Resource utilization efficiency of dry extraction of pulse protein to design an optimized strategy for plant protein processing

Farzin Eslami

Department of Bioresource Engineering

McGill University, Montreal, Quebec.

March 2023

A thesis submitted to McGill university in partial fulfilment of the

Requirement of the degree of the Master of Science

Acknowledgement

I would want to begin by thanking my family, who always believed in me even when I doubted myself. I am grateful beyond words for the financial assistance they have provided as well as the mental support they have provided through my program. My deepest gratitude goes out to my beloved younger sister, with whom I have never been able to spend enough quality time because of my commitments to academics. I promise I will make it up to you.

I want to convey my deep appreciation and gratitude to my supervisor, Professor Michael Ngadi, for providing me with this great chance and topic to study on. His advice, encouragement, and support have been crucial in pursuing my academic goals. He has opened doors to a universe of possibilities that I never imagined were available because of his experience and understanding. I am really thankful for the opportunity to work under his guidance and for the information, experience, and skills I have received due to our professional relationship.

A very special thank you goes out to Dr. Peter Adewale, my co-supervisor, for keeping a close eye on me over the last two years and ensuring that I am progressing in the correct direction. I could never have gotten this far without your guidance and assistance, given all of the challenges and disappointments I encountered in the beginning.

I also would like to express my sincere gratitude to my friends for their indisputable assistance, both academically and mentally.

Farzin Eslami

Preface and contribution of authors

This thesis has been written in accordance with the McGill University guidelines for thesis preparation. Specifically, the manuscript-based format was adopted for the thesis. It contains five chapters, which are being prepared for publication.

Farzin Eslami (the primary author) performed the literature review, gathered the data, analyzed the results, and authored the papers. The majority of the study was laboratory based in the Department of Bioresource Engineering, Macdonald Campus of McGill University, Montreal.

Dr. Michael Ngadi (co-author), McGill Professor at McGill University, Macdonald Campus, Sainte-Anne-de-Bellevue, Quebec, oversaw the study, offered technical guidance, and assisted in the evaluation and revision of the manuscripts.

Dr. Peter Adewale a PhD graduate of the Department of Bioresource Engineering, aided in the organization and revision of the review article for publication, as well as data collecting and scientific contributions throughout the project.

Abstract

This study aimed to optimize pulse protein processing by assessing the efficiency of protein extraction and evaluating the energy and other resources required for the milling and air classification unit processes. The data envelopment analysis (DEA) technique was used to determine the resource utilization efficiencies of the extraction process, and the results were integrated into a relative efficiency score using linear programming. The study found that the Pure technical efficiencies for milling and air-classification unit operations were 0.98 and 0.89, respectively, indicating that 2 and 11% of all input resources could be reduced while maintaining the same output. The benchmarking results showed that the ideal energy requirement for milling and air classification would be 3.24 Wh and 0.01 MJ, respectively.

Milling is a critical step in optimizing protein extractability during plant protein extraction, and the selection of milling equipment depends on energy efficiency, feed choice, and desired flour properties. However, the decision-making on the mill type heavily relies on the energy required to reduce the particle size, which is determined by the Bond's work index. This study evaluated the Bond's work index for chickpeas, lentils, and peas through laboratory experiments and developed mathematical equations to predict the index and specific energy based on the pulse variety's characteristics. The study found good correlation coefficient values greater than 0.94, indicating that the proposed models, together with other product characteristics, could support decision-making in exploring the sustainability of milling equipment for a desired size reduction.

In conclusion, this study provides valuable insights into optimizing protein processing through efficient resource utilization and energy-efficient milling equipment selection. The proposed models for predicting the Bond's work index and specific energy could be used to support

decision-making in exploring the sustainability of milling equipment, particularly for pulse varieties.

Résumé

Cette étude avait pour objectif d'optimiser le traitement des protéines de légumineuses en évaluant l'efficacité de l'extraction de protéines et en évaluant l'énergie et les autres ressources requises pour les processus d'usinage et de classification par air. La technique d'analyse enveloppement des données (DEA) a été utilisée pour déterminer l'efficacité d'utilisation des ressources du processus d'extraction, et les résultats ont été intégrés dans un score d'efficacité relative en utilisant la programmation linéaire. L'étude a révélé que l'efficacité technique pure pour les opérations d'usinage et de classification par air était de 0,98 et 0,89, respectivement, indiquant que 2 et 11 % de toutes les ressources d'entrée pourraient être réduites tout en maintenant la même production. Les résultats de l'étalonnage ont montré que la demande d'énergie idéale pour l'usinage et la classification par air serait de 3,24 Wh et 0,01 MJ, respectivement.

L'usinage est une étape critique pour optimiser l'extraction de protéines pendant l'extraction de protéines végétales, et la sélection de l'équipement d'usinage dépend de l'efficacité énergétique, du choix de l'alimentation et des propriétés de farine désirées. Cependant, la prise de décision sur le type de moulin dépend fortement de l'énergie requise pour réduire la taille des particules, qui est déterminée par l'indice de travail de Bond. Cette étude a évalué l'indice de travail de Bond pour les pois chiches, les lentilles et les pois par des expériences en laboratoire et a développé des équations mathématiques pour prédire l'indice et l'énergie spécifique en fonction des caractéristiques de la variété de légumineuses. L'étude a révélé de bonnes valeurs de coefficient de corrélation supérieures à 0,94, indiquant que les modèles proposés, avec d'autres caractéristiques du produit, pourraient soutenir la prise de décision en explorant la durabilité de l'équipement d'usinage pour une réduction de taille désirée.

En conclusion, cette étude fournit des informations précieuses pour optimiser le traitement des protéines par une utilisation efficace des ressources et une sélection d'équipement d'usinage économe en énergie. Les modèles proposés pour prédire l'indice de travail de Bond et l'énergie spécifique pourraient être utilisés pour soutenir la prise de décision en explorant la durabilité de l'équipement d'usinage, en particulier pour les variétés de légumineuses.

Table of contents

List of Figures

List of Tables

Abbreviations

	Full form
AE	Alkaline extraction
BCC	Banker–Charnes–Cooper
CCR	Charnes, Cooper, and Rhodes
CRS	Constant return to scale
DMU	Decision making unit
DRS	Decreasing return to scale
FAO	Food and Agriculture Organization
IEP	Isoelectric precipitation
IP	Isoelectric point
IRS	Increasing return to scale
LCA	Life cycle assessment
LCIA	Life-cycle impact assessment
DEA	Data envelopment analysis
ML	Machine learning
NIRS	Non-increasing return of scale
OHC	Oil holding capacity
OW	Oil in water
PFT	Program follow through
PTE	Pure technical efficiency
RR	Size reduction ratio
SD	standard deviation
SE	Scale efficiency
SEM	Scanning electron microscope
TE	Technical efficiency
UF	Ultrafiltration
VRS	Various return to scale
WHC	Water holding capacity
WO	Water in oil

1 Introduction

1.1 Background

The world is constantly changing and evolving, and this has never been truer than with its population growth. According to recent projections, by 2050 the world's population is expected to exceed 9 billion (Compton et al., 2018), which is a staggering figure when considering the amount of resources that will be required to sustain this population. One of the biggest areas of concern is the food industry, which is expected to see a 60% increase in demand by 2050 (Compton et al., 2018). With the world's population growing at such a rapid rate, it is easy to see why the demand for food will increase so dramatically. However, it is important to note that the food industry is one of the largest consumers of natural resources such as water and energy (Compton et al., 2018). This means that the projected increase in demand for food will have significant implications for the environment and the ability to manage these resources sustainably.

Plant-based protein industries, such as pea protein extraction, are also expected to experience significant growth in response to the rising demand for sustainable protein products (Tassoni et al., 2020). However, as with all food industries, there is a crucial need to optimize the extraction processes used in these industries. Doing so it would be possible to minimize waste and reduce the amount of water, energy, and raw materials required to produce these products. The need for conservation measures is clear, as these resources are finite and must be used responsibly if sustainable growth is the goal. As such, it is imperative that pulse protein processing industries take a proactive approach to reduce their consumption of these resources.

Different extraction methods can be used to process pulse protein. Pulse protein extraction methods can be generally categorized into two groups namely dry and wet fractionation methods (Schutyser et al., 2015). Wet fractionation processes are extremely resource dependant and use considerable amount of water and energy while dry fractionation processes are more resource efficient (H.-G. Zhu et al., 2021). On the other hand, wet fractionation methods produce products of higher protein purity compared to dry fractionation (Schutyser et al., 2015). The concept of optimizing the processes, which was coined in the 1990s, includes objectives of reducing the consumption of resources while maintaining or enhancing the volume and quality of product (Maxime et al., 2006). Therefore, the goal of industries is to locate and quantify resource inefficiencies' and select optimum design conditions in order to minimise the inefficiencies (Carrasquer et al., 2017).

Different tools have been developed for calculating the resources utilization efficiency during protein extraction processes such as Life cycle assessment (LCA), water/energy footprint and Data envelopment analysis (DEA). LCA is an analytical tool that captures the overall environmental impact of a product (Curran, 2013). However, LCA does not provide information on efficiency perspectives of a processing plant. Water/energy footprint packages also captures total amount of direct and indirect water/energy needed to produce certain amount of product while they do not give an insight on efficiency (Maltha, 2015). On the other hand, DEA has promising potential to calculate the resource utilization efficiency of food processing plants. DEA unlike old traditional methods such as regression analysis which compares each observation with the mean value of the sample, compares each observation with the best performing unit

(Mardani et al., 2017). This along with other advantages of DEA makes it the best option to analysis resource utilization efficiency in pulse processing industry.

1.2 Rationale

While there is an abundant number of scientific papers addressing the difference in resource utilization between dry and wet extraction methods, the resource utilization efficiency of such processes has been neglected, and research on improving these procedures is sparse. Previous research simply evaluated the present sustainability of food enterprises and did not give or evaluate prospective improvement options for these firms.

It is vital to drive the sustainability of the food product or process by utilizing unique methodologies that include resource use management. One may readily evaluate all of the performances of various unit processes by doing so, and then select a method that delivers superior economic performance as well as resource utilization efficiency.

Furthermore, there are few research studies addressing the resource utilization efficiency of pulse protein extraction by concentrating on each unit operation and its input/output correlation.

Organizations should embrace a sustainability strategy that would help both the environment and the economy. As a result, driving both sustainability components necessitates a resource management strategy. Literature suggests that resource management has an underlying economic advantage. Thus, a study reporting on resources consumption efficiency of these extraction processes can greatly contribute to the body of knowledge.

1.3 Research objectives

This research aims to assess resource utilization efficiencies during dry extraction of pulse protein to design an optimize strategy for legume protein processing. This objective comprises of the following sub-objectives:

1. To study energy and raw material use efficiency during industrial pulse protein processing based on dry methods.
2. To conduct a benchmark analysis for pulse protein dry fractionation processes and design the optimal process.
3. To identify the grinding characteristics of dry peas, lentils, and chickpeas by computing Bond's work index constant and studying the particle size distribution of these pulses in response to different grinding times using the ImageJ software program.

2 Review of Literature

2.1 General information

2.1.1 History

Pulses are considered ancient crops since they were initially domesticated 8000 years ago in parts of Iran and Turkey, and they were first grown by humans approximately 3000 years ago (Tiwari et al., 2020). The Leguminosae family is vast, with 650 genera and 18000 species, and it has a special place in the world's diet after cereal grains (Tiwari et al., 2020). "Pulse" and "Legumes" are two of the most commonly used terms to define this family, and they are interchangeable; however, it is important to know that all pulses are legumes but not all legumes are pulses (Tiwari et al., 2020).

Because of evolving consumer attitudes toward dietary choices based on health and more environmentally sustainable options, the food industry has been exploring for protein components to replace those sourced from animals during the last decade (Karaca et al., 2011). Pea protein (*Pisum sativum L.*) is one such protein that has attracted much attention due to its excellent nutritional profile, availability, and affordability (Shevkani et al., 2015; Stone, Karalash, et al., 2015).

2.1.2 Main suppliers

Dry and green peas are produced in varying amounts over the globe, with certain countries serving as the key suppliers of worldwide demand as shown in table 2.1. According to Food and Agriculture Organization (FAO), Canada was the leading provider of dry peas in 2020, with 4594300 tonnes. In addition, China was one of the most important suppliers of green peas with 11254738 tonnes.

Table 2.1: Dry and green pea production

Domain	Area	Item	Year	Unit	Value	Flag Description
Crops and livestock products	Australia	Peas, dry	2020	tonnes	210500	Official data
Crops and livestock products	Australia	Peas, green	2020	tonnes	17499	FAO data based on imputation methodology
Crops and livestock products	Canada	Peas, dry	2020	tonnes	4594300	Official data
Crops and livestock products	Canada	Peas, green	2020	tonnes	50169	Official data
Crops and livestock products	China	Peas, dry	2020	tonnes	1440627	Aggregate, may include official, semi-official, estimated or calculated data
Crops and livestock products	China	Peas, green	2020	tonnes	11254738	Aggregate, may include official, semi-official, estimated or calculated data
Crops and livestock products	India	Peas, dry	2020	tonnes	796735	FAO data based on imputation methodology
Crops and livestock products	India	Peas, green	2020	tonnes	5703000	Official data
Crops and livestock products	Russian Federation	Peas, dry	2020	tonnes	2740075	Official data
Crops and livestock products	Russian Federation	Peas, green	2020	tonnes	116116	Official data
Crops and livestock products	United States of America	Peas, dry	2020	tonnes	985790	Official data
Crops and livestock products	United States of America	Peas, green	2020	tonnes	279336	Official data

Table 2.2 contains statistics on the lentil and chickpea production yield of the leading producers. India and Canada were the main producers of chickpea and lentils with 11090000 and 2867800 tonnes, respectively.

Table 2.2: Lentil and Chickpeas production

Domain	Area	Item	Year	Unit	Value	Flag Description
Crops and livestock products	Australia	Chickpeas	2020	tonnes	281200	Official data
Crops and livestock products	Australia	Lentils	2020	tonnes	525848	Official data
Crops and livestock products	Canada	Chickpeas	2020	tonnes	214400	Official data
Crops and livestock products	Canada	Lentils	2020	tonnes	2867800	Official data
Crops and livestock products	China	Chickpeas	2020	tonnes	16368	Aggregate, may include official, semi-official, estimated or calculated data
Crops and livestock products	China	Lentils	2020	tonnes	164381	Aggregate, may include official, semi-official, estimated or calculated data
Crops and livestock products	India	Chickpeas	2020	tonnes	11080000	Official data
Crops and livestock products	India	Lentils	2020	tonnes	1180000	Official data
Crops and livestock products	Russian Federation	Chickpeas	2020	tonnes	291133	Official data
Crops and livestock products	Russian Federation	Lentils	2020	tonnes	115556	Official data
Crops and livestock products	United States of America	Chickpeas	2020	tonnes	193820	Official data
Crops and livestock products	United States of America	Lentils	2020	tonnes	336160	Official data

2.2 Pea protein ingredients and characteristics

Legumes are high in protein and carbohydrates, low in fat, and high in vitamins and minerals (Joyce Boye et al., 2010). Although the proteins are abundant in lysine, they are low in methionine and tryptophan (Mertens et al., 2012). Legume proteins can be divided into two categories; globulin proteins, which are salt soluble; and water-soluble albumin proteins, which are the second major class of proteins (Karaca et al., 2011). There are two types of globulin proteins: legumin (11S, 300–400 kDa) and vicilin (7S, 150–180 kDa) and due to their differing amino acid profiles, and structures, both have distinct functional characteristics. As a result, pea protein products' functionality should be determined by their legumin/vicilin ratios as well as the raw material's cultivar and growing environment (Mertens et al., 2012).

2.2.1 Protein structure

Field pea contains 23.1–30.9% protein, 1.5–2.06% fat, and trace elements such as vitamins, minerals, phytic acid, polyphenols, saponins, and oxalates, and all these constituents vary in proportion depending on the variety, harvest maturity, and growing environment (Gueguen, 1983). Pea carbohydrates range between 60 and 65%, and composed mostly of starch (35–40%; 24.0–49.0% amylose) and dietary fiber (10–15% insoluble and 2–9% soluble) (Tiwari et al., 2020). It also contains non-starch carbohydrates such as sucrose, oligosaccharides, and cellulose (Hoover et al., 2010). Pea protein is dominated by two types of proteins, albumins and globulins, which account for 10%–20% and 70%–80% of the total protein, respectively (Duranti & Scarafoni, 1999; Karaca et al., 2011). Albumins are regarded as water-soluble metabolic proteins that have a greater quantity of the essential amino acids tryptophan, lysine, threonine, and methionine in pea than globulins do (Joyce Boye et al., 2010). Globulins are classified as salt-soluble storage proteins and are composed mostly of legumin and vicilin proteins, with trace quantities of a third kind known as convicilin. Albumin proteins range in size from 5 to 80 kDa and include enzymes, protease inhibitors, amylase inhibitors, and lectins (Joyce Boye et al., 2010). Legumin is a hexameric protein with a sedimentation coefficient of 11S and a molecular mass ranging from 300 to 400 kDa (Kijowski, 2001; Mertens et al., 2012).

Vicilin proteins are trimeric proteins with a molecular mass of 150–170 kDa and a 7S sedimentation coefficient and unlike legumin, which is bound together by covalent disulfide bonds, vicilin is held together by hydrophobic interactions (Kijowski, 2001). Convicilin has a molecular mass of 70 kDa and is the third storage protein found in peas and other pulses (Joyce Boye et al., 2010). Convicin's amino acid profile differs from that of legumin and vicilin, and unlike vicilin, it consists of sulfur-containing amino acids (Boulter, 1983). According to the extraction procedure used to manufacture the protein component, the extrinsic elements (e.g., pH, temperature) might cause the protein structure to differ from the previously described structure. These may have an effect on protein functionality.

2.2.2 Legumin/vicilin ratio

Field peas' legumin/vicilin (Lg/Vn) ratios vary from 0.4 to 2.0 at maturity (Schroeder, 1982). During seed development, the Lg/Vn ratio rises due to the different rates of synthesis of the 11S and 7S. Vicilin production is dominant from early development until 17 days after flowering, but legumin is quickly produced in the latter phases of growth, beginning 20 days after flowering and continuing until maturity (Chandler et al., 1984). Wright and Boulter (1972) observed a nine-fold rise in legumin in faba bean seed between days 40 and 50 of growth, compared to a two-fold increase in vicilin. Lg/Vn ratios ranged from 0.23 to 0.50 for wrinkled pea cultivars and from 0.31 to 1.67 for smooth pea cultivars, according to JI Boye et al. (2010). Legumin and vicilin are the most ecologically conscious proteins in pea, and they are very sensitive to external variables such as agronomic practices and environmental conditions (Mertens et al., 2012). When grown under sulfur-deficient circumstances, vicilin production is sustained throughout growth, but synthesis of the more sulfur-rich legumin is severely hampered (Chandler et al., 1984).

2.2.3 Effect of cultivar and environment on protein content

The key aims in field pea breeding projects for both food and feed are cultivars with high yield, early maturity, and resistance to lodging and illness (Vera et al., 1999). Potential cultivars should be evaluated at numerous locations over many years to assess the level of environmental impacts on genotypes due to variations in performance in response to environmental factors such as soil type, rainfall, and temperature (Acikgoz et al., 2009; Nikolopoulou et al., 2007).

The impacts of specific environmental factors on genotype performance have been investigated. High temperatures and minimal rainfall have been linked to greater protein content (Nikolopoulou et al., 2007). Nikolopoulou et al. (2007) for example, discovered that between two sites with a rainfall differential of 209 mm, pea seed cultivated in the drier area was 7 percent richer in protein on average. A study by Reichert and MacKenzie (1982) examined dehulled peas (cultivar Trapper) cultivated at four different sites in Saskatchewan, Canada. They observed that protein level was strongly correlated with starch, fat, ash, soluble sugar, and neutral detergent fiber content (NDF).

2.3 Protein isolate extraction methods

2.3.1 Alkaline/isoelectric precipitation process

Alkaline extraction followed by isoelectric precipitation (AE/IEP) makes use of legume proteins' strong solubility in alkaline environment and their limited solubility between pH 4 and 5 (Joyce Boye et al., 2010). This is the most frequently documented technique of legume protein extraction in the literature (Gueguen, 1983; Hoang, 2012). In summary, de-fatted legume flour, with or without the seed coat, is dispersed in water, adjusted to an alkaline pH using sodium, potassium, or calcium hydroxide (Gueguen, 1983). This process might take up to 180 minutes to maximize the amount of protein soluble in the solution (Joyce Boye et al., 2010). To facilitate solubilization, the temperature might be raised to 50–60 °C (Hall, 1996). It is then centrifuged, and the supernatant is collected, after which the pH is adjusted to its isoelectric value using hydrochloric or sulfuric acid, if necessary. Centrifugation is used to collect the precipitated protein, which is then washed, neutralized, and dried using a drum, spray, or freeze drying technique (Gueguen, 1983). Optimal processing conditions may result in isolation yields of 80–94%, although the parameters utilized in a specific procedure might alter isolate yield, purity, and functionality (Hoang, 2012).

2.3.2 Ultrafiltration

To separate proteins of interest from the supernatant fraction, ultrafiltration (UF) and/or diafiltration membranes with particular molecular weight cutoffs may be used instead of IEP (Joyce Boye et al., 2010). The use of UF often offers milder conditions for the extracted proteins, allowing their functionality to be increased, and delivers greater yields than those generated with IEP (Mondor et al., 2012).

2.3.3 Salt extraction process

Salt extraction (SE) is a technique that takes use of the salting-in and salting-out processes that occur in proteins, followed by a desalting procedure to reduce the ionic strength of the environment in which the proteins are found (Joyce Boye et al., 2010). In brief, flour is mixed for 10–60 minutes in a salt solution of required ionic strength at a 1:10 (weight-to-volume) ratio (Gueguen, 1983). Then the insoluble material should be removed by settling, decanting, screening, filtering, or centrifuging (Joyce Boye et al., 2010). Finally, the supernatant is desalted and dried. The concentration and type of salt or salt combination used are determined by the salting-in properties of the protein to be extracted (Ahmed, 2017). Salting-out characteristics of any unwanted proteins are also crucial since proteins precipitate at various ionic strengths (Ahmed, 2017). SE has the benefit of not requiring excessive alkaline or acidic pH or high temperature.

2.4 Functional properties

2.4.1 Solubility

Protein solubility in a solution is defined as the balance of protein–protein (hydrophobic) and protein–solvent (hydrophilic) interactions (Hall, 1996). In most cases, water or buffer is used as the solvent. To describe protein solubility in terms of "nitrogen solubility," one might refer to the extraction of nitrogen from protein and nonprotein sources, such as nucleic acid and free amino acids, in solubility experiments (Lam et al., 2018).

Protein solubility is influenced by a number of parameters, including solvent pH, ionic strength, temperature, and the composition of organic solvent (Damodaran et al., 2007). Solubility is enhanced at pH levels above and below the Isoelectric point (IP) because of the electrostatic repulsion caused by the positive and negative net charges on the protein surface (Hall, 1996). At its isoelectric pH, a protein's solubility is the lowest since it has a no net charge. The lowest solubility of pea protein isolates is found between pH 4 and 6, regardless of the extraction method or the cultivar of pea plant studied (Taherian et al., 2011; Withana-Gamage et al., 2011).

Protein solubilization often increases as temperature rises from 0–50 °C to a point where non-covalent bonds (e.g., hydrogen bonds) get disrupted and secondary and tertiary structures are eliminated (Hall, 1996).

2.4.2 Water-holding capacity

Water-holding capacity (WHC) is described as the volume of water that can be absorbed per gram of protein material (Joyce Boye et al., 2010). The shape of the protein matrix, particularly the size of the pores, has an impact on the association between water and protein (Hall, 1996). A higher electrostatic attraction toward water is seen by proteins that are greatly charged (Stone, Avarmenko, et al., 2015). Similarly, WHC has the smallest value at a protein's isoelectric pH due to the strong protein-protein bond. Salt ions bind water to proteins, hence WHC rises at low salt concentrations (Damodaran et al., 2007).

2.4.3 Oil-holding capacity

The quantity of oil that may be absorbed per gram of protein is characterized as the oil-holding capacity (OHC) or oil absorption capacity (Lin & Zayas, 1987). The aliphatic chains of lipids attach to the nonpolar side chains of amino acids, allowing them to interact. As a result, proteins with increased hydrophobicity have a higher proclivity to store oils (Sanjeewa, 2008; Withana-Gamage et al., 2011). The matrix structure of a protein, the kind of lipid contained, and the distribution and stability of lipids may all affect OHC levels (Hall, 1996).

2.4.4 Emulsification properties and stability

An emulsion is a dispersion or suspension of two immiscible liquids formed by mechanical agitation (Hall, 1996). Food emulsions are either oil-in-water (O/W) or water-in-oil (W/O) type, such as milk and butter, respectively (Alzagtat & Alli, 2002). The presence of electrostatic repulsive forces increases the stability of emulsions away from the protein's IP and at low ionic strength (Liu et al., 2010). It is possible to increase protein stability by using partly denatured proteins and more polar oils. This is because hydrophobic groups are exposed and less unraveling of proteins is required (Damodaran, 2005).

2.4.5 Foaming properties

When gas bubbles are dispersed inside a liquid (typically water) or solid continuous phase, they are referred to as foams. Creating foams may be accomplished by a variety of methods, including sparging (pushing gas into the liquid phase through an aperture), whipping (beating ambient air into the liquid phase), shaking, or pouring (such as a glass of beer) (Hall, 1996). The amount of interfacial area that may be generated by a protein is referred to as its foaming capacity (FC) (Damodaran et al., 2007). It is proportional to the average hydrophobicity of proteins and may be boosted by partial denaturation to enhance surface activity (Damodaran, 2005; Kinsella, 1981). At a protein's isoelectric pH, foams are the most stable due to their negligible electrostatic repulsion (JI Boye et al., 2010).

2.4.6 Gelation and viscosity

Gelation is among the most essential functional features of globular proteins since it is utilized to change the texture of food (Ikeda & Nishinari, 2001). One way to describe a protein gel is as a three-dimensional structure that is well defined, and it is constructed from protein molecules that are embedded in an aqueous solvent (Corredig, 2006). Heat treatment, pH, salts, pressure or shearing, and the presence of different solvents may all cause protein gelation (Culbertson, 2005). The vast majority of protein gels seen in food are produced with the use of heat treatment. Several studies have investigated heat-induced gelation of pea proteins, which has been shown to be influenced by a variety of variables such as cultivar, extraction technique, protein heterogeneity, solvent parameters, and heating procedure (O'Kane et al., 2004; Shand et al., 2007).

2.5 Protein Concentrate extraction method

Wet fractionation methods provide highly pure protein isolate products. However, as previously stated, these methods are substantially resource-dependent, and due to the hostile acidic environment, proteins experience denaturation through the process. The dry fractionation method is considered more sustainable because of its energy efficiency and high yield (Schutyser et al., 2015). The following section outlines the most widely utilized unit operations for running a dry fractionation process of pulse protein.

2.5.1 Dehulling

The process of dehulling pulses before milling and separating may have an effect on the fractions' physical qualities, chemical composition, and techno-functional properties (Fernando, 2017). The removal of hulls is referred to as the dehulling procedure (seed coats). The process of dehulling some pulses (such as dry peas and lentils) is easy, while it might be difficult for other pulses (dry beans) (Fernando, 2021; Narasimha et al., 2003). Dehulling pulses with loose seed coverings is best done using an attrition type dehuller, such as a hammer mill, which works by the use of impact force (Wang, 2005). On the other hand, abrasive dehullers are appropriate for dehulling pulses with more securely adherent seed coverings (Wang, 2005). Dehulling aids in the decrease of antinutritional elements such as soluble phenolics, which are largely found in the seed coat (Fernando, 2020). Pre-treatments are used to free the seed coat from the cotyledon. Pre-treatments such as soaking and tempering with water or oil are often used to facilitate dehulling during pulse milling (Fernando, 2021).

2.5.2 Milling

Dry separation of protein-rich fractions necessitates the use of finely powdered material. The milling phase must be carefully selected to breakdown the cotyledon into pieces without significantly harming the starch granules (Joyce Boye et al., 2010). Impact mills are typically used to crush pulses when particle size reduction is the primary goal (Wood & Malcolmson, 2021). Impact mills include centrifugal mills, pin mills, and hammer mills. Impact mills grind seeds by 'throwing' the seed against a screen with the blades, hammers, and pins (Fernando, 2020). Milling characteristics such as grinding force, rotor speed, sieve, and material's physical structure may affect the particle size distribution of the product (Fernando, 2020). The effectiveness of separating components such as carbohydrates and protein is strongly influenced by particle size (Pelgrom, Boom, et al., 2015b). As shown in figure 2.1, starch granules are the bigger particle in the cotyledon, with a diameter of around 20 µm, while protein bodies are only 1-10 µm (Schutyser et al., 2015).

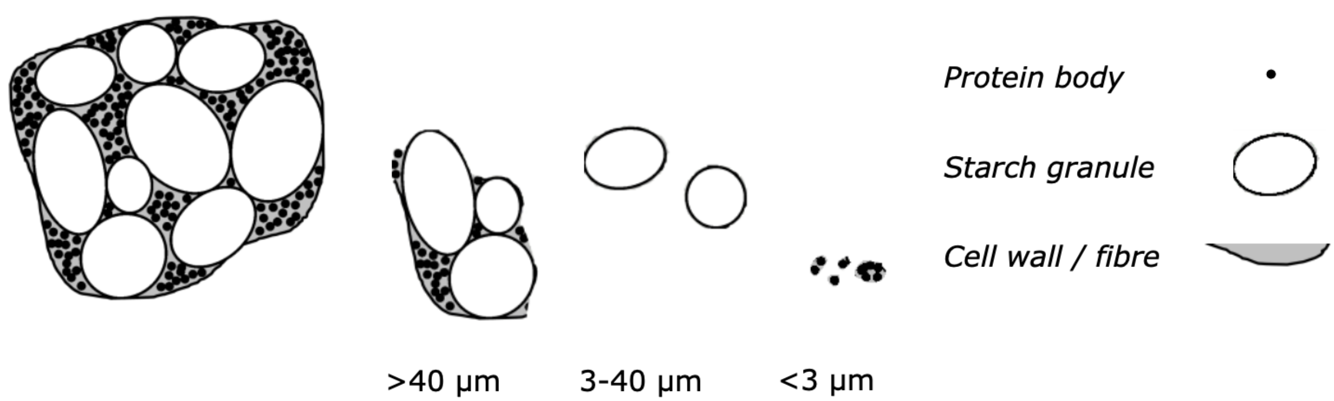

Figure 2.1: Microscopic view of starch granules and Protein bodies. Adapted from (Schutyser et al., 2015).

2.5.3 Air Classification

The most frequent method used for the production of flours that are rich in protein and starch from crops is air classification (Joyce Boye et al., 2010). Particles that have been ground are segregated according to the aerodynamic characteristics that have been derived from their density and particle size. In one phase of air classification, coarse and fine fractions are separated on the basis of an optimal set point of particle size. This point determines the foundation for separation. For most pulse protein-starch separations, the ideal setpoint is about 20 µm, which is slightly below the size of most starch granules (Schutyser & Van der Goot, 2011). Classifying with the help of air often requires the use of centrifugal air classifiers that are equipped with a rotor or wheel (Dijkink et al., 2007).

There is a direct correlation between the milling parameters and the effectiveness of the air classification (Pelgrom et al., 2013). In order to properly fractionate the components of a cell using air classification, the flour particles must be sufficiently fine and disaggregated. A faster milling speed may effectively separate the protein bodies from the starch granules. However, over milling may result in particles that are excessively fine, resulting in high van der Waals interactions between particles and poor flow behavior (Dijkink et al., 2007). Poor particle flow may cause particles to stick to the machine walls, reducing milling and air classification output (Pelgrom et al., 2014).

Another factor affecting air classifier separation efficiency is classifier speed (Pelgrom et al., 2014). Pelgrom et al. (2014) found that increasing classifier wheel speed decreased lupine flour particle size and boosted protein content in the fine fraction.

Air classification is an energy efficient process that does not need the use of any chemical reagents. However, one of the drawbacks of air classification is that certain particles, both fine and coarse, may be placed in the incorrect fraction (Lundgren, 2011).

2.6 Resource utilization efficiency

Resource utilization efficiency of food processing sectors is essential to achieve sustainable growth. To this end, scientists have devised a variety of methodologies, each with their own set of advantages and disadvantages. The following section discusses a number of commonly used methodologies and explains their benefits and slacks to conclude the most beneficial approach for this research.

Life Cycle Assessment (LCA) is one of the strategies that is used the most often. The goal of Life Cycle Assessment (LCA) is to analyze the environmental effects of the food supply chain from a systems viewpoint, suggesting improvement options (Hellweg & Milà i Canals, 2014). LCA provides tremendous power in the early stages of product and process design, when significant adjustments may still be possible. Companies use LCA to map the primary impact drivers of their entire product ranges. A LCA evaluation may be conducted in four phases, regardless of the system boundaries (Hellweg & Milà i Canals, 2014). The first step is a description of the goal and scope, which involves identifying the study's objectives and establishing system boundaries (Sharma et al., 2011). The second step, inventory analysis, combines inputs and outputs for each process in the life cycle and aggregates them throughout the whole system (Sharma et al., 2011). In the third step, life-cycle impact assessment (LCIA), emissions and resources are classified according to their effect categories and transformed to comparable impact units (Sharma et al., 2011). The last step involves interpreting the inventory and impact assessment data in order to answer the study's objectives (Sharma et al., 2011). While LCA possesses various advantages, Because of the vast quantity of collected and simulated data and the simplified modeling of complicated environmental cause-effect chains, it has substantial uncertainty (Sharma et al., 2011). More crucially, LCA is commonly being used to examine the efficiency of food-producing processes in terms of environmental impacts rather than resource utilization efficiency.

One of the most extensively used methods to assess resource utilization efficiency of the processes is Data envelopment analysis (DEA). M. J. Farrell published an article on The Measurement of Productive Efficiency in the journal of the Royal Statistical Society in 1957 (Mardani et al., 2017). This article served as the foundation for DEA. DEA arose from a research conducted by E. Rhodes under the guidance of A. Charnes and W. W. Cooper to assess the success of an educational program for underprivileged students in the United States (Mardani et al., 2017). The study compared the performance of school districts who participated in program follow through (PFT) to those that did not. Estimating the relative efficiency of schools with numerous outputs and inputs without pricing information led to the invention of the ratio variation of DEA, known by its authors' initials - CCR (Charnes, Cooper, and Rhodes). DEA is a technique for estimating the efficiency of homogenous organizational units, known as decision Making Units (DMUs), which employ the same inputs to achieve the same outputs (Mardani et al., 2017). The applications of DEA were used in a number of different ways in order to evaluate the activity of various objects, such as hospitals, universities, energy concerns, metropolitan regions, commercial businesses, and associated components of the activity of countries, places, and other such entities as can be seen in table 2.3.

Table 2:3: Summary of papers which utilized DEA methodology in non-food industries

Article No	Reference	Study area	Study objectives	Key findings
1	Sueyoshi and Goto (2018)	Environmental efficiency	A unique application of DEA for environmental evaluation based on non-radial and radial data was discussed	According to the findings of this research, the energy business had the best investment goal in terms of quantity of pollution reduction and ROA
2	Sueyoshi and Goto (2014)	Environmental efficiency	A novel use of the DEA radial technique to analyze business sustainability in Japan was presented	The findings of this article demonstrated that energy enterprises in Japan lack corporate governance capacities; moreover, the findings suggest that technological innovation might enhance energy sector performance
3	Bi et al. (2014)	Environmental efficiency	Environmental performance was measured using the Non-radial DEA framework	The DEA-based clustering model was discovered to be appropriate for connecting with input-output production aspects in this work. According to this research, 2005 is the greatest year for energy efficiency
4	Kim et al. (2011)	Environmental efficiency	Research was conducted using the DEA to examine environmentally friendly logistics in railroad mode switching	This study found that transportation costs were more important than other factors in the model
5	Giannoulis et al. (2014)	Economic and eco-efficiency	DEA was used to study the effectiveness of switchgrass cultural parameters for the	According to the findings of this study, the bale at 22 kg is the most expensive harvesting

			manufacture of pellets from four different N-fertilizations	procedure, and there was a decrease in efficiency scores as nitrogen levels rose
6	Robaina-Alves et al. (2015)	Economic and eco-efficiency	DEA was used to examine the resource efficiency problems in European nations	Ireland, Hungary, Slovakia, and Portugal were most efficient, while Italy, Denmark, Bulgaria, and Romania were least efficient
7	Lahouel (2016)	Economic and eco-efficiency	The DEA approach was used in French businesses as a benchmarking and monitoring tool for energy eco-efficiency	According to the findings of this article, three organizations were eco-efficient, and this eco-efficiency was more connected to environmental efficiency; also, the number of workers, company size, and turnover were negatively associated with eco-efficiency scores
8	Cui et al. (2014)	energy efficiency problems	Calculated energy efficiency in nine nations between 2008 and 2012 using DEA and Malmquist index	The findings of this article revealed that the most critical determinants of energy efficiency were management and technological indices
9	Apergis et al. (2015)	energy efficiency problems	DEA was used to assess the energy efficiency of OECD nations	This research discovered that capital-intensive nations were more energy efficient than labor-intensive one
10	Morfeldt and Silveira (2014)	energy efficiency problems	In the European Commission's steel and iron industry, DEA was used for calculating energy usage	According to the study's findings, energy usage overestimates energy efficiency gains in European steel companies

11	Wu et al. (2016)	energy efficiency problems	By giving a decomposition model for investigating energy inefficiency, DEA was used to assess energy efficiency	According to the findings of this investigation, energy congestion was the key driving reason behind energy inefficiency
12	Sueyoshi and Yuan (2015)	Sustainable energy	China's new policy path was evaluated for its social sustainability using DEA	According to the findings of this research, the Chinese government should endeavor to distribute economic resources in various cities in the northwest of China
13	Liu et al. (2015)	Energy performance	DEA was used to assess the performance of the wind power sector	This study discovered that the pace of expansion in wind power capacity implementation has a substantial impact on wind turbine performance in the manufacturing business
14	Chen (2015)	Economic and eco-efficiency	Analyzed China's ecological and economic indicators	According to the findings of this research, China's transition to an ecologically-based economic system is still fragile and in need of environmental rules that may provide long-term stability to the process
15	Baležentis et al. (2014)		Farms in Lithuania were analyzed using DEA to see how efficiency changes over time	The results of the clustering analysis indicated that the efficiency change routes particular to the examined sample varied in both their average levels and ranges.

3 Resource utilization efficiency assessment of pulse protein dry extraction processes using Data Envelopment Analysis (DEA)

Abstract

This study employed data envelopment analysis (DEA) technique to assess resource utilization efficiencies of extraction of pulse protein to design an optimized strategy for protein processing. With the help of linear programming, multiple inputs and outputs of a decision-making unit (DMU) were integrated into a relative efficiency score. Based on various return to scale, the results demonstrate that the mean value of pure technical efficiency for milling and air-classification unit operations are 0.98 and 0.89, respectively, confirming the milling's reasonably strong performance despite the lack of appropriate air classification efficiency in utilizing the inputs. These numbers indicate that 2 and 11% of all the input resources into the process could be reduced while maintaining the same output. Moreover, benchmarking results revealed that the ideal energy requirement for milling and air classification would be 3.24 Wh and 0.01 MJ, respectively for 0.5 Kg of mass input.

3.1 Introduction

The world population would be over 9 Billion by 2050 (Compton et al., 2018). Consequently, the demand for food is expected to increase by 60% (Compton et al., 2018). Food-producing sectors, particularly protein industries, strongly correlate with environmental effects through their high energy consumption (Compton et al., 2018). Thus, more animal-derived protein means more environmental side effects. Plant-derived proteins such as peas and other pulses have shown a great potential to meet the growing protein demand (Ren et al., 2021). Peas are of great interest due to their rich and various nutritious profile with high protein, vitamin, and fiber content (Ren et al., 2021). Different researchers studied the protein content of pulses, and they all reported a considerable protein content. Protein contents of pea, lupine, lentil, faba, mung and black bean have been found to be 24, 39, 28, 30, 22, and 23% respectively.

Protein extraction processes of pulses are generally categorized into two groups, wet and dry fractionation processes (Yang et al., 2021). Wet fractionation processes are extremely resource-dependent and consume a considerable amount of water, organic solvent, and energy (Adenekan et al., 2018). Water and organic solvents are used to solve the pulse's protein, and the energy is used to dry the final product. On the other hand, dry fractionation processes are more eco-friendly since they do not require water for protein solving and energy for dehydrating the final product (Xing et al., 2020). Hence, dry fractionation processes are of more interest to exploit for future large-scale protein production.

Researchers have developed various parametric and non-parametric methods to assess productive efficiency based on mathematical linear programming techniques. Data envelopment analysis (DEA), unlike parametric approaches, does not require assumptions to link inputs and outputs (Izadikhah, 2022; Seiford & Thrall, 1990). All data points are enveloped in the DEA technique in such a way that they all fall on or below the efficient border (Coelli, 1995; Singh et al., 2021) . DEA has been extensively used in the resource utilization efficiency of different food sectors. Kyrgiakos et al. (2021) tried to assess the cotton production efficiency in Turkey with the help of DEA and found that 42 of the 107 evaluated cotton farms (39.3%) are working effectively, while the average achieved score is 0.91. In a similar study Işgın et al. (2020) evaluated the input resources of cotton farms, and the results indicated that small-scale farmers utilize their cotton farming resources more effectively than medium- and large-scale producers. Singh et al. (2019) investigated the energy input-output connection in wheat farming using the rice-wheat and cotton-wheat cropping systems and findings demonstrated that energy input was much greater in wheat cultivated under a cotton-wheat cropping system due to irrigation water consumption. Masuda (2016) also evaluated the eco-efficiency of wheat growers in Japan with the joint methodology of Life cycle assessment and DEA. Adeyonu et al. (2019) and his colleagues examined sweet potato production efficiency in Nigeria and found that, access to credit enhanced farm technical efficiency by 3.5% while decreased farm scale efficiency by 1.9%. According to this study the three most important obstacles affecting output were labor scarcity, limited access to upgraded technology, and insect pest infestation. Grape production efficiency was investigated by Namdari et al. (2021) using both CCR and BCC models. It was discovered that the overall energy savings estimated to be 14.3% of total input energy. Yenihebit et al. (2020) evaluated the irrigated tomato production in Ghana's Upper East Region using an input-oriented DEA approach and observed that, on average, farmers operate at 97% of their maximum efficiency. Payandeh et al. (2021) employed a joint Data envelopment analysis and Life cycle assessment (LCA) to evaluate greenhouse gas emissions of farms and found 934 MJ could be saved per hectare.

DEA was also used by Li et al. (2021) to measure production efficiency of rice fields and found that most paddy fields might benefit from increased scale size. Energy utilization efficiency and environmental effects of poultry production in Isfahan, Iran, were investigated by Payandeh et al. (2017) and found that there is 10% excess energy use that could be saved. Jomthanachai et al. (2021) proposed a novel joint DEA and machine learning (ML) methodology for risk management where ML serves as a good approach for monitoring the impact of strategy adjustments on the expected variables. Even though researchers have covered the resource utilization efficiency of different food stocks, little attention has been given, to our knowledge, to pulses' protein, particularly the process of extracting protein from such legumes.

In light of the paucity of research on the aforementioned food sector, this study, focusing on dry fractionation process unit operations (milling and air classification), attempts to evaluate their resource utilization efficiency and recommend optimum input levels. This research will considerably aid pulse protein companies in evaluating their energy and raw material consumption performance.

3.2 Methodology

A gate-to-gate system boundary was considered for dry extraction methods since the goal was to find resource-consuming hot spots. Gate-to-gate is a partial DEA examining the limited value-added process in the entire production chain, which in the case of this research gate to gate is referred to as raw material and protein-rich products. Cradle-to-gate evaluations may also be constructed by linking gate-to-gate modules at a future stage in the production chain that is most relevant to each module. The dry fractionation procedures separate protein from starch and other elements by making use of the significantly smaller size of protein bodies in comparison to the size of starch granules. As can be seen in figure 3.1, the process of dry fractionation begins with a milling unit operation, during which the raw material is crushed down to a certain diameter. Then the fine flour is fanned in an air classier to split into protein-rich and starch-rich fractions.

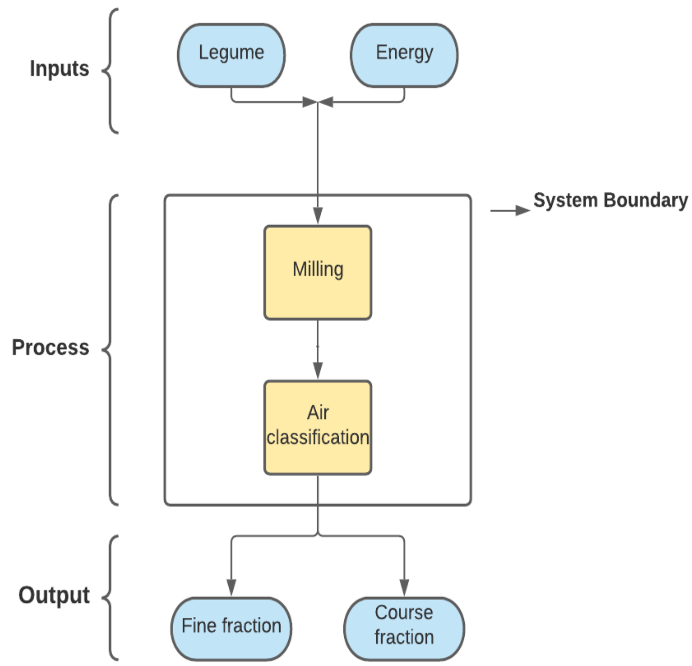

Figure 3.1: Dry fractionation unit operations and system boundary

3.2.1 Data collection

Data collection for the dry fractionation process was entirely literature-based. Two sets of scientific papers were used for this purpose—first, articles whose primary focus was on the yield and purity of the final product, and second, articles whose focus was on resource utilization of dry extraction methods. Tables 3.1 and 3.2 summarize the articles used in this study to gather and extract the required data for analyzing the resource utilization efficiency of milling and air classification, respectively.

Table 3.1: Dry fractionation data extraction resources (Milling)

Pulse	Milling specifications	Inputs	Outputs	Reference
Dry yellow pea	ZPS50 Impact mill, milling speed: 8000 rpm, classifier wheel speed 4000 rpm, air flow 40 m^3/h	Pea 0.5 kg Energy 70.3 Wh	Yield 0.36 Kg PSD $(D50)^{-1}$ 0.05	(Xie et al., 2022)
Pea	AFG100 Jet mill, milling speed: 8000 rpm, classifier wheel speed 2500 rpm, air flow 52 m^3/h	Pea 0.75 kg Energy 73.25 Wh	Yield 0.56 Kg PSD $(D50)^{-1}$ 0.03	(Pelgrom et al., 2013)
Pea	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 4000 rpm, air flow 52 m^3/h	Pea 0.75 kg Energy 57.54 Wh	Yield 0.54 Kg PSD $(D50)^{-1}$ 0.04	(Pelgrom et al., 2013)
Pea	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 3400 rpm, air flow 60 m^3/h	Pea 0.75 kg Energy 19.32 Wh	Yield 0.57 Kg PSD $(D50)^{-1}$ 0.02	(Pelgrom, Wang, et al., 2015)
Pea	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 6000 rpm, air flow 80 m^3/h	Pea 0.5 kg Energy 9.98 Wh	Yield 0.34 Kg PSD $(D50)^{-1}$ 0.05	(Pelgrom et al., 2014)
Lupine	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 2500 rpm, air flow 80 m^3/h	Pea 0.5 kg Energy 6.09 Wh	Yield 0.35 Kg PSD $(D50)^{-1}$ 0.01	(Pelgrom et al., 2014)
Pea	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 2500 rpm, air flow 46 m^3/h	Pea 0.5 kg Energy 7.96 Wh	Yield 0.44 Kg PSD $(D50)^{-1}$ 0.05	(Pelgrom et al., 2014)
Pea (Wrinkle)	Pin mill, milling speed: 5000 rpm, classifier wheel speed not stated, air flow not stated	Pea 0.75 kg Energy 260.7 Wh	Yield 0.65 Kg PSD $(D50)^{-1}$ 0.04	(Van der Poel et al., 1989)
Pea (Wrinkle)	Pallmann mill, milling speed: 5000 rpm, classifier wheel speed not stated, air flow not stated	Pea 0.75 kg Energy 48.58 Wh	Yield 0.64 Kg PSD $(D50)^{-1}$ 0.02	(Van der Poel et al., 1989)
Dry yellow pea	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 4000 rpm, air flow not stated	Pea 0.5 kg Energy 24.32 Wh	Yield 0.12 Kg PSD $(D50)^{-1}$ 0.06	(Geerts et al., 2017)
Dry yellow pea	impact mill, milling speed: 4000 rpm, classifier wheel speed not stated, air flow not stated	Pea 0.5 kg Energy 88.30 Wh	Yield 0.43 Kg PSD $(D50)^{-1}$ 0.05	(Fernando, 2021)
Faba bean	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 3500 rpm, air flow not stated	Pea 0.5 kg Energy 16.18 Wh	Yield 0.39 Kg PSD $(D50)^{-1}$ 0.05	(Dumoulin et al., 2021)
Mungbean	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed not stated, air flow not stated	Pea 5 kg Energy 139.1 Wh	Yield 4.78 Kg PSD $(D50)^{-1}$ 0.03	(Yang et al., 2022)
Mungbean (Dehulled)	ZPS50 impact mill, milling speed:4000 rpm, classifier wheel speed not stated, air flow not stated	Pea 5 kg Energy 43.56 Wh	Yield 4.78 Kg PSD $(D50)^{-1}$ 0.03	(Yang et al., 2022)
Lentils	ZPS50 impact mill, milling speed: 8000 rpm, classifier wheel speed 2000 rpm, air flow not stated	Pea 0.7 kg Energy 10.72 Wh	Yield 0.67 Kg PSD $(D50)^{-1}$ 0.02	(Funke et al., 2022)
Pea	ZPS50 impact mill, milling speed:8000 rpm, classifier wheel speed 5000 rpm, air flow not stated	Pea 0.5 kg Energy 3.24 Wh	Yield 0.44 Kg PSD $(D50)^{-1}$ 0.04	(Möller et al., 2021)
Faba bean (Dehulled	Alpine 100 UPZ pin disc mill, milling speed:17800 rpm, classifier wheel speed 5000 rpm, air flow not stated	Pea 0.6 kg Energy 35.22 Wh	Yield 0.48 Kg PSD $(D50)^{-1}$ 0.03	(do Carmo et al., 2020)
Lupine	ZPS50 impact mill, milling speed:8000 rpm, classifier wheel speed 4000 rpm, air flow 80 m^3/h	Pea 0.5 kg Energy 37.25 Wh	Yield 0.48 Kg PSD $(D50)^{-1}$ 0.03	(Wang et al., 2016)
Lupine	ZPS50 impact mill, milling speed:8000 rpm, classifier wheel speed 8000 rpm, air flow 80 m^3/h	Pea 0.5 kg Energy 13.76 Wh	Yield 0.26 Kg PSD $(D50)^{-1}$ 0.08	(Wang et al., 2016)

Black Bean	Hammer mill, milling speed: 16800 rpm, classifier wheel speed not equipped, 800 um sieve, air flow not stated	Pea 1 kg Energy 55.37 Wh	Yield 0.91 Kg PSD $(D50)^{-1}$ 0.01	(Fernando & Manthey, 2021)

Table 3.2: Dry fractionation data extraction resources (air classification)

Pulse	Air classification specifications	Inputs	Outputs	Reference
Pea	ATP50 air-classifier, classifier speed: 8000, air flow 52 m^3/h, 23 Celsius	Pea Flour 0.5 Kg Energy 0.012 MJ	Yield 0.12 Kg Purity 57.1 gP/100 g db	(Schutyser et al., 2015)
Pea	ATP50 air-classifier, classifier speed: 5000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.023 MJ	Yield 0.78 Kg Purity 51.1 gP/100 g db	(Pelgrom et al., 2013)
Pea	ATP50 air-classifier, classifier speed: 6000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.024 MJ	Yield 0.6 Kg Purity 53.7 gP/100 g db	(Pelgrom et al., 2013)
Pea	ATP50 air-classifier, classifier speed: 8000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.025 MJ	Yield 0.42 Kg Purity 56.5 gP/100 g db	(Pelgrom et al., 2013)
Lupine	ATP50 air-classifier, classifier speed: 7000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.024 MJ	Yield 0.12 Kg Purity 53.7 gP/100 g db	(Pelgrom, Wang, et al., 2015)
Lupine	ATP50 air-classifier, classifier speed: 13000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.027 MJ	Yield 0.06 Kg Purity 58.9 gP/100 g db	(Pelgrom, Wang, et al., 2015)
Pea	ATP50 air-classifier, classifier speed: 10000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.026 MJ	Yield 0.39 Kg Purity 55.6 gP/100 g db	(Pelgrom, Boom, et al., 2015b)
Pea	Alpine A 100 MZR classifier, classifier speed: 13000, air flow not stated, 15 Celsius	Pea Flour 1 Kg Energy 0.027 MJ	Yield 0.6 Kg Purity 65 gP/100 g db	(Van der Poel et al., 1989)
Pea	Classifier model not stated, classifier speed: 5000, air flow not stated, 15 Celsius	Pea Flour 1 Kg Energy 0.023 MJ	Yield 0.32 Kg Purity 43.9 gP/100 g db	(Fernando, 2021)
Lentil	ATP50 classifier, classifier speed: 7750, air flow not stated, 15 Celsius	Pea Flour 1 Kg Energy 0.050 MJ	Yield 0.35 Kg Purity 53.6 gP/100 g db	(Dumoulin et al., 2021)
Mungbean (Dehulled)	ATP50 classifier, classifier speed: 8000, air flow 52 m^3/h, 15 Celsius	Pea Flour 7.5 Kg Energy 0.19 MJ	Yield 2.4Kg Purity 45.7 gP/100 g db	(Yang et al., 2022)
Lentil (Dehulled)	ATP50 classifier, classifier speed: 6000, air flow 52 m^3/h, 15 Celsius	Pea Flour 2.5 Kg Energy 0.060 MJ	Yield 0.83Kg Purity 42.83 gP/100 g db	(Funke et al., 2022)
Lentil (Dehulled)	ATP50 classifier, classifier speed: 12000, air flow 52 m^3/h, 15 Celsius	Pea Flour 2.5 Kg Energy 0.067 MJ	Yield 0.54 Kg Purity 54 gP/100 g db	(Funke et al., 2022)
Pea	ATP50 classifier, classifier speed: 5000, air flow 52 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.023 MJ	Yield 0.41 Kg Purity 57.2 gP/100 g db	(Möller et al., 2021)
Pea	Minisplit air classifier, classifier speed: 12500, air flow 220 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.027 MJ	Yield 0.47 Kg Purity 38 gP/100 g db	(do Carmo et al., 2020)
Faba bean (Dehulled)	Minisplit air classifier, classifier speed: 15000, air flow 220 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.028 MJ	Yield 0.52 Kg Purity 48 gP/100 g db	(do Carmo et al., 2020)
Lupine	ATP50 classifier, classifier speed: 10000, air flow 80 m^3/h, 15 Celsius	Pea Flour 1 Kg Energy 0.026 MJ	Yield 0.33 Kg Purity 57.6 gP/100 g db	(Lie-Piang et al., 2021)

The energy requirements of the grinding process were calculated according to De Bakker (2014) and (Taylor et al., 2020):

Bond's law: $E=0.3162W_i\left[\frac{1}{\sqrt{L2}}-\frac{1}{\sqrt{L1}}\right]$ (3.1)

where, E is the net energy required for crushing and W_i is the work index. L1 and L2 equate to average particle size in feed and end product, respectively. Work indexes were determined by assessing the size reduction ratio of each sample throughout the milling process.

The energy required for the air-classification process was determined according to Eswaraiah et al. (2008) and Sun et al. (2021). To determine the energy requirements of air classifiers, a series of formulae must be used. To begin, the Flow Number (N_Q) should be computed using the Reynolds number, k_1, and the effective and maximum gap widths g(e)/g(max). Using the calculated value of the Flow number, the Power Number (Np) can be calculated. Finally, the actual energy consumption of the air classifier can be determined using the power number, N, D, and ρ.

$N_Q=K_1(\varphi)\ (N_{Re})^{0.85}\ (\frac{g(e)}{g(max)})^{0.1}$ (3.2)

$N_p=k_2(N_Q)^{-3.33}$ (3.3)

$P=N_p\ N^3D^5\rho$ (3.4)

Where $K_1(\varphi)=2.5*10^{-7}$, $k_2=2.2*10^{-8}$, $N_{Re}=ND^2\ \rho_a/\mu_a$, N is the wheel speed in the revolution per second, D is the diameter of the fan blade, ρ_a and μ_a density and viscosity of air, N_Q flow number, N_p power number and P power consumption.

3.2.2 Data envelopment analysis

Determination of productive efficiency may be done using a variety of parametric and non-parametric methodologies. Parametric algorithms estimate function parameters statistically through assuming a certain functional structure between inputs and outputs and units are compared to an average producer in such approaches. Non-parametric methodologies such as DEA, which was introduced by Charnes et al. (1978) are currently the most prevalent methodology. This method is a data-driven frontier analysis methodology that constructs a piecewise linear surface on top of the data points, which is considered an efficient frontier (Zhou et al., 2008; Q. Zhu et al., 2021). Unlike parametric approaches, DEA does not require a predetermined functional connection between inputs and outputs or prior knowledge of input and output weights (Bhunia et al., 2021; Mohammadi et al., 2011). Moreover, DEA allows using inputs in the form of different scales since the model adjusts with the weights (Bhunia et al., 2021; Zhou et al., 2008).

In DEA, an inefficient DMU can be made efficient by lowering the input levels while keeping the outputs constant (input-oriented) or by increasing the output levels while keeping the inputs constant (output-oriented). In this study, the input-oriented approach was deemed more appropriate because there is better control over the inputs than the outputs. Moreover, as a suggestion, input conservation for given outputs seems to be a reasonable logic (Bhunia et al., 2021; Charnes et al., 1978).

3.2.2.1 Technical efficiency

Technical efficiency (TE) is a measure of how well DMUs perform in comparison to other DMUs in a sample. There are multiple inputs/outputs associated with each DMU. TE of DMUs is determined by calculating the sum of weighted output values to the sum of weighted inputs and it is defined using the Eq (3.5). This ratio, in the ideal case, could be equal to one where all inputs are entirely converted to outputs. However, this hardly happens in actual processes due to a lack of efficiency, as it is shown blow.

$$TE_j = \frac{u_1 y_{1j} + u_2 y_{2j} + \cdots + u_n y_{nj}}{v_1 x_{1j} + v_2 x_{2j} + \cdots + v_m x_{mj}} = \frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \tag{3.5}$$

s.t.

$$\frac{\sum_{r=1}^{n} u_r y_{rj}}{\sum_{s=1}^{m} v_s x_{sj}} \leq 1 \qquad ; \forall j$$

$$u_r, v_s \geq 0 \qquad ; \forall r \ \forall s$$

where, TEj denotes the DMU's technical efficiency, x and y represent input and output, and v and u denote input and output weights, respectively. The number of inputs (s = 1, 2, …, m), the number of outputs (r= 1, 2,..., n), and the number of jth DMUs (j= 1, 2,..., k) are all represented by the letters s, r, and j.

This fractional approach is simply convertible to a linear programming model (Bhunia et al., 2021; Charnes et al., 1978). Following model, Eq (3.6) is linear input-oriented format of Eq (3.5) which is also known as multiplier form. If Eq (3.5) gets multiplied by $\sum_s v_s x_{sj}$ and all terms be drawn to the left side, the Eq (3.6) would be obtained. However, this linear programming model has an infinite number of solutions. To avoid this, one can impose the constrain $\sum_s v_s x_{sj} = 1$. It is worthy to mention that since $\sum_s v_s x_{sj} = 1$ has a positive value of one, the less than sign does not change during this transition.

$$\theta_j = \text{Max} \sum_r u_r y_{rj} \tag{3.6}$$

u_r, v_s

s.t.

$\sum_r u_r y_{rj} - \sum_s v_s x_{sj} \leq 0 \quad ; \forall j$

$\sum_s v_s x_{sj} = 1$

$u_r, v_s \geq 0 \quad ; \forall r \; \forall s$

where, θ is the technical efficiency. Model 3.6 is denoted as the input oriented CCR DEA model which assumes constant return to scale (CRS) (Avkiran, 2001). CRS assumes that large and small producers are equally efficient in converting inputs to output.

3.2.2.2 Pure Technical efficiency

The CCR model takes into account both technical and scale efficiency. Thus, the BCC model was established in DEA to determine the pure technical efficiency of DMUs, often known as local efficiency (Banker et al., 1984; Zhao et al., 2022). The BCC model is based on various return to scale (VRS) assumptions. The mathematical equation of the BCC model is similar to the CCR model with only one difference that the BCC model has a convexity constraint, $N1'\lambda = 1$. The following is an input-oriented linear programming model version of the BCC model (Coelli, 1995; Zhao et al., 2022).

$$\min_{\theta,\lambda} \quad \theta, \qquad (3.7)$$

s.t. (such that)

$-y_i + Y\lambda \geq 0$,

$\theta x_i - X\lambda \geq 0$,

$N1'\lambda = 1$

$\lambda \geq 0$,

Where θ is a scalar, $N1'\lambda$ is convexity constraint, N is N x 1 vector of constants, Y denotes output matrix, X denotes input matrix.

The efficiency score for the i-th firm will be the value of θ. This linear programming problem needs to be solved N times, one for each of the firms in the sample. θ ranges from 0-1 with 1 indicating that the firm is technically efficient according to (Farrell, 1957; Gao et al., 2022).

3.2.2.3 Scale Efficiency

Scale efficiency (SE) provides numerical data on scale characteristics. The ratio of the average product of a firm operating at a point to the average product of another firm operating at a technically ideal scale point can be understood as this scale efficiency metric. A scale efficiency score of one (1) indicates that the farm is scale efficient, whereas a value less than one (1) indicates that the farm is scale inefficient. To assess if DMUs are only "locally efficient" or "globally efficient," this research also analyzes scale efficiency by assessing the relationship between technical and pure technical efficiency, as shown below (Bhunia et al., 2021; Nassiri & Singh, 2009).

$$\text{Scale efficiency} = \frac{\text{Technical efficiency}}{\text{Pure technical efficiency}} \tag{3.8}$$

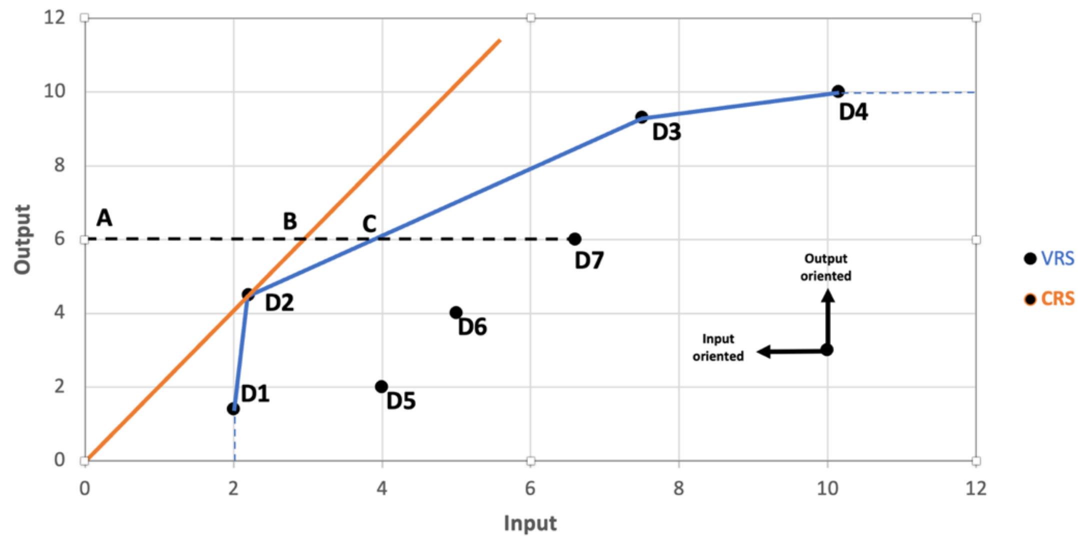

Figure 3.2: DEA demonstration of various efficiencies Figure 3.2, based on (Chauhan et al., 2006) and (Sueyoshi & Goto, 2018) results, is a simplified version of this research with only one input and one output giving visual information on three types of efficiency. In this figure, the envelope of the data set with constant returns to scale and various to scale is represented by the straight orange and blue lines, respectively. The DMU on orange line is efficient, with a technical efficiency of one. Likewise, the pure technical efficiency of all the DMUs on the piecewise blue line is one. Finally, the DMUs such as D2, which is on both orange and blue line, have a scale efficiency score of one.

Using the CRS assumption and Figure 3.2, it can be shown that AB is the optimal input necessary to produce output B. However, under VRS circumstances, the input requirement could be increased to AC to achieve B. The different efficiencies may now be defined as follows (Sueyoshi & Goto, 2018):

Pure technical efficiency = AC/AD,

Technical efficiency = AB/AD,

Scale efficiency = AB/AC.

3.2.2.4 Increasing return to scale and Decreasing return to scale

DMUs perform under three return to scale variations known as constant return to scale (CRS), increasing return to scale (IRS), and decreasing return to scale (DRS). The SE score has a flaw in that it does not reveal if a DMU is functioning under IRS or DRS. This flaw may be readily avoided using an additional analysis model called Non-increasing return of scale (NIRS) by changing the convexity constraint $\lambda=1$ of the VRS model with $\lambda\leq1$. (Scheel, 2000; Singh et al., 2021). Considering θ_{NIRS} as the efficiency score of the ith DMU based on the NIRS model, DMUs' return to scale status may be assessed by comparing θ_{NIRS} with θ_{VRS}:

1) If $\theta_{VRS} \neq \theta_{NIRS}$, DMU is increasing return to scale.
2) If $\theta_{VRS} = \theta_{NIRS}$, DMU is decreasing return to scale.

This study considers all three variations of return to scales analyzing DMUs. CRS, IRS, and DRS imply that a proportionate increase in all inputs leads to exactly the same, the more and the less proportionate increases in output, respectively.

3.2.2.5 DEA input/output analysis parameters

DEA software requires inputs and outputs parameters for analyzing the DMUs. For the milling unit operation research, legumes' mass, protein code, and energy were chosen as input metrics, while yield and $(D50)^{-1}$ were chosen as output indicators. Air classifiers were also analyzed based on flour mass, protein code, and energy as input metrics and purity and yield as output factors.

This study considered pea, lupine, lentil, faba, and mung bean for protein dry extraction efficiency. These legumes have varying quantities of protein, hence a "Protein Code" metric was created to enable a fair comparison. With almost 24% protein, Pea was chosen as a baseline and was given the protein code of 1. The protein code of other legumes was simply computed by dividing their average protein amount by 24.

The average particle size achieved after the milling process is a critical component in determining the milling process efficiency. In this study, D50, a particle size distribution parameter, was used to account for the diameter of the end product. The largest particle diameter below which 50% of the sample volume exists is known as D50, or also known as the median particle size by volume (Irham et al., 2018).

3.2.2.6 Super Efficiency

When the number of DMUs is minimal compared to the entire number of variables in the study, DEA lacks the ability to differentiate between efficient DMUs (Angulo-Meza & Lins, 2002; Xie et al., 2022). A variety of techniques are used to improve DEA's discriminating ability. In this study, the benchmark ranking approach is employed to rate DMUs. Efficient DMUs are ranked based on the number of times they appear in the reference set of inefficient DMUs. Those efficient DMUs that appear more frequently in the reference set are considered super-efficient for two reasons; First because they are efficient and that they are also close to input–output levels of inefficient DMUs in the group.

To estimate the resource utilisation efficiency of plant protein extraction processes, an input-oriented multi-stage data envelopment analysis technique was employed using DEAP software provided by the University of Queensland.

3.3 Results and discussion

3.3.1 Dry fractionation unit operations' analysis data points

Table 3.3 provides detailed information on every 45 DMUs' input/outputs. As previously stated, each DMU represents one milling process where the size reduction of the feed occurs. Each DMU has five different parameters that show the input/outputs values. Protein Code, mass input, and Energy are input parameters, while yield and D50 values are output parameters.

Each parameter has a specific unit. Mass input and Energy are based on Kg and Wh, respectively. Protein code scores do not have a unit since they are all a division of two numbers. In terms of outputs, the Yield is measured in kilograms. D50 is the particle size below which 50% of sample volume exists, and thus, $(D50)^{-1}$ also does not have a unit. Based on table 3.3, one can conclude that the input pea and the final desired diameter significantly affect the milling energy required.

Table 3.3: Milling DMUs' data points

DMU	Yield	D50 score	Mass input	Milling energy	Protein code
1	0.56	0.037	0.75	73.25	1
2	0.55	0.043	0.75	111.98	1
3	0.30	0.111	0.75	1142.06	1
4	0.65	0.038	0.75	51.01	1
5	0.55	0.043	0.75	57.54	1
6	0.12	0.100	0.75	415.37	1
7	0.58	0.023	0.75	19.32	1
8	0.48	0.002	0.5	1.28	1
9	0.36	0.018	0.5	6.27	1

10	0.33	0.033	0.5	8.98	1
11	0.34	0.050	0.5	9.98	1
12	0.48	0.002	0.5	1.28	1.67
13	0.36	0.017	0.5	6.09	1.67
14	0.33	0.025	0.5	9.10	1.67
15	0.35	0.050	0.5	10.03	1.67
16	0.44	0.052	0.5	7.96	1
17	0.36	0.056	0.5	8.42	1
18	0.33	0.125	0.5	14.94	1
19	0.65	0.040	0.75	260.70	1
20	0.65	0.040	0.75	50.07	1
21	0.65	0.040	0.75	48.58	1
22	0.65	0.025	0.75	48.58	1
23	0.65	0.025	0.75	51.69	1
24	0.12	0.067	0.5	24.32	1
25	0.43	0.058	0.5	88.30	1
26	0.37	0.058	0.5	141.37	1
27	0.40	0.050	0.5	16.18	1.29
28	4.78	0.033	5	139.10	0.96
29	4.78	0.033	5	43.56	0.96
30	0.67	0.029	0.7	10.72	1.21
31	0.45	0.040	0.5	3.24	1
32	0.52	0.033	0.6	33.33	1

33	0.53	0.036	0.6	34.24	1
34	0.48	0.033	0.6	35.22	1.29
35	0.50	0.026	0.6	37.25	1.2
36	0.45	0.017	0.5	3.52	1.67
37	0.36	0.025	0.5	6.51	1.67
38	0.34	0.050	0.5	11.96	1.67
39	0.26	0.083	0.5	13.76	1.67
40	0.91	0.016	1	55.37	0.96
41	0.91	0.016	1	41.12	0.96
42	0.91	0.017	1	41.12	0.96
43	0.94	0.014	1	144.19	0.96
44	0.92	0.017	1	44.95	0.96
45	0.94	0.014	1	92.51	0.96

Table 3.4 contains extensive information on each of the 32 DMUs' input/outputs. As in the case of air classification, each DMU is referred to as one fractionation process where fine flour is separated into one fine and one coarse fraction. Air classification, like milling, has five separate parameters that demonstrate the input/outputs values. The input parameters are Pea flour, Protein Code, and Energy, while Yield and Purity are the output parameters. Each parameter has its own unit. Pea flour and Energy are measured in Kg and MJ, respectively. Yield and purity are also calculated in Kg and g Protein/100 g dry basis.

Table 3.4: Air Classification DMUs' data points

DMU	Yield	Purity	Protein Code	Pea flour	Energy (10^{-2})
1	0.122	57.1	1	0.5	1.26
2	0.78	51.1	1	1	2.342
3	0.6	53.7	1	1	2.41
4	0.42	56.5	1	1	2.53
5	0.3	57.3	1	1	2.63
6	0.21	58.2	1	1	2.71
7	0.325	43.9	1	1	2.34
8	0.128	53.7	1.66	1	2.48
9	0.101	58.7	1.66	1	2.63
10	0.061	58.9	1.66	1	2.75
11	0.13	54	1.66	1	2.48
12	0.11	58.7	1.66	1	2.63
13	0.06	60	1.66	1	2.75
14	0.394	55.6	1	1	2.63
15	0.06	65	1	1	2.75
16	0.129	62.4	1	1	2.48
17	0.157	55.9	1	1	2.41
18	0.198	55.4	1	1	2.53
19	0.194	55.7	1	1	2.53
20	0.325	43.9	1	1	2.34
21	0.126	55.9	1	1	2.63
22	0.35	53.6	1.20	1	5.04
23	2.4	45.7	0.95	7.5	19.02
24	0.835	42.83	1.20	2.5	6.04
25	0.542	54	1.20	2.5	6.79
26	0.419	57.2	1	1	2.34
27	0.47	38	1	1	2.73
28	0.53	35	1	1	2.82
29	0.54	55	1.20	1	2.82
30	0.52	48	1.20	1	2.82
31	0.228	42.9	1	1	2.3
32	0.33	57.6	1.66	1	2.63

3.3.2 Dry fractionation DEA efficiency overview

The findings of the multi-stage input-oriented BCC and CCR DEA models are presented in this section. As shown in table 3.5, the average PTE score for milling unit operation is 0.98, indicating that the majority of DMUs are performing well, if not flawlessly. The minimal PTE value, on the other hand, was discovered to be 0.87, indicating that a DMU wastes significantly 13% of all inputs. DMUs were found to have a scale efficiency of 0.89 on average, indicating that they are working at 89% of their optimal scale and there is a great potential for improvement. Because TE had the largest standard deviation (SD) among the other efficiency scores, and PTE had the least SD value, it can be deduced that TE's SD is mostly made up of SE's standard deviation. (Maganga et al., 2018) calculated the technical efficiency of pigeon pea farms in Malawi and found that the range of technical efficiency was 22 to 84%, with a mean value of 53 percent. (Ekawati, 2019) also discovered that rice milling processes in Indonesia have an efficiency level of 90%.

In the same way, analysing table 3.5 might lead to inferences regarding to air classification unit operation. Average TE, PTE, and SE scores were found to be 0.81, 0.89, and 0.91, respectively. Unlike milling, TE's standard deviation is primarily composed of PTE's SD. The average PTE score was found to be 0.89, indicating that air classification unit operations are significantly inefficient and up to 11% of all the inputs could be saved while maintaining the same output. Furthermore, the lowest score determined for PTE was 0.6, meaning that a substantial fraction of DMUs squander up to 40% of input material. The average scale efficiency of DMUs was determined to be 0.91, meaning that they work on 91% of their optimum scale, or that they are 9% scale inefficient.

Table 3.5: Milling and Air classification efficiency performance summary

	Milling				Air classification			
Particular	Average	SD	Min	Max	Average	SD	Min	Max
Technical efficiency	0.88	0.1	0.53	1	0.81	0.15	0.55	1
Pure Technical efficiency	0.98	0.02	0.87	1	0.89	0.15	0.6	1
Scale efficiency	0.89	0.1	0.53	1	0.91	0.09	0.68	1

Figure 3.3 portrays the efficiency score distribution for milling and air classification, respectively. As illustrated, the VRS, orange bar, had the highest score in the last bin, implying good performance of milling equipment which is also in line with the calculated average PTE score provided in table 3.5. The PTE score was likewise in the 0.9-1.0 range, indicating that there is a decent room for improvement and reduction of inputs. In the 0.9-1.0 and 0.5-0.6 categories, scale efficiency had the greatest and lowest frequency values, respectively. This means that, despite the fact that a large number of DMUs are running at a scale that is relatively acceptable, there are still DMUs that are considerably scale inefficient, working at 60% of their optimal scale.

Unlike milling, PTE, or varied return to scale, had the largest frequency in the 0.9-1 category, indicating that the majority of the DMUs in this study were not fully efficient and could save up to 10% while providing the same output. PTE also had a considerable frequency value in the 0.6-0.7 and 0.8-0.9 groups, showing the extreme need to improve input resource utilization efficiency of air classifications. The 0.9-1 group had the highest scale efficiency score, indicating that air classification DMUs have a good scale performance. On the other hand, SE revealed a high frequency in the 0.7-0.8 group, demonstrating that certain DMUs are only operating at 80% of their ideal capacity.

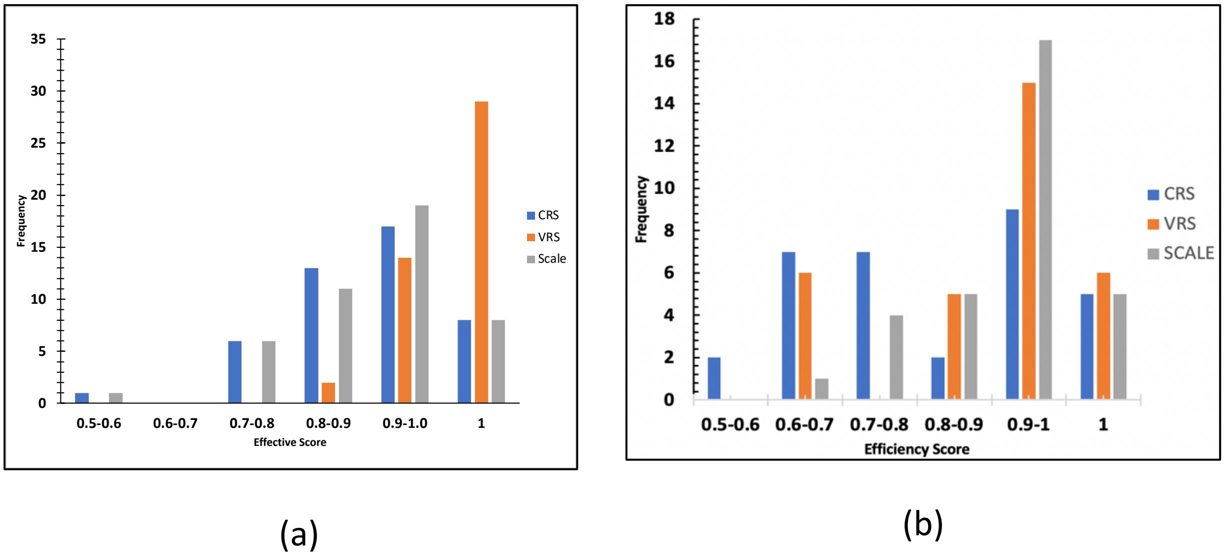

Figure 3.3: CRS, VRS, and scale efficiency score distribution. (a): milling, (b): air classification

3.3.3 Dry fractionation TE, PTE, SE scores

The performance of each milling DMU is documented in Table 3.6. Out of 45 processes (PRS), 8 (17%) and 29 (65%) of the DMUs were deemed efficient in terms of CRS and VRS, respectively. Out of 29 efficient DMUs, only 8 of them had a scale efficiency of unity, implying that they were globally efficient and operated at the most productive scale size, but the remainder of 21 efficient DMUs were only locally efficient due to their scale size disadvantage. The return to scale status of DMUs has also been included in table 3.6. Out of 45 DMUs, only 8 had a constant return to scale status, implying that a proportionate increase in all inputs leads to an exact proportionate increase in output. However, rest of the DMUs were following increasing return to scale scheme, implying that a proportionate increase in all inputs leads to more than the proportionate increase in output.

Table 3.7 summarises the performance of each air classification DMU. The average technical efficiency scores, assuming CRS and VRS, were calculated to be 0.81 and 0.89, respectively, implying a lack of acceptable performance of air classification DMUs. Only 5 (15%) and 6 (18%)

of the DMUs were identified to be efficient out of 32, assuming CRS and VRS, respectively. The status of DMUs' return to scale has also been provided in table 3.7. Unlike milling unit operation, air classification DMUs displayed all three kinds of returning to scale. DMUs number 1, 2, 15, 23, and 26 were constant return to scale, while DMUS 9, 10, 12, 13, 29, and 32 were decreasing return to scale implying that a proportionate increase in all inputs leads to a less proportionate increase in output and the rest of the DMUs were increasing return to scale.

Table 3.6: Milling efficiency assessment results

DMU	Technical efficiency		Scale efficiency	Return to scale
	CRS	VRS	(CRS/VRS)	
PRS01	0.813	0.981	0.829	Irs
PRS02	0.811	0.981	0.827	Irs
PRS03	0.889	0.995	0.894	Irs
PRS04	0.935	0.981	0.0.953	Irs
PRS05	0.811	0.981	0.827	Irs
PRS06	0.8	0.991	0.808	Irs
PRS07	0.814	0.983	0.828	Irs
PRS08	1	1	1	Crs
PRS09	0.762	1	0.762	Irs
PRS10	0.735	1	0.735	Irs
PRS11	0.801	1	0.801	Irs
PRS12	1	1	1	Crs
PRS13	0.761	1	0.761	Irs
PRS14	0.716	1	0.716	Irs
PRS15	0.821	1	0.821	Irs
PRS16	1	1	1	Crs
PRS17	0.86	1	0.86	Irs
PRS18	1	1	1	Crs
PRS19	0.939	0.981	0.957	Irs
PRS20	0.939	0.981	0.957	Irs
PRS21	0.939	0.981	0.957	Irs
PRS22	0.911	0.981	0.929	Irs
PRS23	0.911	0.981	0.929	Irs
PRS24	0.536	1	0.536	Irs
PRS25	0.998	1	0.998	Irs
PRS26	0.882	1	0.882	Irs
PRS27	0.917	1	0.917	Irs
PRS28	1	1	1	Crs
PRS29	1	1	1	Crs
PRS30	1	1	1	Crs
PRS31	1	1	1	Crs
PRS32	0.931	0.002	0.938	Irs

PRS33	0.954	0.992	0.962	Irs
PRS34	0.861	0.872	0.987	Irs
PRS35	0.88	0.895	0.983	Irs
PRS36	0.955	1	0.955	Irs
PRS37	0.77	1	0.77	Irs
PRS38	0.801	1	0.801	Irs
PRS39	0.743	1	0.743	Irs
PRS40	0.951	1	0.951	Irs
PRS41	0.951	1	0.951	Irs
PRS42	0.951	1	0.951	Irs
PRS43	0.982	1	0.982	Irs
PRS44	0.961	1	0.982	Irs
PRS45	0.982	1	0.982	Irs
Mean	**0.888**	**0.990**		

Table 3.7: Air Classification efficiency assessment results

DMU	Technical Efficiency		Scale Efficiency (CRS/VRS)	Return to scale
	CRS	VRS		
PRS01	1	1	1	Crs
PRS02	1	1	1	Crs
PRS03	0.998	0.999	0.989	Irs
PRS04	0.977	0.999	0.978	Irs
PRS05	0.954	0.998	0.956	Irs
PRS06	0.941	0.998	0.943	Irs
PRS07	0.768	0.998	0.77	Irs
PRS08	0.557	0.6	0.928	Irs
PRS09	0.6	0.601	0.998	Drs
PRS10	0.602	0.614	0.98	Drs
PRS11	0.56	0.6	0.933	Irs
PRS12	0.6	0.601	0.998	Drs
PRS13	0.613	0.684	0.896	Drs
PRS14	0.955	0.998	0.957	Irs
PRS15	1	1	1	Crs
PRS16	0.997	1	0.997	Irs
PRS17	0.908	0.997	0.911	Irs
PRS18	0.903	0.997	0.906	Irs
PRS19	0.906	0.997	0.909	Irs
PRS20	0.768	0.998	0.77	Irs
PRS21	0.886	0.997	0.889	Irs
PRS22	0.782	0.827	0.946	Irs
PRS23	1	1	1	Crs
PRS24	0.691	0.821	0.842	Irs
PRS25	0.753	0.82	0.918	Irs
PRS26	1	1	1	Crs
PRS27	0.712	0.998	0.713	Irs
PRS28	0.684	0.999	0.685	Irs
PRS29	0.848	0.945	0.897	Drs

PRS30	0.764	0.827	0.924	Irs
PRS31	0.73	0.998	0.731	Irs
PRS32	0.675	0.837	0.806	Drs
Mean	**0.817**	**0.899**	**0.912**	

3.3.4 Super efficiency and benchmarking

In order to develop the best dry fractionation practice for pea protein extraction, it is vital to identify the amount of the ideal input. The super-efficiency method explained in methodology has been equipped to determine the best practices, and the results are provided in table 3.8. DMU number 31 had the greatest frequency of milling unit operations at 30 times, followed by DMU number 18 at 17 times. Similarly, air classification PRS01 and PRS23 stood out among other efficient DMUs by being used 28 and 22 times as inefficient nearby DMUs, respectively. Considering highly frequent DMUs for both milling and air classification, one may determine appropriate input quantities for both processes. Thus, ideal inputs and outputs for milling and air classification are presented in table 3.9. Möller et al. (2021), utilizing a ZPS50 impact mill set at 8000 rpm and a classifier wheel set at 5000, outperformed alternative processes with the same function in terms of energy, raw material utilization, and added value, as established by referencing the publication from which these statistics were extracted. Similarly, tracing back to the efficient air classifier Berghout et al. (2015) using an ATP50 air-classifier set at 8000 with an air flow of 52 (m^3/h) produced the most significant results in energy, pulse flour utilization, and purity, among other experiments.

Table 3.8: Super Efficiency result

Milling			Air classification		
DMU No.	Frequency	Benchmark Rank	DMU No.	Frequency	Benchmark Rank
PRS31	30	1	PRS01	28	1
PRS18	17	2	PRS23	22	2
PRS42	17	3	PRS02	15	3
PRS08	14	4	PRS15	12	4
-	-	-	PRS26	3	5

Table 3.9: Milling and Air Classification ideal input values

	Output				Input			
Milling	Yield	Unit	D50		Mass input	Unit	Energy	Unit
	0.45	Kg	25		0.5	Kg	3.24	Wh
Air Classification	Yield	Unit	Purity	Unit	Pea Flour	Unit	Energy	Unit
	0.123	Kg	57.1	g/100g db	0.5	Kg	0.013	MJ

Figure 3.4 illustrates the correlation of the energy input and D50 score to the Constant return to scale technical efficiency of the milling processes. The X, Y, and Z axes represent energy, D50, and TE scores, respectively. Because the majority of the numbers are in the 0.95-1 range, it is concluded that the combined impact of energy and D50 score had a favorable influence on the TE score. This association is also observed when the single influence of energy on the TE score is considered, which is not the case when the solo effect of the D50 score is considered.

Figure 3.5 illustrates the correlation of the energy input and retained mass to the Constant return to scale technical efficiency of the air classification processes. The X, Y, and Z axes represent energy, retained mass, and TE scores, respectively. Poor retained mass was shown to be related with low TE scores. Green areas of the plot, which represent the 0.9-1 efficiency score, have spread throughout the graph. It is concluded that, although low mass retention may have a negative impact on CRS TE, greater values have no significant impact.

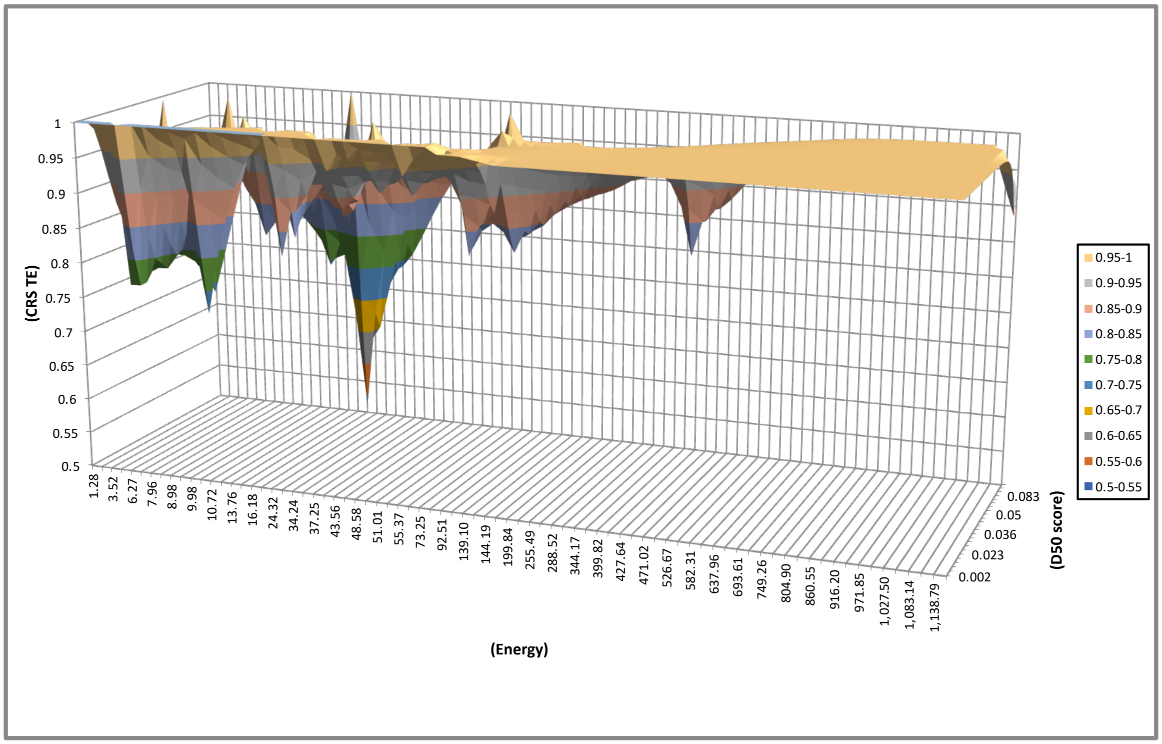

Figure 3.4: Milling energy and D50 correlation to efficiency score

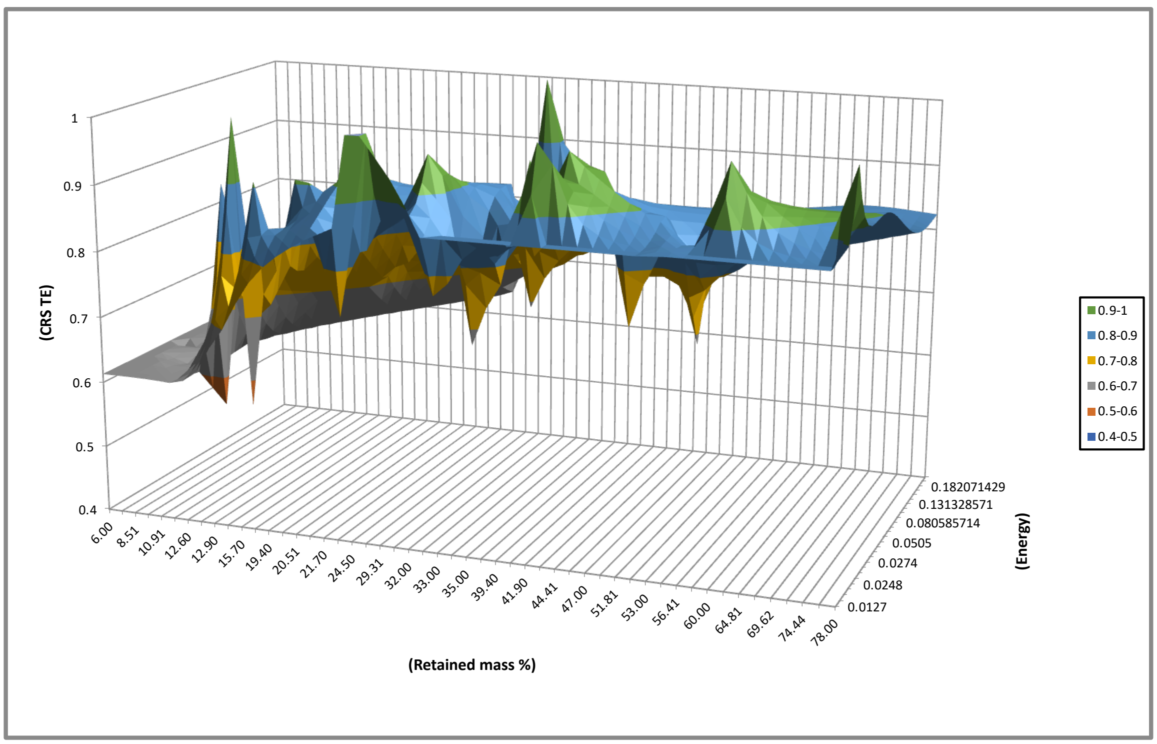

Figure 3.5: Air classification energy and retained mass correlation to efficiency score

3.4 Conclusion

A multi-stage input-oriented data envelopment analysis method was used to study the resource utilization efficiency of plant-protein dry fractionation processes. Various models have been equipped to determine Technical efficiency, Pure Technical Efficiency, and Scale efficiency. The results show that the milling consumes significantly more energy than the air classification unit. However, considering VRS analysis model for calculating Pure Technical Efficiency, air classification unit operation could benefit more from better energy utilization. The average PTE score for milling and air classification was 0.98 and 0.89, respectively, justifying the lack of acceptable efficiency in air classification and relatively good performance of milling. Milling scale efficiency values varied from 0.53 to 1, while air classification scale efficiency scores ranged from 0.68 to 1. Using super efficiency method, efficient DMUs were ranked based on number of times they were considered as peers for inefficient DMUs. The results indicated that DMUs number 31 and 1 with energy consumption values of 3.24 Wh and 0.013 MJ were the best practice for milling and air classification in terms of energy consumption, respectively.

Bridging Text

The previous study aimed to investigate the resource utilization efficiency of two primary pulse protein dry fractionation unit operations: milling and air classification. After thorough research and analysis, it was determined that air classification unit operation could benefit more from the optimization of consumed resources compared to milling.

It was also noticed that milling energy measurements, which were done by utilizing Bond's equation, are heavily reliant on knowing the work index range of that food commodity. By doing a comprehensive literature review, it was noticed that although there was some study on the work index of some agricultural materials, pulses were completely neglected. Thus, the next chapter was designed to address this gap and to build a framework for future studies investigating the work indexes of other food materials.

4 Parametric Modeling and Prediction of Energy Requirements for Pulse Milling

Abstract

Milling is a critical unit operation required in optimizing protein extraction from pulses. Selection of appropriate milling equipment depends on the energy required to reduce the particle sizes. The present study aimed to obtain data that will help address these research gaps for chickpeas, lentils, and peas and presents a pathway for future studies in evaluating the work index of pulses. All pulses' grinding properties were assessed by means of evaluating the energy consumed and work index with respect to different grinding times and mean particle size. The work index range for chickpeas, lentils, and peas was investigated through laboratory experiments to be 9.33 - 53.94 kWh/kg, 11.82 – 55.66 kWh/kg and 11.9 – 58.01 kWh/kg, respectively. The laboratory scale results were analyzed using linear and multivariable regression analysis. From here, mathematical equations were developed to predict the Bond's index and specific energy based on the characteristics of the pulse variety using regression analysis, which yielded good correlation coefficient values greater than 0.94. The proposed models, together with other product characteristics, could support decision-making, especially when exploring the sustainability of milling equipment for a desired size reduction.

4.1 Introduction

There has been an increase in demand for plant-derived protein due to increasing consumer concerns about the environmental damage associated with alternative animal-based products (Allotey et al., 2022; Detzel et al., 2022; Westhoek et al., 2014). The Food and Agricultural

Organization's support for sustainable diets as well as dietary recommendations in developed countries that advocate consumption of whole grains, pulses, fruits, and vegetable-based diets also encouraged the rising consumption of plant based proteins (Organization, 2019). Although many different plant-based protein sources such as cereals, nuts and fruits exist (Hurrell, 2003), legumes are the most frequent source because of their affordability, high protein content, and nutritional profile (Pelgrom, Boom, et al., 2015a). Pulses also have advantageous functional qualities for food preparations, including desirable solubility, emulsifying, foaming, gelling, and water/fat binding capabilities (Melendrez-Ruiz et al., 2019).

Pulses comprise carbohydrate components entwined in a protein framework and other biological components such as fats and fibres (Rajendran et al., 2018; Vogelsang-O'Dwyer et al., 2021). As a result the proteins are acquired through extraction processes that release the protein components, followed by protein separation (or recovery) and centrifugation stages (Schutyser et al., 2015). Protein isolation from pulses is often accomplished using dry and wet extraction (Fernando, 2021). Milling is an important unit operation required for the protein extraction. The protein can be separated from starch and other components by taking advantage of its smaller dimensions compared to starch granules' size (3-12 µm) (Assatory et al., 2019; Fernando, 2021). Since grinding is energy-intensive, measuring energy consumption and determining alternative energy-saving routes are required. (Goswami & Singh, 2003). It is challenging to identify the minimum energy necessary for a specific size reduction technique. Previous studies have highlighted factors that influence energy consumption during grinding of plant products. These factors include the ratio of pre-milling to post-milling particle size distribution (Ghorbani et al., 2010), moisture content (Jha & Sharma, 2010), hardness (Dziki, 2008), pre-treatment before grinding (Ngamnikom & Songsermpong, 2011), machine type, speed (Garg et al., 2010), and screen size (Garg et al., 2010). Energy requirement for grinding can be determined by considering work index and applying Bond's law. Chakkaravarthi et al. (1993) investigated grinding of carrot grits into powder using a hammer mill. The authors reported a work index in the range between 80 and 1610 $kWht^{-1}$. In a follow-up study, Walde et al. (2002) estimated the work index of bulk wheat samples to be between 40 and 80 $kWht^{-1}$. Similarly, Walde et al. (1997) estimated the Bond's work index for gum karaya samples to be between 478 - 757 $kWht^{-1}$. For grinding of pepper, work index was estimated as 4610 – 42220 $kWht^{-1}$ Murthy (2001) whereas for maize it was from 81 to 283 $kWht^{-1}$ during hammer millings. These studies indicate that the required work index for grinding operations depends on the material to be grinded. There is scare data on energy requirements for pulses. Given that plant-based protein is anticipated to contribute more than $4.5 billion to Canada’s GDP growth (Mehra), there is a need to investigate the potential energy requirements and opportunities to minimize energy consumption and improve efficiency of pulse milling operations. The goal of this study was seeking to identify the characteristics of dry peas, lentils and chickpeas during grinding by estimating the Bond’s work index. Additionally, this study investigates the particle size distribution of these pulses in response to varying grinding times and particle size distribution. Finally, we extended the conventional data collection and reporting from the laboratory experiment to include linear and multivariate models to predict the specific energy required and work index for grinding a variety of pulses. The remaining part of the paper proceeds as follows: section 4.2 presents the experimental, mathematical, and statistical approach employed in the study. Section 4.3 analyzes the data gathered and presents the results, statistical significance, and performance of the developed models. The final section draws together the various finding and implications of the study.

4.2 Experimented study

4.2.1 Method Approach

Figure 4.1 presents the method framework used in the study. A total of 45 samples of different varieties of pulses were obtained and milled for different times using a digital grinder. Particle size distributions of the milled samples were assessed using a scanning electron microscope (SEM). The samples were analyzed in triplicates. Based on the results from step two, theoretical milling models were used to estimate the milling characteristics such as Bond's index, Kick's constant, and size reduction ratios. The milling characteristics, pulse characteristics, and time were considered distinct parameters and state variables for projected predictions. The projected prediction was achieved with the help of linear and multivariate models, which were further compared with the experimental results. Once the model parameters were obtained, test statistics such as the R-Squared, Adjusted R-Squared and Sum of Squared Error (SSE) were applied to determine the reliability and predictive quality of the model. In addition to the quantitative tools other graphical tools were employed to validate the reliability of the regression models developed.

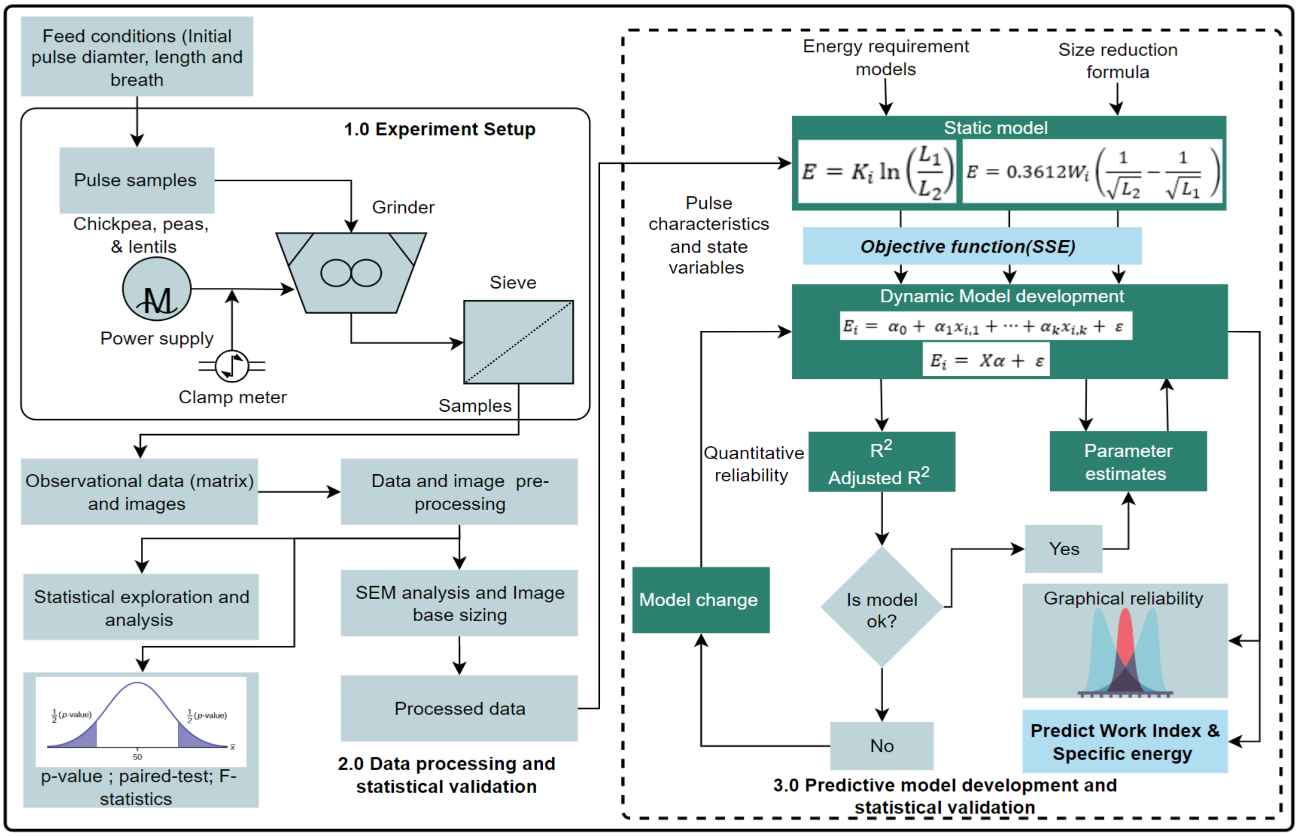

Figure 4.1: Theoretical framework applied to the milling and modelling of the milling process

4.2.2 Sample preparation

Three pulse varieties namely peas, lentils and chickpeas, were purchased from a nearby local store. The pulses were cleaned and the physical characteristics of each grain namely length, and diameters were measured using a Vernier Caliper with accuracy of $\pm$ 0.022 mm. For each pulse category, 20 seeds were randomly selected and measured. Sizes were recorded as average values $\pm$ standard deviations (SD). Milling was done using a digital laboratory grinder (CGOLDENWALL Commercial Electric Grain Grinder, Canada) with a capacity of 2.5 kg and a power rating of 3600 W. The pulse flours were prepared by grinding 450 g of a pulse at different grinding durations (15, 30, 60, 90, and 120 s). Each grinding flour preparation was done in triplicate. A clamp meter (KAIWEETS Digital Clamp Meter T-RMS 6000, USA) was used to measure the electrical current drawn during the milling operations. The electrical power for a single phase was estimated using the data collected by the clamp meter and the following Equation 4.1.

$$P = \frac{I \times V \times pf}{1000} \quad (4.1)$$

where P is the power (kW), I is the current (A), V is the voltage (V), and pf is the dimensionless power factor derived from the clamp meter. The ratio of the actual power flowing to the load to the apparent power in the circuit is known as the power factor of an electrical power system. The electrical energy consumed during the pulse milling was calculated as per Equation 4.2.

$$E = P \times t \quad (4.2)$$

where t is the milling time (s), and E is the energy (kWh).

4.2.3 SEM analysis and sample preparation

The milled samples were examined with an electron microscope (SEM TM3000 Hitachi High Technologies Corporation, Tokyo, Japan). Samples for imaging were prepared using a stub covered with a conductive copper tab where each tab was split in half so that 2 samples could be examined in one run. The height of the stub was maintained at 1 mm to provide the greatest image quality. The samples were applied to the tab and smeared to ensure particles adhered to the tab and shaken to remove non-immobilized flour. Images were taken at 500x magnification. Image analysis was conducted following the standard ISO 13322–1 (De Temmerman et al., 2014; Richter et al., 2012).

4.2.4 Seed hardness and particle size analysis

The seed hardness of all legume seeds was determined according to (Pelgrom, Wang, et al., 2015). Twenty cotyledons per legume were, flat-side down, compressed by a 57 mm cylindrical probe attached to a Texture Analyser (Instron 4502 universal testing machine, Canton, USA) equipped with a 500 N load cell at a crosshead speed of 25 mm/min for peas and chickpeas and 3 mm/min for lentil.

Image analysis method were developed to quantify particle sizes and distributions for starch and protein granules. The open source ImageJ software (Gomez-Perez et al., 2020) from the National Institute of Health (NIH) was used to process the SEM images. The image analysis was done following the recommendations of Stolze et al. (2019). Firstly, SEM images of the flour samples were uploaded to the ImageJ software. In the case of this study, in the Set Scale window was entered 200 into the “Known Distance” box and the “Unit of Measurement” box was set to µm and checked “Global”. It was found that automated thresholding could not adequately differentiate particle size distributions for starch and proteins. This was partly due to the agglomeration of protein particles, starch granules and insufficient size reductions of protein-starch matrixes. Hence, 2 separate analyses were conducted on each image by setting the threshold at 170 and 130 to delineate protein and starch particles, respectively. Then the 2 datasets were combined to obtain a comprehensive particle size distribution dataset for each milling condition. The data was analysed using Python 3.10.10. The average final particle size (L_2) for each sample was estimated from the particle size distribution profile. L_2 represents the average diameter of the pulse flour post-milling. The initial particle size (L_1) was measured before the milling operation. The energy requirements and Kick’s constants of each milling process were estimated using Equations 4.3 and 4.4

$$E = 0.3612 W_i \left(\frac{1}{\sqrt{L_2}} - \frac{1}{\sqrt{L_1}} \right) \tag{4.3}$$

$$E = K_i \ln \left(\frac{L_1}{L_2} \right) \tag{4.4}$$

where W_i is the Bond's work index and K_i is Kick's constant. Equation 4.3 was transformed into Equation 4.5 to estimate the work index of pulses.

$$W_i = \frac{W_W}{0.3612*m}\left(\frac{1}{\sqrt{L_2}} - \frac{1}{\sqrt{L_1}}\right)^{-1} \quad (4.5)$$

Where W_w is the power consumed, and *m* is the weight of the samples.

4.2.5 Statistical analysis

4.2.5.1 Typical statistical analysis

The Statistical Package for Social Science 13.0 (SPSS Version 13, IBM, Statistics Corp., IL USA) software was applied to calculate descriptive statistics measures such as the mean, median and standard deviation of the different samples. The data obtained from the SPSS analysis were reported as mean ± standard deviation. Pearson correlation analysis and the test-statistic (t) for the paired T-test ($p<0.05$) were also conducted to investigate the difference between the means of the various milled pulse characteristics. The comparison of means of the different characteristics was achieved by applying the paired-sample t-test with a 0.05 significance level.

4.2.5.2 Model variable and least square estimation

The pulse and milling characteristics included in the ordinary and multivariate linear regression include the variety, milling time, pulse diameter and size reduction ratio. The response variables considered are the specific energy and work index. Equation 4.6 presents the general form of the multivariate model employed in this study.

$$E_i = \alpha_0 + \alpha_1 x_{i,1} + \cdots + \alpha_k x_{i,k} + \varepsilon \quad (4.6)$$

Equation 4.6 was simplified to derive Equation 4.7. Equations 4.6 and 4.7 predicted the specific energy and work indexes, respectively.

$$E_i = X\alpha + \varepsilon \quad (4.7)$$

Where the variables ***E, α*** and ε can be expanded in the equation below:

$$E = \begin{pmatrix} E_1 \\ E_2 \\ \vdots \\ E_n \end{pmatrix} \quad x = \left(\begin{pmatrix} x_{1,1} & \cdots & x_{1,k} \\ \vdots & \ddots & \vdots \\ x_{n,1} & \cdots & x_{n,k} \end{pmatrix} \right) \quad E = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{pmatrix} \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \quad (4.8)$$

From Equation 4.8, the ordinary least squares error for each model parameter, thus ***α,*** can be estimated by calculating the residual vector, then consequently the squared length of this vector. This was achieved by employing the relations in Equations 4.9 (residual model) and 4.10 (sum of squared error model).

$$e = E - x\boldsymbol{\alpha} \quad (4.9)$$

$$SSE = \sum_{i=1}^{n} e_i^2 = e^T e = \|e\|^2 = (E - x\boldsymbol{\alpha})^T (E - x\boldsymbol{\alpha}) \quad (4.10)$$

However, since the ***α*** values estimated from Equation 4.9 through the squared length of the residual is zero, Equation 4.10 reduces to Equation 4.11 and 4.12, respectively.

$$\frac{dSSE}{d\alpha} = 0 \quad (4.11)$$

$$\hat{\alpha} = (x^T x)^{-1}(x^T E) \quad (4.12)$$

4.2.5.3 Model diagnostics

After estimating the parameters of the models, three commonly used statistical indices were used to assess the different models' estimation of the specific energy and work index. These include R-Squared (Equation 4.13), Adjusted R-Squared (Equation 4.14) and Sum of Squared error (Equation 4.12).

$$R^2 = \frac{[\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})]^2}{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2} \quad (4.13)$$

$$AdjR^2 = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - k - 1}\right] \quad (4.14)$$

Where X_i and Y_i are the observations and estimation values at the ith time step, respectively. $\bar{X}$ and $\bar{Y}$ are the average value of simulations and estimations, n is the number of samples, and k is the number of independent regressors. Aside from the quantitative tools, other graphical tools, such as the kernel density of the residuals, were employed to evaluate the predictive quality and reliability of the models.

4.3 Results and discussion

4.3.1 Particle Size Image results

Figure 4.2 shows the SEM micrographs of the pulse samples ground for 15 sec and 2 minutes. Starch granules can be seen as larger particles compared to smaller protein particles. Chickpea and pea flours have more starch to the protein matrix than lentil flour. Located around the larger irregular shaped starch particles are discernible micro-spherical structures, representing protein matrix disrupted during milling. Smaller particles seen around the spherical structures might be minerals and fibre components of the different pulses. The results corroborate the work of Tyler et al. (1981), who reported on the effect of seed harness on high starch-protein agglomerates in legumes. Also, Ma et al. (2011) reported a high concentration of carbohydrates in chickpeas and peas as opposed to lentils. Again, Figures 4.2 (e) and (f) show high concentrations of spherical structures of protein matrix in lentils compared to chickpeas and peas. This supports previous work by JI Boye et al. (2010), who reported higher protein content in Lentils (25.78 w/dw%) than chickpeas (22.62 w/dw%) and peas (19.00 w/dw%) after milling. The SEM profile provides a more reliable approach to visualize the protein-starch distribution of each sample.

.

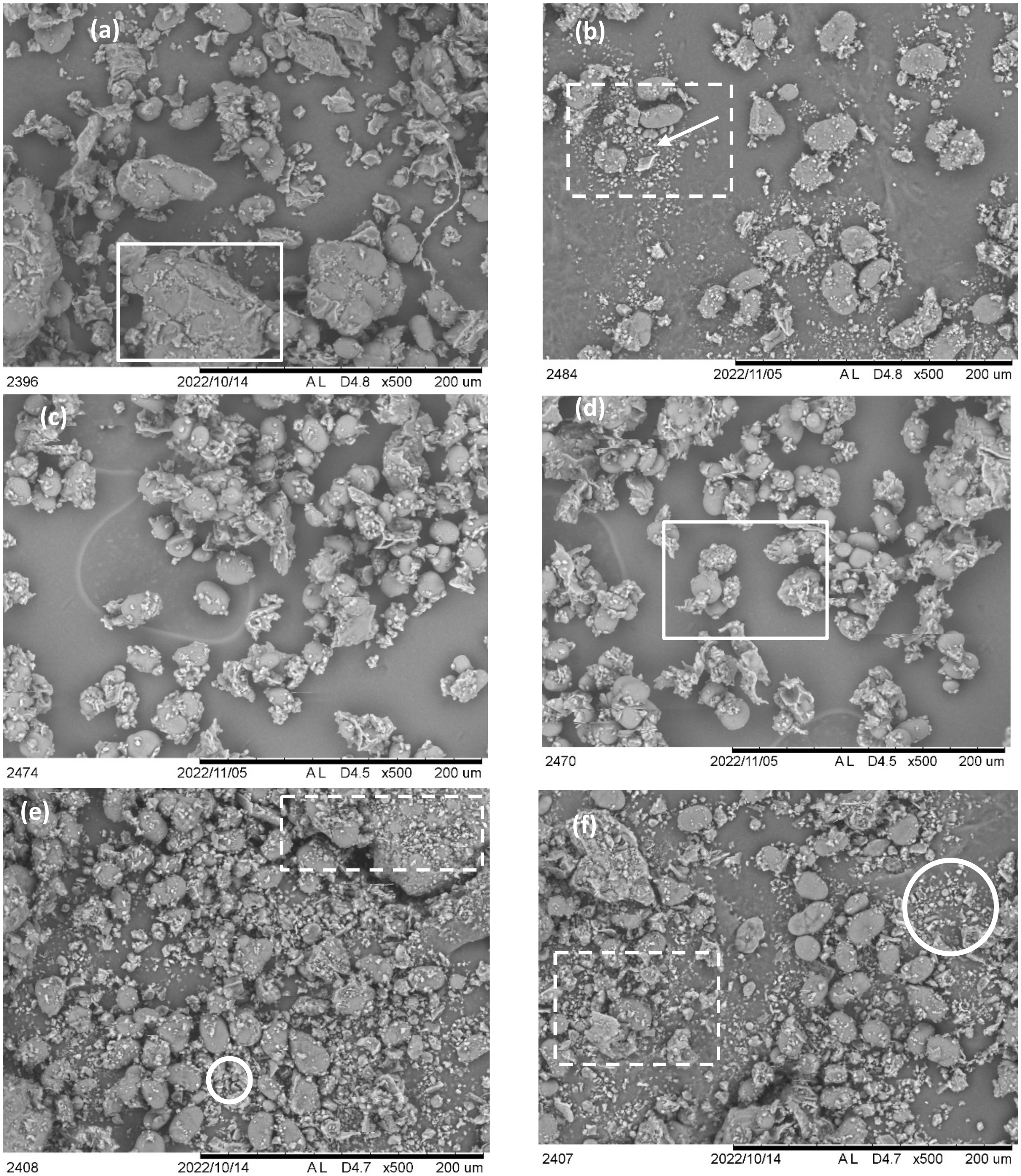

Figure 4.1: SEM images for pulses after grinding for 15 sec and 2 min for starch protein clusters (a) peas flour after 15 sec, (b) peas flour after 2 min, (c) Chickpeas flour after 15 sec, (d) Chickpeas flour after 2 min, (e) Lentils flour after 15 sec, (f) Lentils flour after 2min.

4.3.2 Grinding data for selected pulses

Table 4.1 presents the Bond's work index and Kicks constant range calculated for each pulse variety using Equations 4.1 to 4.3. The data shows that a decrease in final product diameter corresponded with an increase in energy requirement. Additionally, increasing grinding time yielded finer particles and a greater bond index. The average flour diameter ranged from 10.21±0.14 µm to 41.88±1.53 µm, 11.08±1.06 µm to 42.00±4.04 µm and 9.45±1.0 µm to 40.52±2.26 µm for Peas, Lentils and Chickpeas samples respectively. Interestingly, all flour diameters ranged between 10.2 to 42.00 µm, with lentils and peas having similar average particle sizes of 21.32 µm. Again, it can be observed that the first 15 sec of grinding corresponded to a lower specific energy requirement for each flour sample and a smaller particle size. Table 4.1 shows a reduction of 62.23% (15 to 30 s) and 60.48% (30 sec to 1 min) for lentil flour samples. Similar observations were made for Peas samples with a reduced rate of 60.76% (15 to 30 s) and 62.76% (30 s to 1 min) recorded. However, 65.5% (15 to 30 s) and 91.62% (30 s to 1 min) particle reduction rate was observed for Chickpeas. The maximum reduction size occurred in the first 30 sec, while the contrary was observed between 1.50 to 2 min of grinding. Thus, the size reduction rate gradually decreased beyond 1 min of grinding. Overall, an average reduction rate of 43.42% was observed for pulse samples as the particle diameter decreased, higher specific energy was required. Perhaps the most interesting aspect of Table 4.1 is that chickpeas samples had a larger feed diameter than peas and lentils; however, this resulted in a finer particle size across all time intervals during milling.

Specific energy requirements between 15 s to 2 min increased by a factor of 8.05, 7.7 and 10.2 for peas, lentils and chickpea samples, respectively. The observed energy trend in samples could be due to the energy required for granular breakage within the first minute of grinding. Again, as particle size reduced, their surface area increased, hence, the higher specific energy required for size reduction. The results suggest that higher specific energy is required during chickpea milling. This is probably due to the initial pulse diameter, which was observed to be 9.31 mm as opposed to 6.78 mm and 6.67 mm for lentil and pea samples, respectively. This observation from this study corroborates the work of Dziki (2008), who reported an increase in specific energy for granular breakage wheat kernels. Indira and Bhattacharya (2006) reported lentils having the highest surface area and the number of particles compared to cowpea, black gram, green gram and Bengal gram pulses upon grinding. In the same study, coarse and fine ground particles ranged between 860 to 75 μm and 210 to 45 μm.

The results regarding the hardness of all three pulses is also presented in table 4.1. Chickpeas were found to be the hardest, with 326.65 (N), followed by peas, with 190.92 (N). Lentils had the least hardness with 129.49 (N), which explains why lentils had the lowest specific energy as compared to peas and chickpeas. Pelgrom, Boom, et al. (2015b) also investigated the hardness of these three pulses which found to be 210, 197, 31 (N) for peas, chickpeas, and lentils, respectively. The difference in hardness values found in this study and Pelgrom, Boom, et al. (2015b) can be explained by the differences in cultivars grown in Canada compared to ones cultivated in Netherlands.

Table 4.1: Grinding data for Peas, Lentils and Chickpeas

Pulse sample	Initial product diameter	Grinding time, min	Specific Energy, E (kWh/kg)	Final particle size (μm)	Kick's constant (kWh/kg)	Bond's work index (kWh/kg)	Hardness (N)

	(mm)						
Pea	6.67	0.25	18.29±0.85	41.88±1.53	3.61	11.90-	190.92 ±
	6.67	0.5	41.73±0.62	25.89±1.99	7.52	58.00	72.38
	6.67	1	81.93±4.95	16.14±1.28	13.60		
	6.67	1.5	120.47±4.95	12.50±1.15	19.19		
	6.67	2	165.79±9.23	10.21±0.14	25.58		
Lentil	6.78	0.25	17.86±0.58	42.00±4.04	3.51	11.82-	129.47 ±
	6.78	0.5	36.98±1.29	25.38±0.63	6.62	55.66	16.41
	6.78	1	77.75±5.08	17.54±1.29	13.05		
	6.78	1.5	119.85±3.12	13.24±0.44	19.21		
	6.78	2	155.50±12.38	11.08±1.06	24.23		
Chickpea	9.31	0.25	14.48±1.22	40.52±2.26	2.66	9.33-	326.65 ±
	9.31	0.5	37.98±0.64	25.21±0.86	6.43	53.949	58.74
	9.31	1	81.19±6.40	15.49±1.62	12.69		
	9.31	1.5	122.62±4.50	12.35±1.56	18.51		
	9.31	2	163.27±3.47	9.45±1.0	23.69		

4.3.3 Particle size distribution

Figure 4.3 presents the density plots obtained from the SEM images for the pulse varieties. In Figures 4.3 (a), (b) and (c), we observe that in each time interval, flour samples exhibit varying particle size distribution. Again, sharp peaks were observed at 1.5 min for all samples and at 2 min for chickpeas and peas. This corresponded to high volumes of particles within the range of 12-14 µm for all samples at 1.5 min of grinding (Figure 4.3 (d)). Also, at 2 min, high particle volumes were observed within the 8-11 µm for chickpeas and peas (Figure 4.3 (e)). Again, we observe that the curves for reduction streams for all samples overlap after 1 minute of grinding. This is clearly seen around 13 µm for peas and lentils and 11 µm for chickpeas. This is probably due to the similar feed particle size between peas (6.67 µm) and lentils (6.78 µm). Moreover, it is clear from Figure 4.3 that the density plots for all samples during the milling process were skewed to the right, thus demonstrating a more significant number of particle distributions within varying particle size intervals for all samples. For example, in the context of peas, a greater number of particles were distributed between 7-10.5 µm, 10-12.5 µm, 13.5-17.5 µm, 22-28 µm and 37 – 45 µm for milling at 0.25 min to 2 min, respectively.

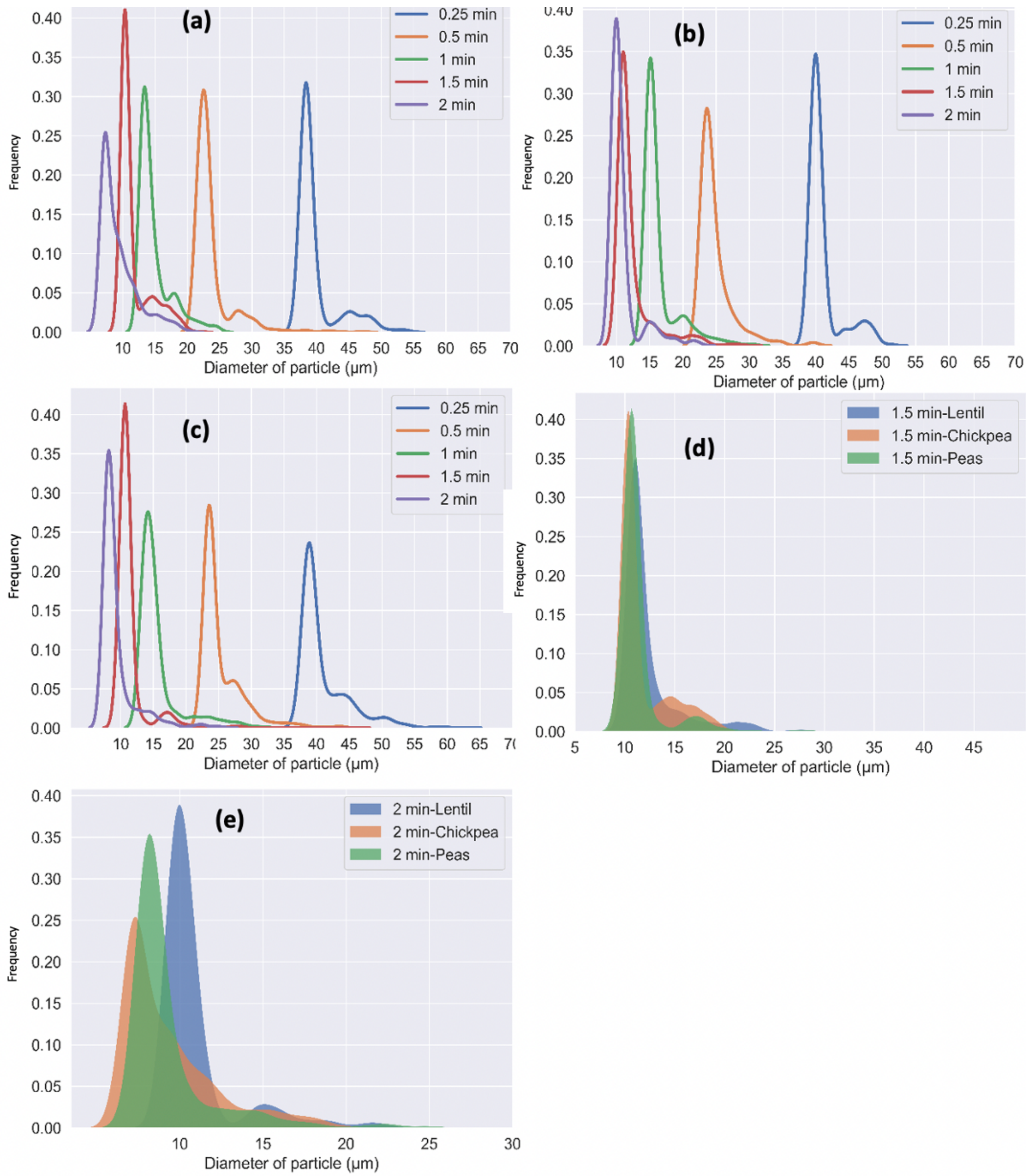

Figure 4.3: Density plot across the flour streams derived from the SEM (a) chickpea, (b)lentil and (c) peas.

4.3.4 Statistical significance analysis

Tables 4.2 to 4.4 present the paired t-Test, which compares the means of product diameter with the work index, specific energy, and size reduction ratio for peas, chickpeas, and lentils. Table 4.2 shows a strong negative correlation between product diameter and specific energy requirements (corr =-0.891, p=0.001), size reduction ratio (corr =-0.930, p-value<0.001), and work index (corr =-0.047, p=0.047). Again, the relationship between size reduction ratio, work index and specific energy demonstrates a positive correlation with (corr>0.900 and p-value<0.001) for all instances. This implies a high statistical significance between the milling characteristics at a 95% confidence interval.

Table 4.2: Paired sample t-test of the effect of product diameter on work index, specific energy, and size reduction ratio at 95% confidence interval for milling of peas samples.

					Significance	
Pair	Corr.	Means difference	t	df	One-Sided p	Two-Sided p
$D_{product} - E_{specific}$	-0.891	-64.32	-3.768	14	0.001	.002
$D_{product} - RR_{size}$	-0.930	-383.2	-7.485	14	<0.001	<.001
$D_{product} - W_{index}$	-0.921	-12.62	-1.798	14	0.047	0.094
$D_{feed} - E_{specific}$		-78.97	-5.546	14	<0.001	<0.001
$D_{feed} - RR_{size}$		-397.86	-8.239	14	<0.001	<0.001
$D_{feed} - W_{index}$		-27.27	-6.737	14	<0.001	<0.001
$RR_{size} - E_{specific}$	0.985	318.88	9.283	14	<0.001	<0.001
$W_{index} - RR_{size}$	0.977	-370.58	-8.357	14	<0.001	<0.001
$E_{specific} - W_{index}$	0.993	-51.7	5.053	14	<0.001	<0.001

**where $D_{product}$ is the diameter of the product; D_{feed} is the diameter of the feed; $E_{specific}$ is the specific energy; RR_{size} is the size reduction ratio; and W_{index} is the work index.

The sample means for the different characteristics differ by 64.32 and 383.2 for the diameter of product-specific energy and size reduction ratio, respectively. The smaller p-value obtained implies that the effect of product diameter on size reduction ratio and specific energy is statistically significant. On the contrary, the two-sided for the product diameter and work index (p-value of 0.094> 0.05) relationship between product diameter and work index indicates statistical insignificance between the two flour and milling characteristics. Again, it can be inferred that the observed absolute difference of means of 12.62 indicates the probability of overlap at a 95% confidence interval.

Table 4.3: Paired sample t-test of the effect of product diameter on work index, specific energy, and size reduction ratio at 95% confidence interval for milling of Lentils samples.

Pair	Corr.	Means difference	t	df	Significance One-Sided p	Two-Sided p
$D_{product} - E_{specific}$	-0.883	-59.74	-3.638	14	0.001	0.003
$D_{product} - RR_{size}$	-0.922	-367.83	-7.831	14	<0.001	<0.001
$D_{product} - W_{index}$	-0.902	-11.36	-1.626	14	0.063	0.126
$D_{feed} - E_{specific}$		-74.80	-5.465	14	<0.001	<0.001
$D_{feed} - RR_{size}$		-382.37	-8.670	14	<0.001	<0.001
$D_{feed} - W_{index}$		-26.43	-6.401	14	<0.001	<0.001
$RR_{size} - E_{specific}$	0.990	307.562	10.051	14	<0.001	<0.001
$W_{index} - RR_{size}$	0.983	-355.94	-8.887	14	<0.001	<0.001
$E_{specific} - W_{index}$	0.993	48.38	5.036	14	<0.001	<0.001

**where $D_{product}$ is the diameter of the product; D_{feed} is the diameter of the feed; $E_{specific}$ is the specific energy; RR_{size} is the size reduction ratio; and W_{index} is the work index.

Similar trends are observed for lentils and chickpeas, as presented in Tables 4.3 and 4.4. However, in this case, we observe a two-sided p-value 0.063 >0.05 and a p-value (0.065> 0.05) for the relationship between product diameter and size reduction ratio for lentil samples and chickpeas, respectively. Again, there is a lower probability of finding a statistical difference between the means of product diameter and size reduction ratio, with an absolute means difference of 11.36 and 11.33 for lentils and chickpeas, respectively.

Table 4.4: Paired sample t-test of the effect of product diameter on work index, specific energy, and size reduction ratio at 95% confidence interval for milling of Chickpea samples

Pair	Corr.	Means difference	t	df	Significance One-Sided p	Two-Sided p
$D_{product} - E_{specific}$	-0.903	63.31	-3.655	14	0.001	0.003
$D_{product} - RR_{size}$	-0.913	11.33	-7.396	14	<0.001	<0.001
$D_{product} - W_{index}$	-0.932	571.64	-1.607	14	0.065	0.130
$D_{feed} - E_{specific}$		74.6	-5.133	14	<0.001	<0.001
$D_{feed} - RR_{size}$		22.62	-7.823	14	<0.001	<0.001
$D_{feed} - W_{index}$		582.93	-5.468	14	<0.001	<0.001
$RR_{size} - E_{specific}$	0.976	51.98	8.415	14	<0.001	<0.01
$W_{index} - RR_{size}$	0.942	560.31	-7.933	14	<0.001	<0.001
$E_{specific} - W_{index}$	0.985	508.33	4.958	14	<0.001	<0.001

**where $D_{product}$ is the diameter of the product; D_{feed} is the diameter of the feed; $E_{specific}$ is the specific energy; RR_{size} is the size reduction ratio; and W_{index} is the work index.

4.3.5 Model Analysis

4.3.5.1 Relationship between work index and size reduction ratio

A linear regression model was employed to derive a relationship between the work index and size reduction ratio for the different pulses. Figure 4.4 presents a linear relationship based on the ordinary least squares methods. The models in Figure 4.4 were derived from data in Table 4.1.

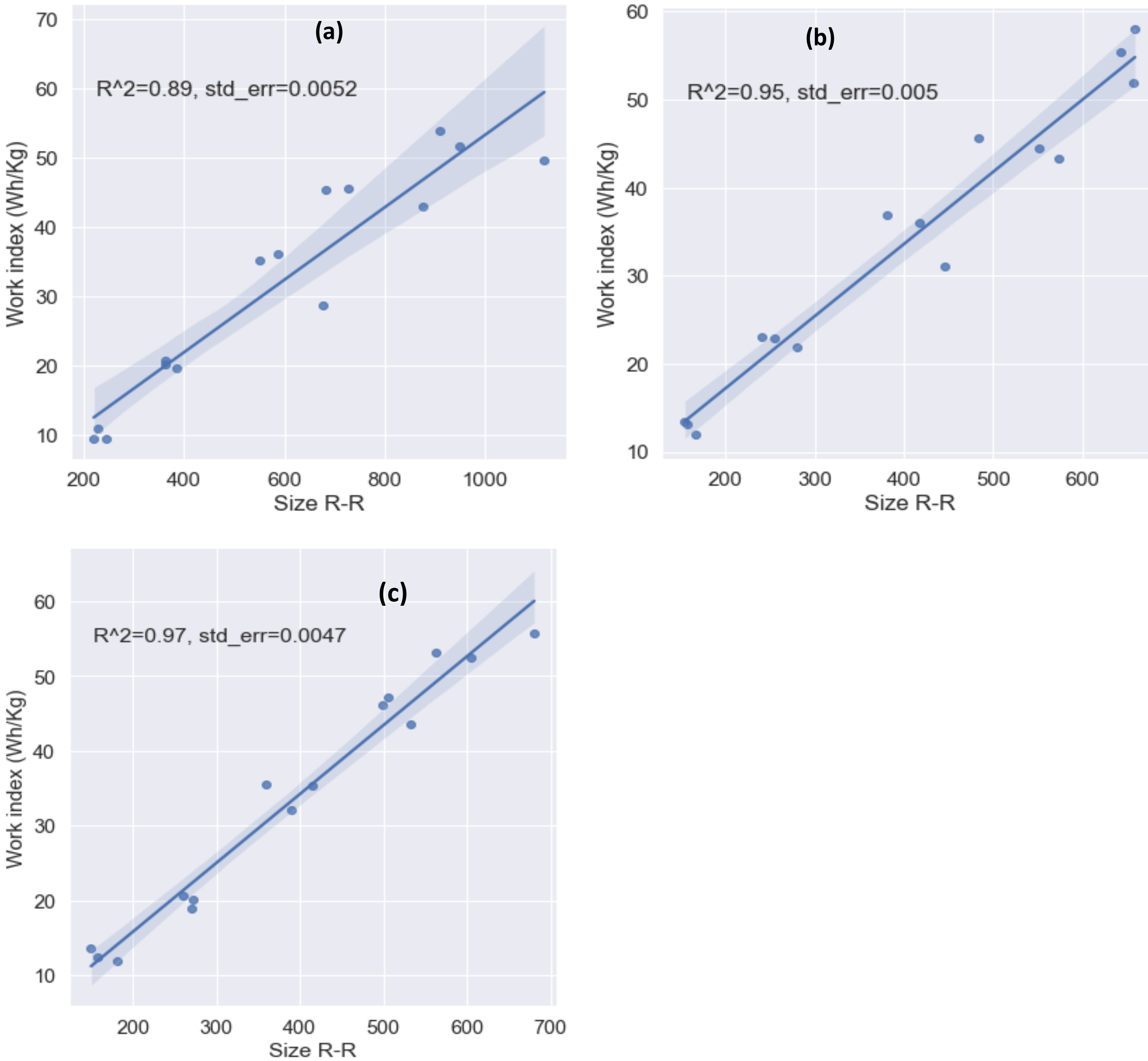

Figure 4.4: Linear regression model fitting of work index against size reduction ratio (a) chickpea, (b) peas and (c) lentil

The model describes the relationship between the size reduction ratio and the work index with R-squared values between 0.887 to 0.965 and an Adjusted R-squared ranging from 0.878 to 0.965. The following equations were fitted with the R-squared of 0.887, 0.967, 0.955 and adjusted R-squared of 0.968, 0.965, 0.951 for chickpea, lentils and pea respective.

$$W_i = 39.83 + 10.52\alpha_{R-R,lentil}, \quad p < 0.05 \qquad (4.15)$$

$$W_i = -26.57 + 3.46\alpha_{R-R,chickpea}, \quad p < 0.05 \qquad (4.16)$$

$$W_i = 0.81 + 0.08\alpha_{R-R,pea} \quad p < 0.05, \qquad (4.17)$$

The above equations help to estimate the work index of chickpeas, peas and lentils for a given size reduction ratio. The work index can then be employed to explore other characteristics of the milling processing.

Table 4.5: Model parameters and statistical characteristics for predicting work index

	Estimate	Standard Error	t-stat	p-value	R-squared	Adj R^2	F-stat
Chickpeas							
Intercept	0.966	3.389	0.285	0.780	0.887	0.878	102
$x_{work\ index}$	0.052	0.005	10.098	<0.001			
Lentil							
Intercept	-2.572	1.986	-1.295	0.218	0.967	0.965	383.1
$x_{work\ index}$	0.092	0.005	15.572	<0.001			
Pea							
Intercept	0.807	2.195	0.368	0.719	0.955	0.951	273.3
$x_{work\ index}$	0.082	0.005	16.533	<0.001			

4.3.5.2 Relationship between work index, product diameter and time

Again, to improve the linear models above to capture more state variables, a multivariate model was developed. The multivariable linear regression method captures the relationship between each product's energy requirement, size reduction ratio and time. Equation 4.18 to 4.20 presents the multiple linear regression equations and show the regression coefficient α_0, the intercept and quadratic coefficients of x_1 and x_2 for the different pulse varieties.

$$E_{chickpea} = -7.765 + 77.043x_{Time,chickpea,} + 0.018x_{R-R,chickpea,} \qquad (4.18)$$

$$E_{lentil} = -16.266 + 50.191x_{Time,lentil,} + 0.116x_{R-R,lentil,} \qquad (4.19)$$

$$E_{peas} = -2.159 + 81.165x_{Time,pea,} + 0.006x_{R-R,pea,} \qquad (4.20)$$

Moving on, Table 4.6 presents the characteristics of Equations 4.18 to 4.20. From the table, it can be observed that an R-square and Adj R^2 value of 0.997 was recorded for chickpea samples. Similarly, the R-square and Adj R^2 of 0.993 and 0.992 were observed for lentil samples. Interestingly, the ANOVA results with p-values <0.05 for lentils and chickpeas indicate that the quadratic models are significant and the goodness of fit. However, conflicting p-values observations were made for samples of lentil pulse. Despite a good R-square and Adj R^2, the p-values observed for the Lentil characteristics were (<0.001, 0.886). The models developed in this section are useful in exploring the effect of characteristics such as milling time, pulse variety, and particle diameter on the specific energy requirement during milling.

Table 4.6: Significant levels of factors in determining.

	Estimate	Standard Error	t-stat	p-value	R-squared	Adj R^2	F-stat
Chickpeas							
Intercept	-7.765	2.747	-2.826	0.015	0.997	0.997	
x_{time}	77.043	6.237	12.353	<0.001			
x_{R-R}	0.018	0.014	1.271	0.228			
Lentil							
Intercept	-16.266	4.979	-3.267	0.007	0.994	0.993	1054
x_{time}	50.191	9.406	5.336	<0.001			
x_{R-R}	0.116	0.036	3.179	0.008			
Peas							
Intercept	-2.159	5.408	-0.399	0.697	0.994	0.993	931
x_{time}	81.165	12.268	0.616	<0.001			
x_{R-R}	0.006	0.043	0.147	0.886			

4.3.5.3 Model diagnostics for validity

Although the model fittings presented in Figure 4.4, Tables 4.5 and 4.6 demonstrate a good prediction of the experimental data, it is not enough to make a complete decision on their application to forecasting the work index and energy requirement during the milling of pulses. Thus, the decision to apply the developed models was extended to include the residual distribution of the model outputs against the experimental data. Figure 4.5 presents the plot of the residuals from the multivariate models in Section 4.3.5.2 as kernel density plots overlayed with the normal mean and standard deviation curve. From Figure 4.5 (a), (b) and (c), we observe that the residual plots for all three cases closely map the normal probability distribution plot. Furthermore, in Figures 4.5 (e), (f) and (g), we observe a reasonable distribution with the mean close to the median for each model, thus indicating a symmetric relationship. However, in Figure 4.5 (e) and (g), we observe two outliers that the adopted regression models do not explain.

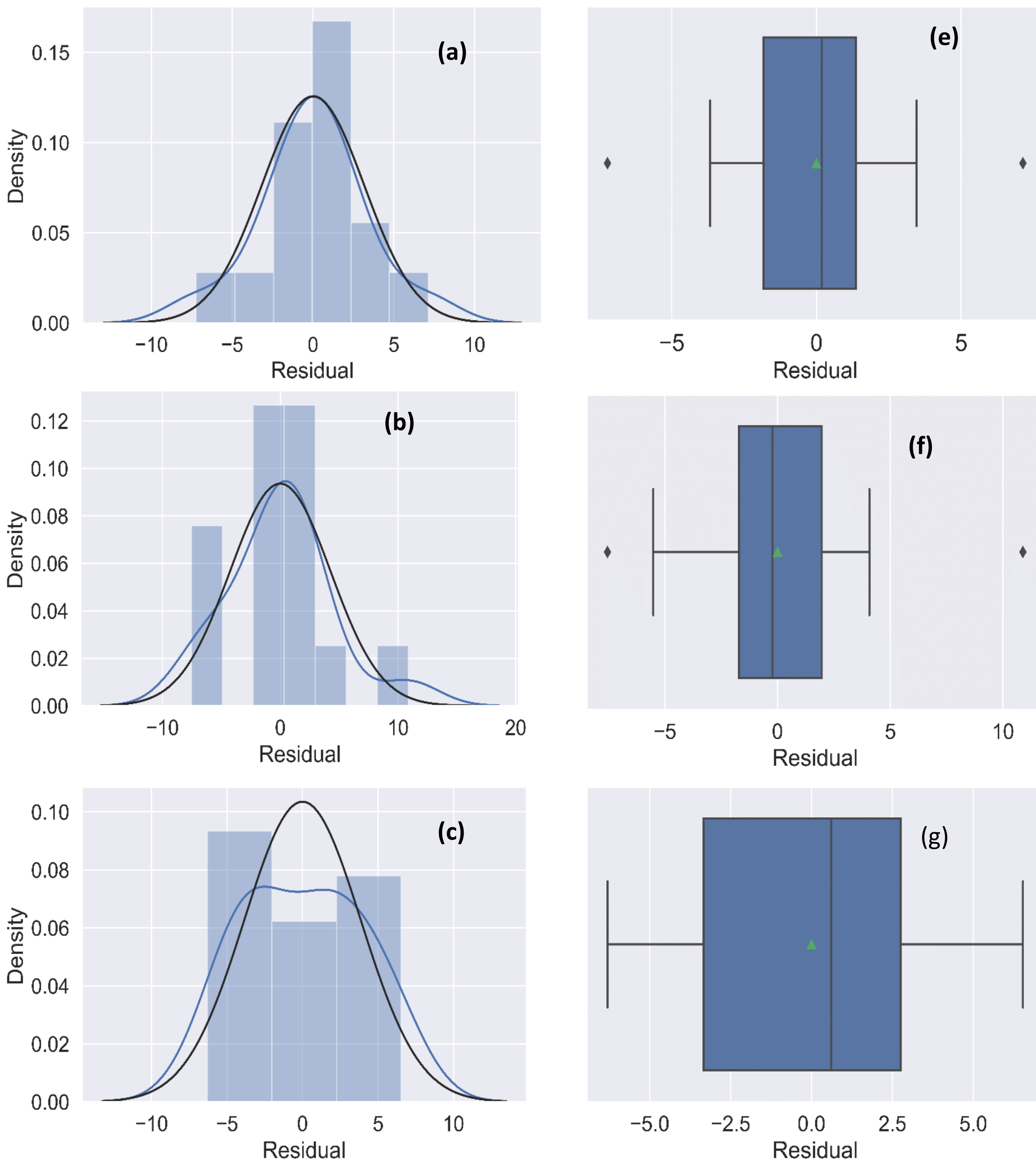

Figure 4.5: Distribution of residuals from multivariable modelling (a) chickpea, (b) peas and (c) lentil

4.4 Implications and industrial relevance of the study

With the rise in awareness and consumer desire to transition to high-quality plant protein, researchers and industries would explore advanced, efficient and sustainable pathways for protein extraction from pulses. In this regard, the current study complements earlier studies by providing a model-based approach to determine the work index and energy requirements during the milling of pulses. With estimates of the energy requirement and work index determined, researchers and industry partners can select the appropriate milling equipment needed to achieve the desired grinding results for a given pulse variety. Additionally, the energy requirement could be extended to explore the sustainability of milling equipment. It could also serve as a criterion along with protein content, yield and other external factors to support the selection of an optimal pulse for milling.

4.5 Conclusion

This study set out to augment the conventional data collection and reporting from the laboratory experiment with linear and multivariate models to predict the specific energy required and Bond's work index for grinding various pulses. In addition, the study also examined the particle size distribution and the relationship between the means of flour characteristics. The Bond's work index of the pulse samples was estimated to be within 11.90-58.00 kWh/kg, 244.94-1118.99 kWh/kg and 156.87-604.28 kWh/kg for chickpeas, lentils and peas. The Bond's Work Index correlated strongly with the particle size ratio and the specific energy requirement with a correlation coefficient < 0.940 and $p<0.001$. Thus, indicating a statistical significance between the results. The results of the investigation show that linear models could accurately characterize the relationship between the work index and specific energy requirements with an R-squared of 0.970, 0.967, 0.955 and adjusted R-squared of 0.887, 0.965, 0.951 for chickpea, lentils, and pea respective. Extending the model to include time, the multivariate models fitted with an R-squared value of 0.997, 0.944 and 0.944 for chickpeas, lentils, and peas. The present study adds to the growing body of research by laying the foundation for estimating the work index and energy requirements for a desired product diameter. Further studies could explore the application of the model to the design of wet and dry fractionation configurations during protein extraction.

5 Summary, conclusions and suggestion for future studies

5.1 Summary and conclusion

Demand for plant-based protein has increased, owing primarily to the rise in vegetarianism. Because of their low cost, high protein concentration, and useful qualities in meal preparation, legumes are the most frequently used plant-based protein. To satisfy the growing demand for protein fragments, research is being done to discover more effective separation and utilization techniques. Thus, this research provided a commendable comprehensive evaluation approach that employed Data Envelopment Analysis to evaluate the resource utilization efficiency of commercial used dry extraction pulse protein processes and to suggest optimal input quantities.

According to the findings, grinding uses considerably more energy than the air categorization device. However, when using the VRS analytical approach to calculate Pure Technical Efficiency, the functioning of an air classification machine may profit more from improved energy usage. The average PTE score for milling and air classification was 0.98 and 0.89, respectively, indicating a dearth of adequate efficiency in air classification and reasonably excellent milling performance. Milling scale efficiency levels differed from 0.53 to 1, while air classifying scale efficiency ratings spanned from 0.68 to 1. According to the findings, the DMUs number 31 (ZPS50 impact mill set at 8000 rpm and a classifier wheel set at 5000) and 1 (ATP50 air-classifier set at 8000 with an air flow of 52) with energy consumption values of 3.24 wh and 0.013 MJ were the best practices for grinding and air categorization, respectively, in terms of the amount of energy consumed.

The purpose of this study was also to determine the grinding features of dry peas, lentils, and chickpeas by calculating Bond's work index constant and examining the particle size distribution of these pulses in reaction to various grinding periods using the ImageJ software tool. The post-milling output width varied from 45 to 8 (μm) based on the milling time, and the specific energy rose from 13 to 175 as the grinding time increased, which was found to be compatible with other papers. To achieve a more reasonable number for future experiments, the work index was linked with the size reduction ratio, and the suggested formulae for peas, lentils, and chickpeas had R square factors of 0.95, 0.96, and 0.88, respectively.

5.2 Suggestion for future studies

1. The model created in this research is relevant to the small-scale food industry; perhaps a larger model with the same structure could be designed for the larger scale food industry incorporating a more complex procedure.
2. Other variables, aside from resource utilization, could be used to promote sustainability in the food industry. This research only looked at resource management. Other research could find additional variables and develop a model that includes the processing component (s).
3. A future research could be based on a model that includes an output-oriented strategy or a combined input and output focused approach.
4. The predictive model for the work index can be further investigated by considering the intrinsic properties of pulses, including moisture content, cultivar, and hardness.

Bibliography

Acikgoz, E., Ustun, A., Gul, I., Anlarsal, E., Tekeli, A., Nizam, I., Avcioglu, R., Geren, H., Cakmakci, S., & Aydinoglu, B. (2009). Genotype x environment interaction and stability analysis for dry matter and seed yield in field pea (Pisum sativum L.). *Spanish Journal of Agricultural Research*, *7*(1), 96-106.

Adenekan, M. K., Fadimu, G. J., Odunmbaku, L. A., & Oke, E. K. (2018). Effect of isolation techniques on the characteristics of pigeon pea (Cajanus cajan) protein isolates. *Food science & nutrition*, *6*(1), 146-152.

Adeyonu, A. G., Balogun, O. L., Ajiboye, B. O., Oluwatayo, I. B., & Otunaiya, A. O. (2019). Sweet potato production efficiency in Nigeria: Application of data envelopment analysis. *AIMS Agriculture and Food*, *4*(3), 672-684.

Ahmed, H. (2017). *Principles and reactions of protein extraction, purification, and characterization*. CRC press.

Al-Karaki, G., & Ereifej, K. (1999). Relationships between seed yield and chemical composition of field peas grown under semi-arid Mediterranean conditions. *Journal of Agronomy and Crop Science*, *182*(4), 279-284.

Allotey, D. K., Kwofie, E. M., Adewale, P., Lam, E., & Ngadi, M. (2022). A meta-analysis of pulse-protein extraction technologies: Impact on recovery and purity. *Journal of food engineering*, 111048.

Alzagtat, A. A., & Alli, I. (2002). Protein-lipid interactions in food systems: a review. *International journal of food sciences and nutrition*, *53*(3), 249-260.

Angulo-Meza, L., & Lins, M. P. E. (2002). Review of methods for increasing discrimination in data envelopment analysis. *Annals of Operations Research*, *116*(1), 225-242.

Apergis, N., Aye, G. C., Barros, C. P., Gupta, R., & Wanke, P. (2015). Energy efficiency of selected OECD countries: A slacks based model with undesirable outputs. *Energy Economics*, *51*, 45-53.

Assatory, A., Vitelli, M., Rajabzadeh, A. R., & Legge, R. L. (2019). Dry fractionation methods for plant protein, starch and fiber enrichment: A review. *Trends in Food Science & Technology*, *86*, 340-351.

Avkiran, N. K. (2001). Investigating technical and scale efficiencies of Australian universities through data envelopment analysis. *Socio-economic planning sciences*, *35*(1), 57-80.

Baležentis, T., Kriščiukaitienė, I., & Baležentis, A. (2014). A nonparametric analysis of the determinants of family farm efficiency dynamics in Lithuania. *Agricultural Economics*, *45*(5), 589-599.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078-1092.

Berghout, J., Pelgrom, P., Schutyser, M., Boom, R., & Van Der Goot, A. (2015). Sustainability assessment of oilseed fractionation processes: A case study on lupin seeds. *Journal of food engineering*, *150*, 117-124.

Bhunia, S., Karmakar, S., Bhattacharjee, S., Roy, K., Kanthal, S., Pramanick, M., Baishya, A., & Mandal, B. (2021). Optimization of energy consumption using data envelopment analysis (DEA) in rice-wheat-green gram cropping system under conservation tillage practices. *Energy*, *236*, 121499.

Bi, G.-b., Song, W., & Wu, J. (2014). A clustering method for evaluating the environmental performance based on slacks-based measure. *Computers & Industrial Engineering*, *72*, 169-177.

Boulter, D. (1983). Protein composition of grains of theleguminosae. *Plant Foods for Human Nutrition*, *32*(3), 247-252.

Boye, J., Aksay, S., Roufik, S., Ribéreau, S., Mondor, M., Farnworth, E., & Rajamohamed, S. (2010). Comparison of the functional properties of pea, chickpea and lentil protein concentrates processed using ultrafiltration and isoelectric precipitation techniques. *Food Research International*, *43*(2), 537-546.

Boye, J., Zare, F., & Pletch, A. (2010). Pulse proteins: Processing, characterization, functional properties and applications in food and feed. *Food Research International*, *43*(2), 414-431.

Carrasquer, B., Uche, J., & Martínez-Gracia, A. (2017). A new indicator to estimate the efficiency of water and energy use in agro-industries. *Journal of Cleaner Production*, *143*, 462-473.

Chakkaravarthi, A., Math, R., Walde, S., & Rao, D. (1993). Grinding characteristics of carrots (Daucus carota L.). *Journal of food engineering*, *20*(4), 381-389.

Chandler, P. M., Spencer, D., Randall, P. J., & Higgins, T. J. (1984). Influence of sulfur nutrition on developmental patterns of some major pea seed proteins and their mRNAs. *Plant Physiology*, *75*(3), 651-657.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, *2*(6), 429-444.

Chauhan, N. S., Mohapatra, P. K., & Pandey, K. P. (2006). Improving energy productivity in paddy production through benchmarking—An application of data envelopment analysis. *Energy conversion and management*, *47*(9-10), 1063-1085.

Chen, S. (2015). The evaluation indicator of ecological development transition in China's regional economy. *Ecological Indicators*, *51*, 42-52.

Coelli, T. J. (1995). Recent developments in frontier modelling and efficiency measurement. *Australian Journal of agricultural economics*, *39*(3), 219-245.

Compton, M., Willis, S., Rezaie, B., & Humes, K. (2018). Food processing industry energy and water consumption in the Pacific northwest. *Innovative food science & emerging technologies*, *47*, 371-383.

Corredig, M. (2006). Protein-protein interactions in food. *FOOD SCIENCE AND TECHNOLOGY-NEW YORK-MARCEL DEKKER-*, *154*, 283.

Cui, Q., Kuang, H.-b., Wu, C.-y., & Li, Y. (2014). The changing trend and influencing factors of energy efficiency: the case of nine countries. *Energy*, *64*, 1026-1034.

Culbertson, J. D. (2005). Food protein functionality. *Handbook of Food Science, Technology, and Engineering*, *4*.

Curran, M. A. (2013). Life cycle assessment: a review of the methodology and its application to sustainability. *Current Opinion in Chemical Engineering*, *2*(3), 273-277.

Damodaran, S. (2005). Protein stabilization of emulsions and foams. *Journal of Food Science*, *70*(3), R54-R66.

Damodaran, S., Parkin, K. L., & Fennema, O. R. (2007). *Fennema's food chemistry*. CRC press.

De Bakker, J. (2014). Energy use of fine grinding in mineral processing. *Metallurgical and materials transactions E*, *1*(1), 8-19.

De Temmerman, P.-J., Lammertyn, J., De Ketelaere, B., Kestens, V., Roebben, G., Verleysen, E., & Mast, J. (2014). Measurement uncertainties of size, shape, and surface measurements using transmission electron microscopy of near-monodisperse, near-spherical nanoparticles. *Journal of nanoparticle research*, *16*, 1-22.

Detzel, A., Krüger, M., Busch, M., Blanco-Gutiérrez, I., Varela, C., Manners, R., Bez, J., & Zannini, E. (2022). Life cycle assessment of animal-based foods and plant-based protein-rich alternatives: an environmental perspective. *Journal of the Science of Food and Agriculture*, *102*(12), 5098-5110.

Dijkink, B., Speranza, L., Paltsidis, D., & Vereijken, J. (2007). Air dispersion of starch–protein mixtures: A predictive tool for air classification performance. *Powder technology*, *172*(2), 113-119.

do Carmo, C. S., Silventoinen, P., Nordgård, C. T., Poudroux, C., Dessev, T., Zobel, H., Holtekjølen, A. K., Draget, K. I., Holopainen-Mantila, U., & Knutsen, S. H. (2020). Is dehulling of peas and faba beans necessary prior to dry fractionation for the production of protein-and starch-rich fractions? Impact on physical properties, chemical composition and techno-functional properties. *Journal of food engineering*, *278*, 109937.

Dumoulin, L., Jacquet, N., Malumba, P., Richel, A., & Blecker, C. (2021). Dry and wet fractionation of plant proteins: How a hybrid process increases yield and impacts nutritional value of faba beans proteins. *Innovative food science & emerging technologies*, *72*, 102747.

Duranti, M., & Scarafoni, A. (1999). Modification of storage protein content and quality in legume seeds. *Journal of New Seeds*, *1*(1), 17-35.

Dziki, D. (2008). The crushing of wheat kernels and its consequence on the grinding process. *Powder technology*, *185*(2), 181-186.

Ekawati, R. (2019). A Proposal on efficiency measuring of rice milling process by using AHP/DEA method. *Journal of Engineering and Management in Industrial System*, *7*(2), 104-109.

Eswaraiah, C., Narayanan, S., & Jayanti, S. (2008). A reduced efficiency approach-based process model for a circulating air classifier. *Chemical Engineering and Processing: Process Intensification*, *47*(9-10), 1887-1900.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253-281.

Fernando, H. S. S. (2017). *Effects of pretreatments on separating the seed coat from the cotyledon of black bean* North Dakota State University].

Fernando, H. S. S. (2020). *Black bean milling and flour functionality* North Dakota State University].

Fernando, S. (2021). Production of protein-rich pulse ingredients through dry fractionation: A review. *Lwt*, *141*, 110961.

Fernando, S., & Manthey, F. A. (2021). Milling method affects the physical properties of black bean flour. *Cereal Chemistry*, *98*(3), 749-758.

Funke, M., Boom, R., & Weiss, J. (2022). Dry fractionation of lentils by air classification-Composition, interfacial properties and behavior in concentrated O/W emulsions. *LWT*, *154*, 112718.

Gao, G., Wang, S., Xue, R., Liu, D., Huang, B., & Zhang, R. (2022). Eco-efficiency assessment of industrial parks in Central China: a slack-based data envelopment analysis. *Environmental Science and Pollution Research*, 1-17.

Garg, S., Lohani, U., & Pandey, J. (2010). Studies on continuous grinding process for dried water chestnut kernel. *J. Eng. Sci. Technol*, *5*, 140-150.

Geerts, M. E., Mienis, E., Nikiforidis, C. V., van der Padt, A., & van der Goot, A. J. (2017). Mildly refined fractions of yellow peas show rich behaviour in thickened oil-in-water emulsions. *Innovative food science & emerging technologies*, *41*, 251-258.

Ghorbani, Z., Masoumi, A., & Hemmat, A. (2010). Specific energy consumption for reducing the size of alfalfa chops using a hammer mill. *Biosystems engineering*, *105*(1), 34-40.

Giannoulis, K. D., Vlontzos, G., Karyotis, T., Bartzialis, D., & Danalatos, N. G. (2014). Assessing the efficiency of switchgrass different cultural practices for pellet production. *Land use policy*, *41*, 506-513.

Gomez-Perez, S., McKeever, L., & Sheean, P. (2020). Tutorial: a step-by-step guide (version 2.0) for measuring abdominal circumference and skeletal muscle from a single cross-sectional computed-tomography image using the National Institutes of Health ImageJ. *Journal of Parenteral and Enteral Nutrition*, *44*(3), 419-424.

Goswami, T., & Singh, M. (2003). Role of feed rate and temperature in attrition grinding of cumin. *Journal of food engineering*, *59*(2-3), 285-290.

Gueguen, J. (1983). Legume seed protein extraction, processing, and end product characteristics. *Plant Foods for Human Nutrition*, *32*(3), 267-303.

Hall, G. M. (1996). *Methods of testing protein functionality*. Springer Science & Business Media.

Hellweg, S., & Milà i Canals, L. (2014). Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, *344*(6188), 1109-1113.

Hoang, H. D. (2012). *Evaluation of pea protein and modified pea protein as egg replacers* North Dakota State University].

Hoover, R., Hughes, T., Chung, H., & Liu, Q. (2010). Composition, molecular structure, properties, and modification of pulse starches: A review. *Food Research International*, *43*(2), 399-413.

Hurrell, R. F. (2003). Influence of vegetable protein sources on trace element and mineral bioavailability. *The Journal of Nutrition*, *133*(9), 2973S-2977S.

Ikeda, S., & Nishinari, K. (2001). On solid-like rheological behaviors of globular protein solutions. *Food Hydrocolloids*, *15*(4-6), 401-406.

Indira, T., & Bhattacharya, S. (2006). Grinding characteristics of some legumes. *Journal of food engineering*, *76*(2), 113-118.

Irham, M., Quriadi, S., Setiawan, I., Miswar, E., Purnawan, S., & Affan, J. (2018). The analysis of d90 and d50 sediment grain size in Alue Naga estuary, Banda Aceh City. IOP Conference Series: Earth and Environmental Science,

Işgın, T., Özel, R., Bilgiç, A., Florkowski, W. J., & Sevinç, M. R. (2020). Dea performance measurements in cotton production of harran plain, Turkey: a single and double bootstrap truncated regression approaches. *Agriculture*, *10*(4), 108.

Izadikhah, M. (2022). DEA Approaches for Financial Evaluation-A Literature Review. *Advances in Mathematical Finance and Applications*, *7*(1), 1-37.

Jha, S. N., & Sharma, R. (2010). Physical, gravimetric and functional characterization of various milling fractions of popped gorgon nut (Euryale ferox). *Journal of food science and technology*, *47*(5), 564-570.

Jomthanachai, S., Wong, W.-P., & Lim, C.-P. (2021). An application of data envelopment analysis and machine learning approach to risk management. *Ieee Access*, *9*, 85978-85994.

Karaca, A. C., Low, N., & Nickerson, M. (2011). Emulsifying properties of chickpea, faba bean, lentil and pea proteins produced by isoelectric precipitation and salt extraction. *Food Research International*, *44*(9), 2742-2750.

Kijowski, J. (2001). Chemical and functional properties of food proteins. *Muscle proteins. Z*.

Kim, H.-G., Choi, C.-Y., Woo, J.-W., Choi, Y., Kim, K., & Wu, D. D. (2011). Efficiency of the modal shift and environmental policy on the Korean railroad. *Stochastic environmental research and risk assessment*, *25*(3), 305-322.

Kinsella, J. E. (1981). Functional properties of proteins: possible relationships between structure and function in foams. *Food chemistry*, *7*(4), 273-288.

Kyrgiakos, L. S., Vlontzos, G., & Pardalos, P. M. (2021). Assessing the efficiency of cotton farms considering qualitative factors under a DEA TOPSIS model. *International Journal of Sustainable Agricultural Management and Informatics*, *7*(4), 343-359.

Lahouel, B. B. (2016). Eco-efficiency analysis of French firms: a data envelopment analysis approach. *Environmental Economics and Policy Studies*, *18*(3), 395-416.

Lam, A., Can Karaca, A., Tyler, R., & Nickerson, M. (2018). Pea protein isolates: Structure, extraction, and functionality. *Food reviews international*, *34*(2), 126-147.

Li, D., Nanseki, T., & Chomei, Y. (2021). Two-Stage DEA of 122 Paddy Fields in Hokuriku Region. In *Empirical Analyses on Rice Yield Determinants of Smart Farming in Japan* (pp. 151-166). Springer.

Lie-Piang, A., Braconi, N., Boom, R. M., & van der Padt, A. (2021). Less refined ingredients have lower environmental impact–A life cycle assessment of protein-rich ingredients from oil- and starch-bearing crops. *Journal of Cleaner Production*, *292*, 126046.

Lin, C., & Zayas, J. (1987). Functionality of defatted corn germ proteins in a model system: fat binding capacity and water retention. *Journal of Food Science*, *52*(5), 1308-1311.

Liu, S., Elmer, C., Low, N., & Nickerson, M. (2010). Effect of pH on the functional behaviour of pea protein isolate–gum Arabic complexes. *Food Research International*, *43*(2), 489-495.

Liu, Y., Ren, L., Li, Y., & Zhao, X.-g. (2015). The industrial performance of wind power industry in China. *Renewable and Sustainable Energy Reviews*, *43*, 644-655.

Lundgren, M. (2011). Composition of fractions from air-classified wheat flour.

Ma, Z., Boye, J. I., Simpson, B. K., Prasher, S. O., Monpetit, D., & Malcolmson, L. (2011). Thermal processing effects on the functional properties and microstructure of lentil, chickpea, and pea flours. *Food Research International*, *44*(8), 2534-2544.

Maganga, A., Grebremedhin, G., & Kambewa, P. (2018). Efficiency of small scale Pigeon pea production: What do we learn from Malawi?

Maltha, R. (2015). *Water footprint of wine production in wineries in Chile: The Creation of a Water Footprint Calculator* University of Twente].

Mardani, A., Zavadskas, E. K., Streimikiene, D., Jusoh, A., & Khoshnoudi, M. (2017). A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renewable and Sustainable Energy Reviews*, *70*, 1298-1322.

Masuda, K. (2016). Measuring eco-efficiency of wheat production in Japan: a combined application of life cycle assessment and data envelopment analysis. *Journal of Cleaner Production*, *126*, 373-381.

Maxime, D., Marcotte, M., & Arcand, Y. (2006). Development of eco-efficiency indicators for the Canadian food and beverage industry. *Journal of Cleaner Production*, *14*(6-7), 636-648.

Mehra, M. A. *MarketsandMarkets INC.* https://www.globenewswire.com/en/news-release/2022/08/03/2491067/0/en/Plant-based-Protein-Market-worth-17-4-billion-by-2027-Exclusive-Report-by-MarketsandMarkets.html

Melendrez-Ruiz, J., Buatois, Q., Chambaron, S., Monnery-Patris, S., & Arvisenet, G. (2019). French consumers know the benefits of pulses, but do not choose them: An exploratory study combining indirect and direct approaches. *Appetite*, *141*, 104311.

Mertens, C., Dehon, L., Bourgeois, A., Verhaeghe-Cartrysse, C., & Blecker, C. (2012). Agronomical factors influencing the legumin/vicilin ratio in pea (Pisum sativum L.) seeds. *Journal of the Science of Food and Agriculture*, *92*(8), 1591-1596.

Mohammadi, A., Rafiee, S., Mohtasebi, S. S., Avval, S. H. M., & Rafiee, H. (2011). Energy efficiency improvement and input cost saving in kiwifruit production using Data Envelopment Analysis approach. *Renewable Energy*, *36*(9), 2573-2579.

Möller, A. C., van der Padt, A., & van der Goot, A. J. (2021). From raw material to mildly refined ingredient–Linking structure to composition to understand fractionation processes. *Journal of food engineering*, *291*, 110321.

Mondor, M., Tuyishime, O., & Drolet, H. (2012). Production of pea protein concentrates by ultrafiltration: Influence of hollow-fibre module. *Innovative food science & emerging technologies*, *14*, 135-138.

Morfeldt, J., & Silveira, S. (2014). Capturing energy efficiency in European iron and steel production—comparing specific energy consumption and Malmquist productivity index. *Energy Efficiency*, *7*(6), 955-972.

Murthy, C. (2001). *Cryogenic size reduction and engineering properties of black pepper* University of Mysore].

Namdari, M., Ghasemi Mobtaker, H., & Rasouli, M. (2021). Using DEA models to measure energy efficiency of grape production. *International Journal of Agricultural Management and Development*, *11*(4), 485-493.

Narasimha, H., Ramakrishnaiah, N., & Pratape, V. (2003). Milling of pulses. *Handbook of Post Harvest Technology*, 427-454.

Nassiri, S. M., & Singh, S. (2009). Study on energy use efficiency for paddy crop using data envelopment analysis (DEA) technique. *Applied Energy*, *86*(7-8), 1320-1325.

Ngamnikom, P., & Songsermpong, S. (2011). The effects of freeze, dry, and wet grinding processes on rice flour properties and their energy consumption. *Journal of food engineering*, *104*(4), 632-638.

Nikolopoulou, D., Grigorakis, K., Stasini, M., Alexis, M., & Iliadis, K. (2007). Differences in chemical composition of field pea (Pisum sativum) cultivars: Effects of cultivation area and year. *Food chemistry*, *103*(3), 847-852.

O'Kane, F. E., Happe, R. P., Vereijken, J. M., Gruppen, H., & van Boekel, M. A. (2004). Characterization of pea vicilin. 2. Consequences of compositional heterogeneity on heat-

induced gelation behavior. *Journal of Agricultural and Food Chemistry*, *52*(10), 3149-3154.
Organization, W. H. (2019). *Sustainable healthy diets: Guiding principles*. Food & Agriculture Org.
Payandeh, Z., Jahanbakhshi, A., Mesri-Gundoshmian, T., & Clark, S. (2021). Improving Energy Efficiency of Barley Production Using Joint Data Envelopment Analysis (DEA) and Life Cycle Assessment (LCA): Evaluation of Greenhouse Gas Emissions and Optimization Approach. *Sustainability*, *13*(11), 6082.
Payandeh, Z., Kheiralipour, K., Karimi, M., & Khoshnevisan, B. (2017). Joint data envelopment analysis and life cycle assessment for environmental impact reduction in broiler production systems. *Energy*, *127*, 768-774.
Pelgrom, P. J., Berghout, J. A., van der Goot, A. J., Boom, R. M., & Schutyser, M. A. (2014). Preparation of functional lupine protein fractions by dry separation. *LWT-Food Science and Technology*, *59*(2), 680-688.
Pelgrom, P. J., Boom, R. M., & Schutyser, M. A. (2015a). Functional analysis of mildly refined fractions from yellow pea. *Food Hydrocolloids*, *44*, 12-22.
Pelgrom, P. J., Boom, R. M., & Schutyser, M. A. (2015b). Method development to increase protein enrichment during dry fractionation of starch-rich legumes. *Food and Bioprocess Technology*, *8*(7), 1495-1502.
Pelgrom, P. J., Vissers, A. M., Boom, R. M., & Schutyser, M. A. (2013). Dry fractionation for production of functional pea protein concentrates. *Food Research International*, *53*(1), 232-239.
Pelgrom, P. J., Wang, J., Boom, R. M., & Schutyser, M. A. (2015). Pre-and post-treatment enhance the protein enrichment from milling and air classification of legumes. *Journal of food engineering*, *155*, 53-61.
Rajendran, S., Kapilan, R., & Vasantharuba, S. (2018). Single cell protein production from papaw and banana fruit juices using baker's yeast. *J Agric Environ Sci*, *18*(4), 168-172.
Reichert, R. D., & MacKenzie, S. L. (1982). Composition of peas (Pisum sativum) varying widely in protein content. *Journal of Agricultural and Food Chemistry*, *30*(2), 312-317.
Ren, Y., Yuan, T. Z., Chigwedere, C. M., & Ai, Y. (2021). A current review of structure, functional properties, and industrial applications of pulse starches for value-added utilization. *Comprehensive Reviews in Food Science and Food Safety*, *20*(3), 3061-3092.
Richter, S., Riediger, K., & Nester, A. (2012). A quantitative analytical method for the identification and characterization of mineralized nanoparticles in food supplements. Solid State Phenomena,
Robaina-Alves, M., Moutinho, V., & Macedo, P. (2015). A new frontier approach to model the eco-efficiency in European countries. *Journal of Cleaner Production*, *103*, 562-573.
Sanjeewa, T. (2008). *Physico-chemical properties of chickpea flour, starch and protein fractions and their utilization in low-fat pork bologna* University of Saskatchewan Saskatoon, SK].
Scheel, H. (2000). EMS: efficiency measurement system user's manual. In: Version.
Schroeder, H. E. (1982). Quantitative studies on the cotyledonary proteins in the genus Pisum. *Journal of the Science of Food and Agriculture*, *33*(7), 623-633.

Schutyser, M., Pelgrom, P., Van der Goot, A., & Boom, R. (2015). Dry fractionation for sustainable production of functional legume protein concentrates. *Trends in Food Science & Technology*, *45*(2), 327-335.

Schutyser, M., & Van der Goot, A. (2011). The potential of dry fractionation processes for sustainable plant protein production. *Trends in Food Science & Technology*, *22*(4), 154-164.

Seiford, L. M., & Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of econometrics*, *46*(1-2), 7-38.

Shand, P., Ya, H., Pietrasik, Z., & Wanasundara, P. (2007). Physicochemical and textural properties of heat-induced pea protein isolate gels. *Food chemistry*, *102*(4), 1119-1130.

Sharma, A., Saxena, A., Sethi, M., & Shree, V. (2011). Life cycle assessment of buildings: a review. *Renewable and Sustainable Energy Reviews*, *15*(1), 871-875.

Shevkani, K., Singh, N., Kaur, A., & Rana, J. C. (2015). Structural and functional characterization of kidney bean and field pea protein isolates: a comparative study. *Food Hydrocolloids*, *43*, 679-689.

Singh, G., Singh, P., Sodhi, G., & Tiwari, D. (2021). Energy auditing and data envelopment analysis (DEA) based optimization for increased energy use efficiency in wheat cultivation (Triticum aestium L.) in north-western India. *Sustainable Energy Technologies and Assessments*, *47*, 101453.

Singh, P., Singh, G., & Sodhi, G. (2019). Applying DEA optimization approach for energy auditing in wheat cultivation under rice-wheat and cotton-wheat cropping systems in north-western India. *Energy*, *181*, 18-28.

Stolze, N., Bader, C., Henning, C., Mastin, J., Holmes, A. E., & Sutlief, A. L. (2019). Automated image analysis with ImageJ of yeast colony forming units from cannabis flowers. *Journal of microbiological methods*, *164*, 105681.

Stone, A. K., Avarmenko, N. A., Warkentin, T. D., & Nickerson, M. T. (2015). Functional properties of protein isolates from different pea cultivars. *Food Science and Biotechnology*, *24*(3), 827-833.

Stone, A. K., Karalash, A., Tyler, R. T., Warkentin, T. D., & Nickerson, M. T. (2015). Functional attributes of pea protein isolates prepared using different extraction methods and cultivars. *Food Research International*, *76*, 31-38.

Sueyoshi, T., & Goto, M. (2014). Environmental assessment for corporate sustainability by resource utilization and technology innovation: DEA radial measurement on Japanese industrial sectors. *Energy Economics*, *46*, 295-307.

Sueyoshi, T., & Goto, M. (2018). *Environmental assessment on energy and sustainability by data envelopment analysis*. John Wiley & Sons.

Sueyoshi, T., & Yuan, Y. (2015). China's regional sustainability and diversified resource allocation: DEA environmental assessment on economic development and air pollution. *Energy Economics*, *49*, 239-256.

Sun, X. D., & Arntfield, S. D. (2011). Dynamic oscillatory rheological measurement and thermal properties of pea protein extracted by salt method: Effect of pH and NaCl. *Journal of food engineering*, *105*(3), 577-582.

Sun, Z., Liang, L., Liu, C., Zhu, Y., Zhang, L., & Yang, G. (2021). CFD simulation and performance optimization of a new horizontal turbo air classifier. *Advanced Powder Technology*, *32*(4), 977-986.

Taherian, A. R., Mondor, M., Labranche, J., Drolet, H., Ippersiel, D., & Lamarche, F. (2011). Comparative study of functional properties of commercial and membrane processed yellow pea protein isolates. *Food Research International*, *44*(8), 2505-2514.

Taylor, L., Skuse, D., Blackburn, S., & Greenwood, R. (2020). Stirred media mills in the mining industry: Material grindability, energy-size relationships, and operating conditions. *Powder technology*, *369*, 1-16.

Tiwari, B. K., Gowen, A., & McKenna, B. (2020). *Pulse foods: processing, quality and nutraceutical applications*. Academic Press.

Tyler, R., Youngs, C., & Sosulski, F. (1981). and Composition of the Starch and Protein Fractions'. *Cereal Chemisty*, *58*(2), 144-148.

Van der Poel, A., Aarts, H., & Stolp, W. (1989). Milling and air classification of two different types of peas-effects on the distribution of antinutritional factors. *Netherlands Journal of Agricultural Science*, *37*(3), 273-278.

Vera, C., Warkentin, T., & Vandenberg, B. (1999). final report to the Saskatchewan Agriculture Development Fund: Breeding field pea cultivars for Saskatchewan (Report No. 19940181). *Agriculture and Agri-Food Canada*.

Vogelsang-O'Dwyer, M., Zannini, E., & Arendt, E. K. (2021). Production of pulse protein ingredients and their application in plant-based milk alternatives. *Trends in Food Science & Technology*, *110*, 364-374.

Walde, S., Balaswamy, K., Shivaswamy, R., Chakkaravarthi, A., & Rao, D. (1997). Microwave drying and grinding characteristics of gum karaya (Sterculia urens). *Journal of food engineering*, *31*(3), 305-313.

Walde, S., Balaswamy, K., Velu, V., & Rao, D. (2002). Microwave drying and grinding characteristics of wheat (Triticum aestivum). *Journal of food engineering*, *55*(3), 271-276.

Wang, J., Zhao, J., De Wit, M., Boom, R. M., & Schutyser, M. A. (2016). Lupine protein enrichment by milling and electrostatic separation. *Innovative food science & emerging technologies*, *33*, 596-602.

Wang, N. (2005). Optimization of a laboratory dehulling process for lentil (Lens culinaris). *Cereal Chemistry*, *82*(6), 671-676.

Westhoek, H., Lesschen, J. P., Rood, T., Wagner, S., De Marco, A., Murphy-Bokern, D., Leip, A., van Grinsven, H., Sutton, M. A., & Oenema, O. (2014). Food choices, health and environment: Effects of cutting Europe's meat and dairy intake. *Global environmental change*, *26*, 196-205.

Withana-Gamage, T. S., Wanasundara, J. P., Pietrasik, Z., & Shand, P. J. (2011). Physicochemical, thermal and functional characterisation of protein isolates from Kabuli and Desi chickpea (Cicer arietinum L.): A comparative study with soy (Glycine max) and pea (Pisum sativum L.). *Journal of the Science of Food and Agriculture*, *91*(6), 1022-1031.

Wood, J. A., & Malcolmson, L. J. (2021). Pulse milling technologies. In *Pulse foods* (pp. 213-263). Elsevier.

Wright, D., & Boulter, D. (1972). The characterisation of vicilin during seed development in Vicia faba (L.). *Planta*, *105*(1), 60-65.

Wu, F., Zhou, P., & Zhou, D. (2016). Does there exist energy congestion? Empirical evidence from Chinese industrial sectors. *Energy Efficiency*, *9*(2), 371-384.

Xie, Q., Li, R., Zou, Y., Liu, Y., & Wang, X. (2022). A two-stage method for improving discrimination and variable selection in DEA models. *IMA Journal of Management Mathematics*, *33*(3), 511-529.

Xing, Q., Utami, D. P., Demattey, M. B., Kyriakopoulou, K., de Wit, M., Boom, R. M., & Schutyser, M. A. (2020). A two-step air classification and electrostatic separation process for protein enrichment of starch-containing legumes. *Innovative food science & emerging technologies*, *66*, 102480.

Yang, J., Zamani, S., Liang, L., & Chen, L. (2021). Extraction methods significantly impact pea protein composition, structure and gelling properties. *Food Hydrocolloids*, *117*, 106678.

Yang, Q., Eikelboom, E., van der Linden, E., de Vries, R., & Venema, P. (2022). A mild hybrid liquid separation to obtain functional mungbean protein. *LWT*, *154*, 112784.

Yenihebit, N., Abunyuwah, I., & Ahiale, E. D. (2020). An efficiency assessment of irrigated tomato (Solanum lycopersicum) production in the Upper East Region of Ghana. *Journal of Development and Agricultural Economics*, *12*(1), 1-8.

Zhao, X., Ma, X., Shang, Y., Yang, Z., & Shahzad, U. (2022). Green economic growth and its inherent driving factors in Chinese cities: Based on the Metafrontier-global-SBM super-efficiency DEA model. *Gondwana Research*, *106*, 315-328.

Zhou, P., Ang, B. W., & Poh, K.-L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European journal of operational research*, *189*(1), 1-18.

Zhu, H.-G., Tang, H.-Q., Cheng, Y.-Q., Li, Z.-G., & Tong, L.-T. (2021). Potential of preparing meat analogue by functional dry and wet pea (Pisum sativum) protein isolate. *LWT*, *148*, 111702.

Zhu, Q., Li, X., Li, F., Wu, J., & Sun, J. (2021). Analyzing the sustainability of China’s industrial sectors: A data-driven approach with total energy consumption constraint. *Ecological Indicators*, *122*, 107235.