transfer station fee, TSR= Transfer station rate, AULT= Actual unprocessed waste to landfill, TULT= Target unprocessed waste to landfill, ULAR=Unprocessed landfill rate, APLT= Processed landfill tonnage, TPLT= Target processed landfill tonnage, PLAR= Processed landfill rate, CWA= Contract waste accepted , CWNA= Contract waste not accepted ,ULPT=Unprocessed landfill performance target, CWP= Contract waste processed ,PLPT= Processed landfill performance target, APFD= Annual performance failure deduction, Mwha= Electricity production MWh/pa, Mwhg= Guaranteed electricity production target, PE= Purchase rate (£13.13/MWh), WVF= Waste volume factor, ETA=

Export threshold adjustment, CWAD= Contract waste accepted at delivery point, MTD=Mileage to delivery point, HR=Haulage rate, NADR=None acceptance deduction rate, CWNA= contract waste not accepted, LM= Annual major Maintenance Fee, M= Months.

A8: O&M contract fee Data

Annual O&M Contact Fee = Base payment + Waste Transfer Stations - Diversion Performance Deduction - Performance Deductions+ Electricity Income Incentive - Mileage Deduction - None Acceptance Deduction + Annual Major Maintenance Fee

Year	By	TSPy	Dy	Py	Ey	My	Ny	Lmy	Result
Year1	3,068,118.27	1,848,329.85	461,462.60	0.00	0.00	792,674.40	75,000.00	1,217,559.00	4,804,870.12
Year2	3,057,734.65	1,839,953.37	462,173.85	0.00	121,951.44	787,997.28	75,000.00	2,037,018.00	5,731,486.33
Year3	3,054,081.82	1,830,513.21	463,220.14	25,000.00	33,591.44	782,726.24	75,000.00	1,980,199.00	5,552,439.09
Year4	3,050,026.15	1,820,175.57	463,668.68	0.00	33,591.44	776,954.08	75,000.00	1,923,951.00	5,512,121.40
Year5	3,047,088.71	1,796,084.88	466,530.00	0.00	33,591.44	763,502.72	75,000.00	3,949,422.00	7,521,154.31

Base Payment = (Fixed O&M Fee RPIX * Indexation) + (Fixed O&M FEE AWE *Average weekly earnings index) + (Variable Fee * Total Tonnage of waste processed * Indexation)

Year	FF RPIX	I	FF awe	I awe	VF	Tonnage	I	Result
Year1	591,730.00	1.00	1,851,303.00	1.00	3.66	170,835.00	1.00	3,068,118.27
Year2	591,776.00	1.00	1,844,222.00	1.00	3.66	169,827.00	1.00	3,057,734.65
Year3	591,776.00	1.00	1,844,222.00	1.00	3.66	168,691.00	1.00	3,054,081.82
Year4	591,776.00	1.00	1,844,222.00	1.00	3.67	167,447.00	1.00	3,050,026.15
Year5	591,730.00	1.00	1,851,303.00	1.00	3.67	164,548.00	1.00	3,047,088.71

Waste transfer stations = ((Number of tonnes waste accepted each transfer station * rate) * Indexation) + (Fixed waste transfer station fee * Indexation)

Year	TST n	TSR y	I	TSF y	I	Result
Year1	170,835.00	8.31	1.00	428,691.00	1.00	1,848,329.85
Year2	169,827.00	8.31	1.00	428,691.00	1.00	1,839,953.37
Year3	168,691.00	8.31	1.00	428,691.00	1.00	1,830,513.21
Year4	167,447.00	8.31	1.00	428,691.00	1.00	1,820,175.57
Year5	164,548.00	8.31	1.00	428,691.00	1.00	1,796,084.88

Diversion Performance Deduction = ((Actual unprocessed waste to landfill - Target unprocessed waste to landfill)*Unprocessed landfill rate*Indexation) + (Processed landfill tonnage - Target processed landfill tonnage)*Processed landfill rate * Indexation)

Year	AULT y	TULT y	ULAR y	I	APLT y	TPLT y	PLAR y	I	Result
Year 1	10,000.00	7,848.24	50.00	1.00	8,000.00	922.51	50.00	1.00	461,462.60
Year 2	10,001.00	7,840.46	50.00	1.00	8,000.00	917.07	50.00	1.00	462,173.85
Year 3	10,002.00	7,826.67	50.00	1.00	8,000.00	910.93	50.00	1.00	463,220.14
Year 4	10,003.00	7,825.41	50.00	1.00	8,000.00	904.21	50.00	1.00	463,668.68
Year 5	10,004.00	7,784.84	50.00	1.00	8,000.00	888.56	50.00	1.00	466,530.00

Target Unprocessed Waste to landfill = Contract waste accepted + Contract waste not accepted * Unprocessed landfill performance target

Year	CWA y	CWNA y	ULPT y	Result
Year1	170,835.00	10,000.00	4.34%	7,848.24
Year2	169,827.00	10,000.00	4.36%	7,840.46
Year3	168,691.00	10,000.00	4.38%	7,826.67
Year4	167,447.00	10,000.00	4.41%	7,825.41
Year5	164,548.00	10,000.00	4.46%	7,784.84

Target Processed Landfill Tonnage = Contract waste processed * Processed landfill performance target

Year	CWP y	PLPT y	Result
Year1	170,835.00	0.54%	922.51
Year2	169,827.00	0.54%	917.07
Year3	168,691.00	0.54%	910.93
Year4	167,447.00	0.54%	904.21
Year5	164,548.00	0.54%	888.56

Performance Deduction = Annual performance failure deduction * Indexation

Year	PSD y	I	Result

Year1	0.00	1.00	0.00
Year2	0.00	1.00	0.00
Year3	25,000.00	1.00	25,000.00
Year4	0.00	1.00	0.00
Year5	0.00	1.00	0.00

Electricity Income Incentive = Electricity production above guaranteed electricity production - Electricity production shortfall			
	Ei y	Ed y	Result
Year1	0.00	0.00	0.00
Year2	121,951.44	0.00	121,951.44
Year3	121,951.44	88,360.00	33,591.44
Year4	121,951.44	88,360.00	33,591.44
Year5	121,951.44	88,360.00	33,591.44

Electricity Production Incentive = Electricity production MWh/pa - Guarenteed electricity production target * £13.13/MWh * Indexation					
Year	Mwha y	MWhg y	Pe	I	Result
Year1	148,503.00	148,503.00	13.13	1.00	0.00
Year2	160,000.00	150,712.00	13.13	1.00	121,951.44
Year3	160,000.00	150,712.00	13.13	1.00	121,951.44
Year4	160,000.00	150,712.00	13.13	1.00	121,951.44
Year5	160,000.00	150,712.00	13.13	1.00	121,951.44

Electricity Production Deduction payment = (((Guarenteed electricity production * Waste volume factor) - Actual level of electricity production)*£40/MWh)+Export threshold adjustment						
Year	MWhg y	WVF y	Mwha y	P d	ETA	Result
Year1	148,503.00	1.00	148,503.00	40.00	0.00	0.00
Year2	150,712.00	1.00	150,712.00	40.00	0.00	0.00
Year3	150,712.00	1.00	148,503.00	40.00	0.00	88,360.00
Year4	150,712.00	1.00	148,503.00	40.00	0.00	88,360.00
Year5	150,712.00	1.00	148,503.00	40.00	0.00	88,360.00

Mileage Deduction = (Contract waste accepted at delivery point * Mileage to delivery point * Haulage rate * Indexation)					
Year	TA t	AM	HR	I	Result
Year1	170,835.00	3.20	1.45	1.00	792,674.40
Year2	169,827.00	3.20	1.45	1.00	787,997.28

Year3	168,691.00	3.20	1.45	1.00	782,726.24
Year4	167,447.00	3.20	1.45	1.00	776,954.08
Year5	164,548.00	3.20	1.45	1.00	763,502.72

None Acceptance Deduction = None acceptance deduction rate * contract waste not accepted			
Year	NADR	CWNA	Result
Year1	15.00	5,000.00	75,000.00
Year2	15.00	5,000.00	75,000.00
Year3	15.00	5,000.00	75,000.00
Year4	15.00	5,000.00	75,000.00
Year5	15.00	5,000.00	75,000.00

Monthly Lifecycle Maintenance Fee = Annual major maintenance fee / 12 * Indexation				
Year	LM y	M	I	Result
Year1	1,217,559.00	12.00	1.00	101,463.25
Year2	2,037,018.00	12.00	1.00	169,751.50
Year3	1,980,199.00	12.00	1.00	165,016.58
Year4	1,923,951.00	12.00	1.00	160,329.25
Year5	3,949,422.00	12.00	1.00	329,118.50

A9: Details of the Risk factors included in the study

Tonnage decline: the risk that the overall quantity of waste in the market may reduce over periods of years. This can result from a reduction of waste produced by the consumer by result of less packaging in consumer goods, or by the fact that waste is further recycled further up the waste chain. This affect the income (i.e. gate fee) that is paid for each tonnage received at EfW facility.

Calorific value change: the risk that waste as an end-of-life product delivered to EfW facilities reduces in calorific value over a period of years and therefore provides less heat value for conversion to electricity output. This could be in relation to change in waste producer markets or by dilution of waste streams from non-combusting products such as scrap metal. Waste is also affected by climate and seasonal change. Wet climate conditions can produce wet wastes and introduce high degree of green waste in spring summer, all of which affect the combustion properties and heat generation.

Landfill diversion targets: these targets assess the growth and size of landfills from one year to the next and are set up by national governments or the European Union. EfW plants are part of the policy strategies to meet the 2020 landfill diversion targets set by the EU. As waste diversion targets are achieved, investments in EfW reflected by allocated ‘PFI credits’ decrease.

KPI Performance: performance measurement standards associated with the O&M contract, designed to ensure optimal performance and service delivery, reward or penalty resulting.

Delivery Fuel: the cost of fuel can increase with political change and oil markets. Waste transport from transfer stations to the remote EfW can be dramatically affected by the fuel prices. Waste that may be diverted will also attract a fuel cost associated with the additional distance to landfill.

Electricity Price: the risk of market changes in relation to electricity export revenue can change with market forces, green incentives and policies, and political and social changes over time.

Waste production: the waste produced by society can vary from region to region and also with time and social reform and change.

Unplanned Downtime: if there are unforeseen problems (e.g. breakdown, unplanned down time) with the EfW facility this will reduce availability from a target value set in the contract around 92%. This will result in reducing waste input to the facility and drive down associated revenue streams. There may also be a penalty for low availability target in the KPI. This is a risk the O&M contractor must mitigate effectively in the EPC contract by quality and reliability of technology selection

A10 : Risk factor calculation result developed using simulation in excel

O&M Contract Fee Calculation

Select Values from Annual fee tab

		Tonnage	Gate Fee		Result
1	**Base Payment**	170,835.00	£18.00		£3,075,030.00
		Tonnage	Handling Fee		Result
2	**Waste Transfer Payment**	170,835.00	£10.80		£1,845,018.00
		Tonnage	Landfill Charge		Result
3	**Waste Diversion Performance**	7,848.00	£60.00		-£470,880.00
		KPI%	Failure Fee		Result
4	**Performance KPI Deduction**	98	£1,000,000.00		-£20,000.00
		Extra MW	Incentive		Result
5	**Electricity Production Incentive**	6000	£13.15		£78,900.00
		Tonnage	Fee	Miles	Result
6	**Mileage Deduction**	170,835.00	£1.45	3.2	-£792,674.40
		Tonnage	Fee		Result
7	**Non Acceptance Fee**	7000	£15.00		£105,000.00
		Tonnage	Fee		Result
8	**Yearly Major Maintenance**	170,835.00	£7.20		£1,230,012.00
	Indexation				**1**
	Final Annual Fee				**£5,050,405.60**
	Monthly Fee				**£420,867.13**

Risk Factor Analysis Tool

	Risk1	Risk2	Risk3	Risk4	Risk5	Risk6	Risk7	Risk8	Results
Risk Result	4757		-1188					-123	£3,137,073
Sensty	50000		10000					5000	
Risk Result	4757		-1188					-123	£1,882,244.07
Sensty	50000		10000					5000	
Risk Result			-1188				-728	-246	-£600,586.43
Sensty			10000				10000	10000	
Risk Result				-2			-1	-2	-£75,864.66
Sensty				100			10	100	
Risk Result	238	63	-297			-0.6	-182	-61	£75,742.50
Sensty	2500	2500	2500			13.15	2500	2500	
Risk Result	4757				-0.1			-123	-£771,170.16
Sensty	50000				1.45			5000	
Risk Result							-510		£97,351.14
Sensty							7000		
									£1,230,012.00
								Annual Fe	£4,974,802
								Monthly F	£414,566.83

A11 : Roles which were sent a questionnaire

SUK PFI Bid Senior Manager	Questionnaire Complete
SUK PFI Bid Manager	Questionnaire Not Complete
SUK Project Director	Questionnaire Complete
SUK Construction General Manager	Questionnaire Complete
SUK Construction Civil Engineer	Questionnaire Not Complete
SUK Technical General Manager	Questionnaire Complete
Suez Environnent Project Manager	Questionnaire Complete

Suez Environnent Project Engineer	Questionnaire Complete
SUK Regional Manager	Questionnaire Not Complete
SUK Plant Manager	Questionnaire Not Complete
SPV Consortium Director	Questionnaire Complete
SPV Consortium Manager	Questionnaire Not Complete

A12 : Planned scenarios to evaluate financial feasibility of AD project (Canada)

		Year1	*Year2*	*Year3*	*Year4*	*Year5*
1	Tip Fee Revenue	216,000	221,400	453,870	697,825	953,694
2	Sale of Compost	293,155	293,155	293,155	293,155	293,155
3	GHG Credits	-	807,300	807,300	807,300	807,300
	Total Revenue	**509,155**	**1,321,855**	**1,554,325**	**1,798,280**	**2,054,150**
	Expenditure					
	Operations and Maintenance					
4	Operations Personnel	267,285	534,570	547,934	561,633	575,673
5	Material and Chemicals	102,500	205,000	210,125	215,378	220,763
6	Maintenance of digester and equipment	101,875	203,750	208,844	214,065	249,416
7	Electricity	83,573	167,147	171,325	175,609	179,999
8	Combined Heat and Power maintenance	102,901	205,802	210,947	216,221	221,626
9	Reduction in Landfill Haul and Disposal	(1,839,435)	(2,278,575)	(2,499,437)	(2,372,928)	(2,410,727)
10	Reduction in Natural Gas cost	(14,307)	(45,783)	(74,397)	(74,397)	(85,843)
11	Contingency 15%	158,701	189,940	194,689	199,556	204,545
12	Electricity offset	(484,240)	(968,480)	(992,692)	(1,017,509)	(1,042,947)
	Total Operations and Maintenance	**(1,521,147)**	**(1,786,629)**	**(2,022,662)**	**(1,882,374)**	**(1,887,495)**
	Financial					
13	Debenture	642,633	710,968	679,741	647,643	614,650

	Interest					
14	Net Amortization	645,847	1,291,693	1,291,693	1,291,693	1,291,693
	Total Financial	**1,288,480**	**2,002,661**	**1,971,434**	**1,939,336**	**1,906,344**
	Total Expenditure	**(232,667)**	**216,032**	**(51,228)**	**56,962**	**18,849**
	Net Position	**741,822**	**1,105,823**	**1,605,553**	**1,741,318**	**2,035,301**

A13: AD Assumptions

1. Commercial organic waste volumes and ICI volumes from an contract partner for resourcing waste charged at new Year 1 preferred rate of $60 per tonne Organics with an annual 2.5% increase. The percentage of ICI volumns to the ADF is gradually increasing from 15% in Year 1 till 100% in 2024.
2. Assumes 24,430 tonnes of compost sold at $12 per tonne. This will be high grade compost produced from the ADF.
3. Assumes 32,290 tonnes of GHG sold at $25 / tonne for 13 years (Year2 -2031). Assumed a conservative estimate of 75% of the assumed credits and price.
4. Assumes 3.0 FTE Plant Operators, 1.0 FTE Millwright, and 1.0 FTE Instrument Tech. Wage rates assumed at Year1 contract rates plus 2.5% per year cost of living.
5. Chemicals and other materials used in the operation of the ADF; Estimates provided from vendor company
6. Digester maintenance and equipment (excluding day-to-day); Estimates provided from vendor company
7. Electric power needed to operate facility. Estimates provided from vendor company
8. Combined Heat and Power Maintenance. Information from engineering consultant, assumption $0.017/kwh
9. Reduction in landfilling costs because of increased capacity in the overall organic waste process. Tonnage and price of $65 / tonne in Year 1 (inflated at 2.5% annually) provided by the Utility.
10. The facility design includes heat capture technology to offset natural gas use and reduce GHG emissions. It is expected to be used in the core group of buildings in proximity to the AD facility. Assumes use of 25% of heat being captured and utilized in Year 1 increasing in steps to 75% (max) in Year 5.
11. Consultant estimate, industry standard
12. Assumes 12.1 million kwh produced and utilized in composting facility to offset grid power. Selling price of 8 cents for distributed power, based on most recent prices and regulatory review.
13. 20-year terms with the following assumptions: starting year: $5.9M @ 2.602%; Year 0: $10.8M @ 2.8%; Year 1: $9.5M @ 3.3%
14. Amortized on a straight-line basis over 20 years beginning with a half year in Year

1.

A14: Risk assessment :Canada Case study

Risk Category	COS				Private Entity				Fortis BC			
	Probability (P)	Severity(S)	Risk Significance Index (P x S)	Risk Impact (Sqrt RSI)	Probability (P)	Severity(S)	Risk Significance Index (P x S)	Risk Impact (Sqrt RSI)	Probability (P)	Severity(S)	Risk Significance Index (P x S)	Risk Impact (Sqrt RSI)
Feedstock Volume Risk	4	4.5	18	4.2	4	3	12	3.5	2.5	2	5	2.2
Feedstock Composition	2.5	2	5	2.2	5	4.5	22.5	4.7	1	1	1	1.0
Technology Reliability	1	1.5	1.5	1.2	5	4.2	21	4.6	3.5	4	14	3.7
Unplanned Maintenance	2.5	2	5	2.2	5	4.4	22	4.7	2.5	2.5	6.25	2.5
Feedstock Based Maintenance	2	1.5	3	1.7	5	4.6	23	4.8	1	1.2	1.2	1.1
Odour Control /Envirmental Compliance	3	3	9	3.0	3	4	12	3.5	3	3	9	3.0
Market Pricing	4	5	20	4.5	3	2.5	7.5	2.7	2.5	2	5	2.2
Ability to supply Biomethane to Grid	3	3	9	3.0	4	4.5	18	4.2	4.5	4.5	20.25	4.5
Changes in Law & Policy	5	5	25	5.0	4	4	16	4.0	2.4	4	9.6	3.1
Unsustainable dept	1	1	1	1.0	4	3.5	14	3.7	1	1	1	1.0
Product Quality	3	4	12	3.5	3	3	9	3.0	1	1	1	1.0

A15: Moisture content and Bulk density of waste categories, [Junaid et al, 2023, Alabdraba et al, 2013]

Waste Characteristics	Materials	Probability Distribution	Mean	Standard Dev	Shape	Scale	Low	High
Moisture content	Paper/Cardboard Mix	Normal	0.2016	0.06276				
	Rigid Plastic	Uniform					0.01909	0.10226
	Film Plastic	Normal	0.1756	0.06834				
	Yard Waste	Normal	0.4718	0.10938				
	Food	Weibull			6.17219	0.6223		
	Diapers & Napkins	Normal	0.4191	0.10813				
	Other Combustible	Weibull			2.64444	0.1941		
	Glass	Beta					0.00001	0.084
	Non-Combustible	Weibull			1.17452	0.0952		
Avg Bulk Density Kg/m3)	Paper/Cardboard Mix	366						
	Rigid Plastic	158						
	Film Plastic	56.9						
	Yard Waste	80						
	Food	364						
	Diapers & Napkins	75.8						
	Other Combustible	110						
	Glass	234.022						
	Non-Combustible	145						
	Wood	54						
	Metals	69.182						

A16: Waste to energy risk allocation and categories under PPP Canada, adapted from [190]

Time Frame/Risk Category	Primary Owner of Risk			Time Frame/Risk Category	Primary Owner of Risk		
	Procuring Authority	**Private Partner**	**Shared**		**Procuring Authority**	**Private Partner**	**Shared**
0 to 4 years				**2 to 3 years**			
Political/regulatory and social risks				**Construction risks**			
Approvals and permitting	☑			Construction contractor default		☑	
Development transparency	☑			Construction delays		☑	
Environmental Assessments	☑			Construction design risks		☑	
Public acceptance	☑			Failure to build to design		☑	
Utility company fees	☑			Resource availability		☑	
Procurement risks				Scope changes by owner	☑		
Contract ambiguities	☑			**Financing risks**			
Delivery of performance standards	☑			Availability of financing			☑
Scope changes	☑			Changes to inflation or interest rates			☑
Termination of contract	☑			Deterioration of financial situation of partners		☑	
Site risks				**Technology obsolescence risks**			
Contamination	☑			Advances and upgrades		☑	
Geotechnical	☑			Technology selection and performance	☑		
Greenfield vs. brownfield considerations	☑						
20 to 30 years				**Asset Handover**			
Feedstock risks				**Completion risks**			
Waste composition			☑	Ambiguities in handover agreement	☑		
Waste input volumes	☑			Commissioning delays		☑	
Operations and maintenance risks				**Revenue risks**			
Labor relations		☑		Market volatility		☑	
Preventative maintenance		☑		Marketability of outputs		☑	
Quality		☑		Price risk		☑	
Unanticipated operating costs		☑		Quality of outputs		☑	
Unscheduled maintenance		☑					
Residuals management risks							
Disposal risks		☑					
Fly Ash		☑					

A17: Questionnaire, PFI Case study

Introduction

This questionnaire is designed to evaluate what are the determining factors that PFI stakeholders may take into consideration when entering into a PFI project for Energy from Waste Projects and project stakeholder opinion of the PFI scheme. It forms a component of a MSc Project Management dissertation “A critical review of PFI contract for EFW Tees Valley Lines 4&5”. The study is a comparison between PFI and a more traditional approach funding such projects. The outcomes are designed to consider all stakeholders and the perceived benefits in each case. All information is considered as confidential and will be presented in a sensitive and anonymous manner both for the individuals and stakeholders concerned. An ethical release form has been presented to Teesside University in order to conduct the study.

Please take 30 minutes to consider and answer the questions. There are 20 in total.

If you are not sure of an answer, enter N/A

<u>Question 1</u>

Please give a brief description of your role within the PFI project STV 4&5.

<u>Question 2</u>

What is your understanding of the reason why PFI was introduced into the UK?

<u>Question 3</u>

What do you consider to be the advantages to the local council who use the PFI scheme to procure EFW facilities?

<u>Question 4</u>

What do you consider to be the disadvantages to the local council who use the PFI scheme to procure EFW facilities?

<u>Question 5</u>

What do you consider to be the advantages to SITA UK who bid the PFI scheme to secure waste treatment contracts for EFW facilities?

<u>Question 6</u>

What do you consider to be the disadvantages to SITA UK who bid the PFI scheme to secure waste treatment contracts for EFW facilities?

<u>Question 7</u>

What is the role of the SPV in the PFI scheme?

Question 8

Transfer of risk to the appropriate stakeholder best suited to deal with that risk, is a key principle of PFI to ensure value for money. What in the case of STV 4&5 are the main risks transferred or shared between parties, Council, SPV and SITA UK that you are aware of?

Question 9

Value for money is an essential element of PFI for the local council, does in your opinion the scheme deliver value for money how is this achieved? Explain your answer.

Question 10

The unitary payment for STV 4&5 is quoted on a government web site, quoting the overall PFI commitment to the public purse as around £25 million per annum over the lifetime of the contract cumulating to 710 million. The unitary payment includes all costs for services as well as the cost of the build, the overall PFI commitment to the public purse for all UK PFI projects peaks in 2017 at £10,140 million repayment. As a member of the public what are your thoughts?

Question 11

What in your opinion is the best option for SITA UK if available, a PFI contracted facility or an internal funded contracted facility, STV 4&5 EFW compared to Suffolk EFW for example, give reasons.

Question 12

There are risks that were allocated to the EPC contractor under the EPC contract, towards the end of the EPC contract the turbine presenting problems, and subsequent claims between parties, would the same risk be allocated in the same manner in both a PFI project and a traditional financed project?

Question 13

Do you see a future for the PFI scheme for EFW once the economic turnaround is complete and government funding may be more readily available to local councils for public sector projects?

Question 14

Has there been an effect on the quality of facility provided under the PFI scheme? Give examples.

Question 15

Has there been an effect on the quality of service provided by SITA UK under the PFI scheme? Give examples.

Question 16

Has there been an overall cost increase or decrease in the services provided by SITA UK under the PFI scheme? Give examples.

Question 17

Please score each criteria below for the selection of a PFI contract, if you were in the position of the local government regarding EFW lines 4&5. Rank 1 lowest priority 5 the highest priority. Circle one priority for each.

		Criteria	Priority 1 lowest 5 highest				
COST	C1	Lowest possible capital expenditure	1	2	3	4	5
	C2	Certainty over contract price, no fluctuation	1	2	3	4	5
	C3	Best value for money overall	1	2	3	4	5
TIME	T1	Earliest possible start on site	1	2	3	4	5
	T2	Certainty over contract duration	1	2	3	4	5
	T3	Shortest possible contract period	1	2	3	4	5
QUALITY	Q1	Top quality, minimum maintenance	1	2	3	4	5
	Q2	Sensitive design, control by employer	1	2	3	4	5
	Q3	Detailed design not critical, leave to contractor	1	2	3	4	5

Question 18

Please score each criteria below for the selection of a PFI contract, if you were in the position of SITA UK regarding EFW lines 4&5. Rank 1 lowest priority 5 the highest priority. Circle one priority for each.

		Criteria	Priority 1 lowest 5 highest				
COST	C1	Lowest possible capital expenditure	1	2	3	4	5
	C2	Certainty over contract price, no fluctuation	1	2	3	4	5
	C3	Best value for money overall	1	2	3	4	5
TIME	T1	Earliest possible start on site	1	2	3	4	5
	T2	Certainty over contract duration	1	2	3	4	5
	T3	Shortest possible contract period	1	2	3	4	5
QUALITY	Q1	Top quality, minimum maintenance	1	2	3	4	5
	Q2	Sensitive design, control by employer	1	2	3	4	5
	Q3	Detailed design not critical, leave to contractor	1	2	3	4	5

Question 19

Please score each criteria below for the selection of a Waste management contract, if you were in the position of the local government regarding Suffolk EFW. Rank 1 lowest priority 5 the highest priority. Circle one priority for each.

		Criteria	Priority 1 lowest 5 highest				
COST	C1	Lowest possible capital expenditure	1	2	3	4	5
	C2	Certainty over contract price, no fluctuation	1	2	3	4	5
	C3	Best value for money overall	1	2	3	4	5
TIME	T1	Earliest possible start on site	1	2	3	4	5
	T2	Certainty over contract duration	1	2	3	4	5
	T3	Shortest possible contract period	1	2	3	4	5
QUALITY	Q1	Top quality, minimum maintenance	1	2	3	4	5
	Q2	Sensitive design, control by employer	1	2	3	4	5
	Q3	Detailed design not critical, leave to contractor	1	2	3	4	5

Question 20

Please score each criteria below for the selection of an EPC contract, if you were in the position of SITA UK regarding Suffolk EFW. Rank 1 lowest priority 5 the highest priority. Circle one priority for each.

		Criteria	Priority 1 lowest 5 highest				
COST	C1	Lowest possible capital expenditure	1	2	3	4	5
	C2	Certainty over contract price, no fluctuation	1	2	3	4	5
	C3	Best value for money overall	1	2	3	4	5
TIME	T1	Earliest possible start on site	1	2	3	4	5
	T2	Certainty over contract duration	1	2	3	4	5
	T3	Shortest possible contract period	1	2	3	4	5
QUALITY	Q1	Top quality, minimum maintenance	1	2	3	4	5
	Q2	Sensitive design, control by employer	1	2	3	4	5
	Q3	Detailed design not critical, leave to contractor	1	2	3	4	5