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REVIEW ARTICLE

Renewable Carbohydrates: Advancements in Sustainable Glucose Production and Optimization

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Abstract
This study explores and optimizes glucose production through various biochemical processes and assesses the potential of diverse feedstock sources to meet the growing demand for renewable carbohydrates. It focuses on glucose production's significance in biological systems and industrial applications, analyzing pathways like enzymatic hydrolysis of polysaccharides and acid hydrolysis of biomass. The kinetics of glucose production are examined, encompassing kinetic models for enzymatic hydrolysis, acid hydrolysis, and fermentation processes. Factors influencing reaction kinetics are explored, and experimental techniques for kinetic parameter estimation are discussed. To address sustainability and resource utilization challenges, the study investigates locally sourced materials like agricultural residues, forest biomass, algal biomass, and food waste as renewable feedstock sources. Optimization strategies for glucose production are presented, using statistical design of experiments and response surface methodology. Techno-economic analysis and life cycle assessments provide a holistic evaluation of environmental and economic aspects associated with glucose production processes. The study's comprehensive approach to glucose production, encompassing both technological advancements and sustainability considerations, offers insights into enzymatic, acid hydrolysis, and fermentation processes, as well as comparing diverse feedstock sources. This knowledge can foster further advancements in the field, benefit industries, and encourage policymakers to promote the integration of renewable carbohydrates in the broader bioeconomy. The research contributes to the global shift towards a greener and more sustainable future, where glucose production plays a key role in building a resilient and eco-conscious society.

Keywords: Glucose production; Enzymatic hydrolysis; Biofuel; Fermentation processes; Bioproduct industries

Introduction

Glucose, a fundamental biomolecule and major source of energy in living organisms, is essential in a variety of biological processes and industrial uses. Because of the growing demand for clean and renewable energy sources, its production and consumption have received substantial attention. Glucose production is critical not just for the food and biofuel industries (Zahonyi et al., 2022), but also for the synthesis of a wide range of bioproducts. Over the years, significant work has been expended on understanding and optimizing the processes involved in glucose synthesis. Previous studies have explored enzymatic hydrolysis of polysaccharides, acid hydrolysis of biomass, and fermentation of sugars as the main pathways for glucose synthesis (Ciolkosz et al., 2022). Various feedstock sources, including agricultural residues, forest biomass, algal biomass, and food waste, have been investigated for their potential in glucose production (Chen et al., 2022; Premjet et al., 2022). However, despite the progress made in this field, several challenges persist. The kinetics of glucose production, influenced by microorganism strains and environmental factors, remain complex and require further exploration. Optimization of the glucose production process to achieve maximum yield and economic efficiency continues to be a pressing concern (Pereira et al., 2021). Additionally, the sustainable and eco-friendly aspects of glucose production demand meticulous evaluation through life cycle assessments and techno-economic analyses.

The primary aim of this comprehensive study is to provide an in-depth exploration of glucose production, considering various biochemical processes, feedstock sources, and optimization strategies. By comparing different enzymatic, acid hydrolysis, and fermentation techniques, this study aims to identify the most efficient and sustainable pathways for glucose synthesis. Furthermore, by examining locally sourced materials and agricultural residues as potential feedstock, the study intends to offer practical insights into utilizing renewable resources for glucose production. Objectives of the study are to investigate the enzymatic hydrolysis of polysaccharides and its kinetics for efficient glucose production, examine the acid hydrolysis of biomass to explore alternative pathways for glucose synthesis, assess the potential of fermentation processes for converting sugars into glucose, compare and evaluate various feedstock sources, including agricultural residues, forest biomass, algal biomass, and food waste, for their suitability in glucose production, optimize glucose production processes using statistical design of experiments and response surface methodology, and analyze the techno-economic aspects and conduct life cycle assessments for a comprehensive evaluation of the sustainability of glucose production methods. This study holds paramount significance for academia, industries, and policymakers alike. By providing a comprehensive overview of glucose production, the research seeks to contribute to the scientific understanding of fundamental biochemical pathways. The optimization strategies and insights into feedstock utilization can pave the way for more sustainable and economically viable glucose production processes. Furthermore, this study's focus on environmentally friendly and renewable carbohydrates aligns with global efforts to transition towards green and eco-conscious solutions. Ultimately, the outcomes of this research aim to drive innovation and advancements in glucose production, fostering a sustainable future for various industries and human well-being.

Literature Review

Background on Glucose Production

Glucose, a simple sugar, holds significant importance as a versatile platform chemical with wide-ranging applications in various industries, including food, pharmaceuticals, biofuels, and bioplastics (Johns, 2021). To meet the growing demand for glucose sustainably, the utilization of renewable feedstocks has become a major focus of research. Among potential feedstocks, lignocellulosic biomass such as sawdust, rice husk, and sugarcane bagasse have drawn attention due to their abundance and potential for valorization. The enzymatic hydrolysis of these feedstocks can liberate glucose, which can then be further optimized using statistical techniques like Response Surface Methodology (RSM) and the Michaelis-Menten model for kinetic analysis (Ude et al., 2020).

Aspergillus niger, a filamentous fungus, is a widely studied microorganism with notable enzymatic capabilities, including cellulase and hemicellulase production. Its potential for converting lignocellulosic biomass into glucose makes it an attractive candidate for glucose production. By harnessing the enzymatic prowess of *Aspergillus niger*, the hydrolysis of cellulose and hemicellulose in sawdust, rice husk, and sugarcane bagasse can be efficiently achieved, leading to enhanced glucose yields. RSM is a powerful statistical tool that allows for the optimization of multiple variables simultaneously. In the context of glucose production from different feedstocks, RSM can explore the effects of parameters such as enzyme concentration, temperature, pH, and reaction time on glucose yield (Jones et al., 2018). The technique provides insights into the interactions between variables and helps identify the optimal process conditions that maximize glucose production. With the aid of RSM, researchers can streamline the experimental design and significantly reduce the number of trials required, making the optimization process more efficient and cost-effective.

Furthermore, understanding the kinetics of the glucose production process is crucial for process design and control. The Michaelis-Menten model, a well-established enzyme kinetics model, can be applied to describe the enzymatic hydrolysis of cellulose and hemicellulose by Aspergillus niger. By determining the kinetic parameters, such as the maximum reaction rate and the Michaelis constant, researchers can gain valuable insights into the enzymatic efficiency and the overall process dynamics (Efrinalia et al., 2022). Comprehensive characterization of the feedstock is essential to comprehend the complex interactions between the microorganism and the substrate during glucose production. Proximate and ultimate analyses provide information on the biomass composition, including moisture content, ash content, and elemental composition. Energy-dispersive X-ray spectroscopy (EDX) offers insights into the elemental distribution within the biomass. Fourier-transform infrared spectroscopy (FTIR) can reveal functional groups present in the biomass, aiding in understanding the structural changes during hydrolysis. Scanning electron microscopy (SEM) enables researchers to visualize the morphology and surface features of the feedstock, providing valuable information on structural changes and enzyme accessibility.

The utilization of lignocellulosic biomass, such as sawdust, rice husk, and sugarcane bagasse, for glucose production using *Aspergillus niger* holds immense promise as a sustainable approach to meet the demand for glucose (Edor et al., 2018). The application of RSM and the Michaelis-Menten model will enhance process optimization and kinetic analysis, leading to improved glucose yields and process efficiency. Additionally, a comprehensive characterization of the feedstock using techniques like EDX, FTIR, and SEM will deepen the understanding of the enzymatic hydrolysis process and aid in optimizing the glucose production from these abundant biomass sources.

Overview of Glucose as a Biomolecule

Glucose, a monosaccharide with the chemical formula $C_6H_{12}O_6$, is a fundamental biomolecule that plays a crucial role in various biological processes (Mondal, 2018; Rationalized, 2023). It serves as a primary source of energy for living organisms and serves as a building block for the synthesis of complex carbohydrates, lipids, and proteins. Glucose is found in almost all living organisms, ranging from bacteria and plants to animals, including humans. It is a central player in cellular metabolism. Through the process of glycolysis, glucose is broken down into pyruvate, generating ATP (adenosine triphosphate) molecules that provide energy for cellular functions (Dienel, 2019; Remesar & Alemany, 2020). Pyruvate can further undergo various metabolic pathways, such as the Krebs cycle and oxidative phosphorylation, to produce additional ATP through cellular respiration. Glucose metabolism is essential for energy production, maintaining cellular homeostasis, and supporting vital cellular processes, such as signal transduction and membrane transport (Parker, 2020). Glucose serves as the primary energy source for most organisms. It is readily metabolized and efficiently converted into ATP through glycolysis and subsequent respiratory pathways (Dienel, 2019). The energy derived from glucose is utilized to perform mechanical work, maintain body temperature, support growth and development, and enable the functioning of vital organs and tissues (Remesar & Alemany, 2020).

Glucose serves as the building block for the synthesis of complex carbohydrates, including starch, glycogen, and cellulose (Adams, 2022). Through the process of polymerization, glucose molecules link together to form chains or branched structures, resulting in the formation of these carbohydrates. Starch and glycogen serve as energy storage molecules in plants and animals, respectively, while cellulose provides structural support in plant cell walls. Glucose is a precursor for the synthesis of various biomolecules (Johns, 2021). It can be converted into other monosaccharides, such as fructose and galactose, through specific enzymatic reactions (Riaukaite et al., 2019). Glucose also serves as the starting point for the synthesis of lipids, amino acids, and nucleotides, which are essential components of cell membranes, proteins, and DNA, respectively (Rationalized, 2023). Glucose concentration in the bloodstream is tightly regulated to maintain optimal physiological function (Flores et al., 2018). In humans, the hormone insulin (Ramos et al., 2021), produced by the pancreas, facilitates glucose uptake by cells, thereby reducing blood glucose levels. The hormone glucagon, also produced by the pancreas, acts in the opposite manner, promoting the release of stored glucose from glycogen, thereby increasing blood glucose levels. This intricate hormonal regulation ensures that cells have a constant supply of glucose for energy production (Shirin et al., 2019).

Enzymatic Hydrolysis of Polysaccharides

Enzymatic hydrolysis is a biochemical process that involves the breakdown of complex polysaccharides into simpler sugars, primarily glucose, through the action of specific enzymes (Weiss et al., 2019). This process plays a crucial role in the production of glucose from biomass, such as cellulose and starch, as it enables the efficient release of glucose units for various industrial applications. The choice of enzymes for enzymatic hydrolysis depends on the type of polysaccharide being targeted (Amandio et al., 2023). Cellulose, for example, requires cellulases, which are enzymes capable of breaking down the β-1,4-glycosidic bonds present in the cellulose chain (ILO, 2020). On the other hand, amylases are used to hydrolyze starch, targeting the α-1,4-glycosidic bonds (Hu et al., 2021). Enzymes can be derived from various sources, including microorganisms (such as fungi and bacteria) or produced through recombinant DNA technology. The selection of the appropriate enzyme(s) depends on factors such as substrate specificity, enzyme stability, cost, and availability (Bhandari et al., 2021).

The structure and composition of the polysaccharide substrate significantly influence the efficiency of enzymatic hydrolysis (Amandio et al., 2023). Factors such as the degree of polymerization, crystallinity, accessibility of the enzyme to the substrate, and the presence of inhibitors or lignin can affect the hydrolysis process. Pretreatment methods, such as physical, chemical, or biological treatments, are often employed to enhance the accessibility of enzymes to the polysaccharide substrate, improving the overall hydrolysis efficiency (Ansanay et al., 2021). Enzymatic hydrolysis follows a complex kinetic process involving several steps, including enzyme-substrate adsorption, enzymatic reaction, and product desorption. The kinetics of enzymatic hydrolysis can be described by various models, such as the Michaelis-Menten model or the Langmuir-Hinshelwood model. These models help in understanding the enzyme-substrate interactions, determining reaction rates, and estimating kinetic parameters such as the maximum reaction rate (V_{max}) and Michaelis-Menten constant (K_m) (Efrinalia et al., 2022). Kinetic studies provide valuable insights into the efficiency of the hydrolysis process and assist in process optimization. Several factors influence the efficiency of enzymatic hydrolysis (Turini et al., 2021):

a) Enzyme Concentration: The amount of enzyme used affects the rate and extent of hydrolysis. Higher enzyme concentrations generally lead to faster hydrolysis; however, there is an optimal enzyme dosage beyond which further enzyme addition may not yield significant improvements.
b) Substrate Concentration: The concentration of the polysaccharide substrate affects the rate of hydrolysis. Initially, as substrate concentration increases, the rate of hydrolysis also increases. However, at high substrate concentrations, the enzyme may become saturated, and the rate of hydrolysis may plateau.
c) Temperature and pH (Jones et al., 2018): Enzymatic activity is highly dependent on temperature and pH. Different enzymes have specific temperature and pH optima for maximum activity. Maintaining optimal temperature and pH conditions is crucial for achieving high enzymatic efficiency during hydrolysis.
d) Enzyme Inhibitors (Ascione et al., 2020): Inhibitors, such as lignin, hemicelluloses, or degradation products, can negatively impact enzymatic hydrolysis. These inhibitors can interfere with enzyme-substrate interactions, reduce enzyme activity, or inhibit enzyme stability. Strategies to minimize or mitigate the effects of inhibitors include enzymatic detoxification, inhibitor removal.

Acid Hydrolysis of Biomass

Acid hydrolysis is a chemical process that utilizes acid catalysts to break down complex carbohydrates in biomass into simpler sugars, including glucose (ILO, 2020). This process is an alternative to enzymatic hydrolysis and is particularly suitable for biomass with high cellulose or hemicellulose content. Acid hydrolysis offers several advantages, such as faster reaction rates and the ability to handle a wide range of feedstocks. Various acid catalysts can be used for biomass hydrolysis, with sulfuric acid (H_2SO_4) and hydrochloric acid (HCl) being the most commonly employed. These strong acids dissociate in water, providing hydrogen ions (H^+) that catalyze the hydrolysis of glycosidic bonds. The choice of acid catalyst depends on factors such as reaction efficiency, cost, safety, and the downstream processing of the hydrolysate (Swiatek et al., 2020).
Optimizing reaction conditions is crucial for achieving efficient acid hydrolysis (Zhang & Sutheerawattananonda, 2020). Factors such as temperature, acid concentration, reaction time, and solid-to-liquid ratio need to be carefully controlled. Elevated temperatures generally increase reaction rates, but excessively high temperatures can lead to sugar degradation (Astuti et al., 2018). Acid concentration influences the rate of hydrolysis, with higher concentrations promoting faster reaction rates. However, high acid concentrations may also result in the formation of inhibitory compounds and increase the risk of corrosion. Reaction time is determined based on the kinetics of hydrolysis, and the solid-to-liquid ratio affects the accessibility of acids to the biomass substrate. During acid hydrolysis, the acid catalysts protonate the glycosidic bonds, leading to their cleavage (Nguyen et al., 2018). The hydrolysis of cellulose and hemicellulose follows different reaction pathways. Cellulose hydrolysis involves the cleavage of β-1,4-glycosidic bonds, resulting in the formation of glucose monomers (Nguyen et al., 2018; Remesar & Alemany, 2020). Hemicellulose, composed of various sugar monomers, undergoes acid-catalyzed hydrolysis to produce a mixture of different sugars. However, acid hydrolysis is more challenging for lignin, a complex and highly resistant polymer, which typically undergoes minimal degradation during acid hydrolysis (Zhang et al., 2023).

Despite its advantages, acid hydrolysis also presents certain challenges (Damayanti et al., 2021; Swiatek et al., 2020):

i. Corrosion and Safety: Strong acids like sulfuric acid can be corrosive and require proper handling and safety precautions. The selection of appropriate equipment and materials is essential to withstand the corrosive nature of acids.
ii. Sugar Degradation: The hydrolysis process, especially at high temperatures and acid concentrations, can lead to the degradation of sugars into unwanted byproducts, such as furans and organic acids. This degradation reduces the overall yield of desired glucose and can interfere with downstream processes.
iii. Inhibitor Formation: Acid hydrolysis can generate inhibitory compounds, including furfural, 5-hydroxymethylfurfural (HMF), and organic acids, which can affect subsequent enzymatic or microbial conversion processes (Katarzyna et al., 2020; Muhammad et al., 2022; Sant et al., 2021; Swiatek et al., 2020). Detoxification methods, such as neutralization, washing, or adsorption, may be required to minimize the impact of inhibitors.
iv. Acid Recovery and Neutralization: After hydrolysis, the acid needs to be separated from the hydrolysate for reuse or neutralization. Acid recovery and neutralization methods are important for cost-effectiveness, environmental considerations, and the overall sustainability of the process.

Despite the challenges, acid hydrolysis remains an important method for biomass conversion due to its versatility and ability to handle a wide range of feedstocks. It offers advantages such as faster reaction rates, scalability, and the potential to utilize various biomass sources. Researchers continue to explore process optimization strategies to improve acid hydrolysis efficiency, minimize sugar degradation, and reduce the formation of inhibitory compounds. To address some of the challenges associated with acid hydrolysis, several advancements have been made. For instance, the use of milder acids or catalysts, such as organic acids or solid acid catalysts, has been explored to mitigate corrosion and improve the selectivity of hydrolysis. Additionally, the integration of acid hydrolysis with other pretreatment techniques, such as steam explosion or liquid hot water treatment, has shown promise in enhancing hydrolysis efficiency and reducing inhibitor formation (Fu et al., 2018; Li et al., 2019).

Fermentation of Sugars for Glucose Production

Fermentation is a biological process in which microorganisms, such as yeasts or bacteria, convert sugars into various products, including ethanol, organic acids, and gases. The fermentation of sugars plays a significant role in glucose production, as it provides an alternative route for converting sugars derived from biomass or other feedstocks into glucose (Damayanti et al., 2021). Various microorganisms are employed in fermentation processes to convert sugars to glucose. Yeasts, such as Saccharomyces cerevisiae, are commonly used for ethanol production (Halka et al., 2018). They possess the ability to metabolize glucose through the glycolysis pathway, producing ethanol as the primary end product. Other microorganisms, such as lactic acid bacteria or certain species of Escherichia coli, can ferment sugars to produce organic acids like lactic acid or acetic acid (Gunkova et al., 2021). The selection of microorganisms depends on the desired end product and the specific requirements of the fermentation process (Behera et al., 2019). The fermentation of sugars involves several stages, including sugar preparation, inoculum development, fermentation, and product recovery (Damayanti et al., 2021). The sugar source, such as glucose, fructose, or sucrose, is prepared by hydrolysis of biomass or through other pretreatment methods (Kiš et al., 2019). The microorganisms are then introduced into the fermentation medium, which provides the necessary nutrients and environmental conditions for their growth and metabolism. The fermentation process is carried out under controlled conditions of temperature, pH, and aeration (Jones et al., 2018). As the microorganisms metabolize the sugars, they produce glucose as an intermediate or end product, depending on the specific fermentation pathway (Teleky et al., 2020).

Several factors influence the efficiency of fermentation for glucose production (Chang et al., 2018; Jones et al., 2018; Kanagasabai et al., 2019; Tse et al., 2021):

a) Sugar Concentration: The concentration of sugars in the fermentation medium affects the rate and extent of glucose production. Higher sugar concentrations can lead to faster fermentation rates but may also result in inhibitory effects on microbial growth and metabolism.
b) Microbial Strain and Characteristics: The selection of an appropriate microbial strain is critical for efficient glucose production. Different strains may exhibit variations in sugar utilization, fermentation rates, and tolerance to inhibitors. Genetic engineering approaches can be employed to enhance the metabolic capabilities of microorganisms for glucose production.
c) Nutrient Availability: Microorganisms require essential nutrients, such as nitrogen, phosphorus, and trace elements, for their growth and fermentation activity. Optimizing nutrient availability through appropriate medium formulation is crucial for maximizing fermentation efficiency.
d) Environmental Conditions: Temperature, pH, and oxygen availability are important environmental factors that impact microbial growth and fermentation. Each microorganism has an optimal range of these parameters, and maintaining the appropriate conditions ensures efficient fermentation and glucose production.
e) Inhibitors and Byproducts: Inhibitory compounds, such as organic acids, furans, or phenolic compounds, can be generated during biomass pretreatment or hydrolysis processes. These inhibitors can affect microbial growth and fermentation efficiency. Detoxification strategies, including physical, chemical, or biological methods, can be implemented to minimize their impact.

Glucose produced through fermentation has diverse applications in various industries: Glucose fermentation to ethanol serves as a key process in biofuel production (Smachetti et al., 2018). Ethanol can be used as a transportation fuel or as a blending component in gasoline, reducing reliance on fossil fuels and contributing to a more sustainable energy sector (Inyang et al., 2022; Salim, González-García, et al., 2019). Glucose is widely used in the food and beverage industry as a sweetener, preservative, or fermentation substrate. It serves as a key ingredient in the production of baked goods, confectionery, beverages, and fermented products such as beer, wine, and spirits. Glucose is utilized as a carbon source for the production of various pharmaceuticals, including antibiotics, vitamins, amino acids, and therapeutic proteins (Simpson et al., 2022). It also serves as a precursor for the synthesis of bioactive compounds and pharmaceutical intermediates. Glucose can be further converted into a wide range of valuable chemicals, such as organic acids (e.g., lactic acid, citric acid), polyols (e.g., sorbitol, mannitol), and other platform chemicals (Nam, 2022). These chemicals find applications in the production of polymers, resins, solvents, and other industrial products. Glucose can be used as an energy source and nutrient supplement in animal feed formulations. It provides readily available energy for livestock and poultry, supporting their growth and production. In agriculture, glucose-based products can be utilized as plant growth regulators, biofertilizers, or biostimulants, enhancing crop yield and quality (Blanco et al., 2020; Roslan & Salimi, 2019).

Bioplastics and Biomaterials: Glucose serves as a building block for the production of bioplastics, such as polylactic acid (PLA), which offers a renewable and biodegradable alternative to conventional plastics. Glucose-based polymers can also be employed in the development of biomaterials for tissue engineering, drug delivery systems, and other biomedical applications (Far et al., 2022; Seddiqi et al., 2021; Sood et al., 2021). The fermentation of sugars for glucose production offers a versatile and sustainable approach to utilize biomass resources and generate valuable products. Advances in microbial engineering, fermentation process optimization, and downstream processing techniques continue to enhance the efficiency and economic viability of glucose production through fermentation. Furthermore, the integration of fermentation with other biorefinery processes allows for the utilization of diverse feedstocks and the production of a wide range of valuable compounds, contributing to the development of a bio-based economy and a more sustainable future (Salim, et al., 2019).

Comparison of Different Biochemical Processes

Biochemical processes for glucose production encompass various methods, including enzymatic hydrolysis, acid hydrolysis, and fermentation. Each of these processes has its advantages, challenges, and suitability for different feedstocks and applications. The efficiency of a biochemical process is measured by the yield of glucose obtained from the feedstock (Kadhum et al., 2019). Enzymatic hydrolysis, utilizing specific enzymes, can achieve high conversion rates of polysaccharides into glucose. However, it may require longer reaction times and can be costlier due to the need for enzyme production. Acid hydrolysis, on the other hand, offers faster reaction rates but may lead to lower glucose yields due to sugar degradation and formation of inhibitory compounds. Fermentation processes can also achieve high conversion efficiencies, particularly when optimized for specific microorganisms and conditions (Recek et al., 2018).

Different biochemical processes have varying compatibilities with different feedstocks. Enzymatic hydrolysis is well-suited for a wide range of biomass sources, including lignocellulosic materials, due to its specificity and ability to target specific polysaccharides (Weiss et al., 2019). Acid hydrolysis can handle diverse feedstocks as well, but certain biomass components, such as lignin, may hinder the process efficiency. Fermentation processes generally require sugars or sugar-rich feedstocks and are commonly used for glucose production from agricultural crops, sugar cane, or molasses (Nwankwo & Ukpabi, 2018). The environmental impact of a biochemical process is a crucial consideration in sustainable production. Enzymatic hydrolysis, being a biologically driven process, is considered environmentally friendly. It operates under mild conditions, produces fewer byproducts, and has lower energy requirements compared to other processes. Acid hydrolysis, while effective, requires the use of strong acids and may generate waste streams containing inhibitory compounds, necessitating proper treatment and disposal. Fermentation processes can also be environmentally favorable, especially when utilizing renewable feedstocks and optimizing process parameters to minimize waste and energy consumption (Salim, et al., 2019).

The purity of glucose obtained from a biochemical process is important, particularly for applications in the food, pharmaceutical, and chemical industries. Enzymatic hydrolysis generally yields high-purity glucose, as specific enzymes target the desired polysaccharides without introducing contaminants (Codato-Zumpano et al., 2023). Acid hydrolysis may result in lower product purity due to the presence of inhibitory compounds or degradation products. Fermentation processes can produce glucose along with other metabolites, requiring additional purification steps to obtain high-purity glucose (Salim, et al., 2019). The economics of a biochemical process depend on factors such as capital and operating costs, feedstock availability and cost, yield, and market demand for the products. Enzymatic hydrolysis, although efficient, can be costlier due to the requirement for enzymes and longer reaction times (Weiss et al., 2019). Acid hydrolysis offers faster reaction rates but may incur additional costs for acid procurement and disposal of waste streams. Fermentation processes, while efficient and commercially viable for certain feedstocks, may require downstream processing and purification steps, impacting overall process economics (Recek et al., 2018).

Locally Sourced Materials for Glucose Production

The utilization of locally sourced materials for glucose production offers several advantages, including reduced transportation costs, increased sustainability, and support for local economies (Cheng et al., 2019). Locally available biomass resources can serve as valuable feedstocks for biochemical processes, contributing to the production of glucose in a more efficient, cost-effective, and environmentally friendly manner (Inyang et al., 2022).

Agricultural Residues as Feedstock

Agricultural residues consist of the non-edible parts of crops that remain after harvest or processing (Kim et al., 2018). They typically contain a combination of cellulose, hemicellulose, lignin, and other minor components. The exact composition varies depending on the type of residue and the specific crop. Cellulose and hemicellulose are polysaccharides that can be hydrolyzed into glucose, while lignin provides structural support to the plant and is more challenging to break down (Jeoh et al., 2017). Agricultural residues are widely available due to the large-scale agricultural activities in many regions. The abundance of these residues makes them attractive feedstocks for glucose production, as they provide a renewable and sustainable resource that can be utilized without competing with food production. The availability of agricultural residues can vary based on factors such as crop type, geographic location, and local agricultural practices.

Preprocessing and Pretreatment: Before agricultural residues can be used as feedstocks for glucose production, preprocessing and pretreatment steps may be required. Preprocessing involves activities such as size reduction (e.g., grinding, chopping) and drying to enhance the feedstock's processability (Prithviraj et al., 2020). Pretreatment methods, such as steam explosion, liquid hot water treatment, or acid pretreatment, can be applied to enhance the accessibility of cellulose and hemicellulose for subsequent hydrolysis (Li et al., 2019; Shukla et al., 2023). Enzymatic hydrolysis is a commonly employed method for converting agricultural residues into glucose. Specific enzymes, such as cellulases and hemicellulases, are used to break down the cellulose and hemicellulose components into glucose (Jayasekara & Ratnayake, 2019). Enzymatic hydrolysis offers several advantages, including high selectivity, mild operating conditions, and compatibility with a wide range of agricultural residues. However, the cost of enzymes and the need for longer reaction times are considerations for process economics.

Acid hydrolysis can also be used to convert agricultural residues into glucose. Strong acids, such as sulfuric acid or hydrochloric acid, are typically employed to break down the polysaccharides into their constituent sugars (Adeoye et al., 2019). Acid hydrolysis offers faster reaction rates compared to enzymatic hydrolysis. However, it may lead to sugar degradation, formation of inhibitory compounds, and corrosion issues, requiring proper process optimization and waste management strategies. To maximize glucose production from agricultural residues, process optimization and integration strategies can be employed (Kiran & Trzcinski, 2017). This includes optimizing factors such as temperature, pH, residence time, enzyme loading (in enzymatic hydrolysis), acid concentration (in acid hydrolysis), and solid-liquid ratios. Integration with other pretreatment techniques or biorefinery concepts, such as combining acid hydrolysis with fermentation or utilizing lignin co-products, can enhance overall process efficiency and resource utilization. The utilization of agricultural residues as feedstocks for glucose production offers several sustainability benefits (Oyola-Rivera et al., 2018). It reduces waste generation, maximizes the use of available biomass resources, and contributes to the development of a circular economy. Additionally, utilizing agricultural residues for bio-based processes helps reduce greenhouse gas emissions by replacing fossil-based feedstocks and minimizing reliance on non-renewable resources.

Forest Biomass and Lignocellulosic Materials

Forest biomass and lignocellulosic materials consist mainly of cellulose, hemicellulose, and lignin, along with smaller amounts of extractives and ash. Cellulose and hemicellulose are polysaccharides that can be hydrolyzed into glucose, while lignin provides structural support to the plant and contributes to the recalcitrance of lignocellulosic materials. The exact composition varies depending on factors such as tree species, age, and growing conditions (Augusto & Boca, 2022). Forest biomass and lignocellulosic materials are abundant and widely available in regions with significant forest resources. They can be sourced from various forestry operations, including timber harvesting, sawmills, and forest management activities. The availability of forest biomass depends on factors such as forest management practices, land-use policies, and sustainability considerations to ensure responsible sourcing. Before forest biomass and lignocellulosic materials can be used as feedstocks for glucose production, preprocessing and pretreatment steps are typically necessary (Jones et al., 2018). Preprocessing involves activities such as chipping or grinding to reduce the size of the biomass and enhance its processability. Pretreatment methods, such as steam explosion, acid pretreatment, or organosolv processes, are often employed to disrupt the lignocellulosic structure and increase the accessibility of cellulose and hemicellulose for subsequent hydrolysis (Ansanay et al., 2021).

Enzymatic hydrolysis is a widely used method for converting forest biomass and lignocellulosic materials into glucose (Zhou et al., 2023). Specific enzymes, such as cellulases and hemicellulases, are employed to break down the cellulose and hemicellulose components into glucose. Enzymatic hydrolysis offers high selectivity, mild operating conditions, and compatibility with various lignocellulosic materials. However, factors such as enzyme cost, enzyme stability, and the presence of inhibitory compounds from pretreatment may impact the efficiency and economics of the process (Li et al., 2019). Acid hydrolysis can also be employed for glucose production from forest biomass and lignocellulosic materials. Strong acids, such as sulfuric acid or hydrochloric acid, are used to hydrolyze the polysaccharides into their constituent sugars. Acid hydrolysis offers faster reaction rates compared to enzymatic hydrolysis. However, it may lead to sugar degradation, formation of inhibitory compounds, and corrosiveness issues, necessitating careful process optimization and waste management strategies (Codato-Zumpano et al., 2023). To maximize glucose production from forest biomass and lignocellulosic materials, process optimization and integration strategies can be implemented. This includes optimizing factors such as temperature, acid concentration (in acid hydrolysis), residence time, solid-liquid ratios, and pretreatment conditions. Integration with other biorefinery processes, such as lignin valorization, fermentation, or co-production of other value-added products, can enhance the overall process efficiency, resource utilization, and economic viability (Okonkwo et al., 2022).

Algal Biomass as a Potential Source

Algal biomass consists of various components, including proteins, lipids, carbohydrates, pigments, vitamins, and minerals. The carbohydrate fraction, which includes glucose and other sugars, can be extracted and utilized for glucose production (Ruiz et al., 2020). The exact composition of algal biomass varies depending on the algal species, cultivation conditions, and growth phase. Algae are found in diverse aquatic environments, including freshwater, marine, and brackish water systems. They can be cultivated in open ponds, closed photobioreactors, or other specialized systems. Algal biomass has the potential to be an abundant and renewable feedstock due to the high growth rates of certain algal species and their ability to utilize sunlight and carbon dioxide for photosynthesis (Yang et al., 2023). Algal biomass can be cultivated using different cultivation systems and techniques. Open pond systems involve the cultivation of algae in large, shallow ponds exposed to sunlight.

Closed photobioreactors provide a controlled environment, allowing for precise control of parameters such as temperature, light intensity, and nutrient availability. Algal cultivation requires appropriate nutrient supply, including carbon dioxide, nitrogen, phosphorus, and micronutrients, to support optimal growth and carbohydrate accumulation (de Souza et al., 2019).

Once the algal biomass has reached the desired growth stage, it needs to be harvested and processed to extract the carbohydrates, including glucose (Huo et al., 2022). Harvesting methods may include mechanical methods (e.g., centrifugation, filtration) or physicochemical methods (e.g., flocculation, sedimentation) to separate the algae from the growth medium. After harvesting, the biomass can undergo further processing steps, such as cell disruption, dewatering, and extraction, to obtain the desired carbohydrate fraction (Hamman et al., 2018). Glucose production from algal biomass can be achieved through enzymatic hydrolysis or acid hydrolysis methods, similar to other biomass feedstocks. Enzymatic hydrolysis involves the use of specific enzymes, such as cellulases and hemicellulases, to break down the carbohydrates into glucose (de Souza et al., 2019). Acid hydrolysis utilizes strong acids, such as sulfuric acid or hydrochloric acid, to hydrolyze the carbohydrates. The choice of hydrolysis method depends on factors such as the algal species, biomass composition, process economics, and desired end products. Algal biomass holds significant potential as a sustainable feedstock for glucose production. Algae have a high photosynthetic efficiency and can utilize carbon dioxide, thus contributing to carbon capture and potentially mitigating greenhouse gas emissions. Algal cultivation can also be integrated with wastewater treatment, nutrient recycling, and the production of other value-added products such as biofuels, bioplastics, or animal feed (Ruiz et al., 2020). However, certain considerations, such as water and nutrient requirements, cultivation system scalability, and potential ecological impacts, should be carefully addressed to ensure the sustainability of algal biomass utilization.

Food Waste and Byproducts

Food waste and byproducts comprise organic materials from agricultural, processing, distribution, and consumption activities. These include fruit and vegetable peels, trimmings, discarded grains, food processing residues, expired products, and other food-related waste. The composition of food waste and byproducts can vary greatly, but they often contain significant amounts of carbohydrates, including glucose and other sugars, along with proteins, lipids, fibers, and other nutrients (Okonkwo et al., 2022). Food waste and byproducts are abundant and readily available throughout the food supply chain. They arise from various sources, including households, restaurants, food processing facilities, and retail sectors. The quantity and availability of food waste and byproducts depend on factors such as consumption patterns, food handling practices, and waste management systems. Efficient utilization of these materials not only reduces waste but also contributes to a circular economy and resource conservation (Yu et al., 2022). Prior to glucose production, food waste and byproducts may require preprocessing and pretreatment steps. Preprocessing involves sorting, cleaning, and potentially size reduction to remove non-biodegradable components and improve processability. Pretreatment methods, such as enzymatic or acid hydrolysis, can be employed to break down complex carbohydrates and enhance the release of glucose (Zhou et al., 2023). Additionally, degrading enzymes or microbial fermentation may be utilized to convert more complex food waste components into glucose or other valuable products.

Enzymatic hydrolysis is a common method for converting food waste and byproducts into glucose. Specific enzymes, such as carbohydrases, can be employed to break down the complex carbohydrates present in these materials (Yu et al., 2022). Enzymatic hydrolysis offers high selectivity, mild operating conditions, and compatibility with a wide range of food waste and byproduct feedstocks. However, factors such as enzyme cost, enzymatic stability, and the presence of inhibitory compounds from the waste stream may affect process efficiency and economics. Acid hydrolysis can also be utilized for glucose production from food waste and byproducts. Strong acids, such as sulfuric acid or hydrochloric acid, are used to break down the carbohydrates into their constituent sugars. Acid hydrolysis offers faster reaction rates compared to enzymatic hydrolysis and can handle a broader range of feedstocks (Ebikade et al., 2018). However, it requires careful control to prevent sugar degradation and the formation of inhibitory compounds, and appropriate waste management strategies are essential due to the corrosive nature of the acids. To maximize glucose production from food waste and byproducts, process optimization and integration strategies are crucial. This includes optimizing factors such as temperature, pH, residence time, acid concentration (in acid hydrolysis), enzyme loading (in enzymatic hydrolysis), and solid-liquid ratios. Integration with other processes, such as anaerobic digestion for biogas production (Abubakar et al., 2022), can further enhance resource utilization and overall process efficiency, reducing waste and generating additional value from food waste and byproducts.

Comparison of Different Feedstock Sources

When considering glucose production, various feedstock sources can be utilized, each with its own characteristics and considerations. Agricultural residues, such as crop straw, corn stover, and sugarcane bagasse, are abundant and widely available (Schiano et al., 2022). They do not compete with food production, making them a sustainable and renewable feedstock option. Agricultural residues often have high cellulose and hemicellulose content, which can be efficiently hydrolyzed into glucose. Agricultural residues may require preprocessing and pretreatment to enhance their processability and increase sugar accessibility (Jones et al., 2018). Some residues have high lignin content, which adds to the recalcitrance and complexity of the feedstock (Blanco et al., 2020). Proper waste management and logistics are essential to ensure a consistent and reliable supply.

Forest biomass and lignocellulosic materials, including wood chips, sawdust, and logging residues, offer a sustainable feedstock source (Blanco et al., 2020). They are abundant, widely available, and can be sourced from managed forests. Forest biomass contains significant amounts of cellulose, which can be converted into glucose (Selivanov et al., 2023). Additionally, lignocellulosic materials can be integrated with the production of other value-added products, such as biofuels or bioplastics. Preprocessing and pretreatment are often required to overcome the recalcitrance of lignocellulosic materials (Elalami et al., 2022). Supply chain logistics and sustainability considerations, including responsible forest management practices, need to be addressed. The presence of lignin may affect the efficiency of glucose production and downstream.

Algal biomass presents a renewable and highly productive feedstock source for glucose production. Algae can be cultivated in various aquatic environments and have the potential to achieve high growth rates and carbon dioxide fixation. Some algae species accumulate significant amounts of carbohydrates, including glucose, which can be extracted and utilized (Ruiz et al., 2020; Smachetti et al., 2018). Algal cultivation can be integrated with wastewater treatment and other biorefinery processes. Algal cultivation requires careful management of nutrients, including carbon dioxide, nitrogen, and phosphorus, to achieve optimal growth and carbohydrate accumulation. Scalability and cost-effectiveness of large-scale cultivation systems remain challenges (Zhang et al., 2020). Harvesting and processing methods for algal biomass can be energy-intensive and require further development for cost reduction (Moreira et al., 2019).

Food waste and byproducts offer a readily available and abundant feedstock source for glucose production (Schiano et al., 2022). They can be sourced from various stages of the food supply chain, reducing waste and contributing to a circular economy. Food waste often contains significant amounts of carbohydrates, including glucose, making it an attractive feedstock option. Food waste and byproducts may require preprocessing, sorting, and potential pretreatment to remove non-biodegradable components and enhance processability (Elalami et al., 2022). The composition of food waste can be diverse and variable, requiring tailored processing approaches. Waste collection, handling, and logistics need to be efficiently managed to ensure a reliable and uncontaminated feedstock supply.

Sugarcane Bagasse, Rice Husk and Sawdust Application

Producing glucose from sugarcane bagasse involves breaking down the complex carbohydrates present in the bagasse into simpler sugars like glucose. Sugarcane bagasse is the fibrous residue left after extracting the juice from sugarcane stalks in the sugar extraction process. It is rich in cellulose and hemicellulose, both of which can be converted into glucose through different processes. General outline of the process to produce glucose from sugarcane bagasse include preparation of Sugarcane Bagasse, pretreatment, enzymatic hydrolysis, fermentation, separation and purification and glucose concentration. Previous work done using the feedstock to produce glucose are found in Roslan & Salimi (2019), Lv et al. (2022) and Bussamra et al. (2020). Glucose produced from rice husk can find applications in various industries, similar to glucose produced from other lignocellulosic biomass sources. Some potential applications include bioethanol production, food and beverage industry, pharmaceutical and nutraceutical industries, chemical feedstock and bioplastics (Dhar et al., 2019).
It's essential to consider that the advantages of glucose production from rice husk depend on various factors, including local agricultural practices, feedstock availability, infrastructure, and the specific application of the glucose produced. Both rice husk and sugarcane bagasse have their unique characteristics, and the choice of feedstock would depend on the specific circumstances and objectives of the glucose production process. Production of glucose from rice husk will also follow the same process steps listed under sugarcane bagasse utilization, beginning with pretreatment (Aredo et al., 2020; Bohn et al., 2021; Cheoh, 2018). The same author also adopts a unique model called the Peleg kinetic model to determine the reaction rate constant. More details are found in Asim et al. (2021) who analyzed the production of food-grade glucose using wheat residues and rice waste. On the other hand, there is limited utilization of sawdust to produce glucose. One among previous studies (within 2018-2023) discovered is a study by Hassan et al. (2018).

Microorganism Strain for Hydrolysis

Biodegradation is the application of biological principle for the purpose of converting food stuff into more palatable nutritional or staple food; it has the potential to improve the nutritional value of fibrous agricultural by-product. Enzymatic hydrolysis of cellulose is carried out by enzyme which is highly specific. *Aspergillus niger* is worldwide in distribution and has been isolated from numerous habitat. Humans are continually exposed to *Aspergillus niger* spores and vegetative forms on foodstuffs and in air. The vast majority of *Aspergillus niger* strains especially those used in industrial fermentation have a history of safe use (Edor et al., 2018). Some species of the fungal genus Aspergillus produce glucoamylase enzymes that can break down starches into glucose. These enzymes are widely used in various industries for starch hydrolysis and glucose production. Apart from *Aspergillus niger* chosen by this study, several other microorganism strains such as *Escherichia coli* may be used (Carreón-Rodríguez et al., 2023).

Methodology

Initial literature review was earlier reported in two sections: 2.1 and 2.2. Of concern to bioengineers is the speed of these production and product optimization. In view of that, kinetics and optimization strategies were well discussed using sourced materials, including, book chapters, thesis, journals, book and conference papers. Usually, a good kinetics study and optimized production of glucose will translate into experts venturing into its manufacture for sustainable growth and benefits that can be driven from it. Thus, the expected results discuss techno-economic analysis, cost, life cycle assessment, and case studies for its industrial application.

Kinetics of Glucose Production

The kinetics of glucose production refers to the study of the rates and mechanisms involved in the conversion of different feedstocks into glucose. Understanding the kinetics is essential for optimizing process conditions, designing reactors, and predicting glucose yields. Several factors influence the kinetics of glucose production, including the type of feedstock, hydrolysis method, enzyme or acid concentration, temperature, pH, and reaction time (Ude et al., 2020). These factors affect the reaction rates by influencing the accessibility of carbohydrates, the catalytic activity of enzymes or acids, and the solubility and stability of the intermediates and products (Sodiqovna, 2020). Optimal process conditions need to be determined to achieve high glucose yields and conversion rates. The kinetics of glucose production can involve different reaction mechanisms depending on the hydrolysis method used. In enzymatic hydrolysis, specific enzymes, such as cellulases and hemicellulases, break down the polysaccharides into glucose molecules through enzymatic cleavage of glycosidic bonds (Hu et al., 2021; ILO, 2020). The reaction typically follows a complex mechanism involving substrate adsorption, enzymatic reaction, and product desorption. Acid hydrolysis, on the other hand, involves the hydrolysis of carbohydrates by strong acids (Andreeva et al., 2021), resulting in the cleavage of glycosidic bonds and the release of glucose.

Mathematical models are widely used to describe and predict the kinetics of glucose production. These models can be based on empirical correlations, mechanistic principles, or a combination of both. Empirical models use experimental data to develop correlations between process variables and glucose production rates. Mechanistic models (Richter et al., 2022; Salazar et al., 2023), on the other hand, are based on the understanding of reaction mechanisms and the application of mass balance and rate equations. These models can provide insights into the underlying reaction kinetics and aid in process optimization and reactor design. The determination of reaction rates is crucial for understanding the kinetics of glucose production. Experimental techniques such as batch assays, continuous flow reactors, or spectroscopic methods can be employed to measure the rates of glucose release or consumption (Halka et al., 2018). By varying process parameters such as enzyme or acid concentration, temperature, or reaction time, the rates can be determined and used to estimate reaction rate constants and activation energies. Kinetic modeling involves the development of mathematical equations that describe the rates of glucose production as a function of various process variables. Model parameters, such as reaction rate constants and activation energies, can be estimated by fitting the model to experimental data using optimization techniques. Parameter estimation methods (Murzin et al., 2021; Yu et al., 2021), such as nonlinear regression or kinetic modeling software, can be employed to obtain accurate parameter values and validate the model's predictive capabilities. The kinetics of glucose production play a crucial role in process optimization. By studying the reaction rates and understanding the underlying mechanisms, process conditions can be optimized to maximize glucose yields, conversion rates, and process efficiency (Bryan et al., 2018; Toif et al., 2021). Kinetic studies also provide insights into the effects of different variables, allowing for the identification of limiting factors and the determination of optimal operating conditions. Table 1 are literature summary of previous work on glucose production.

Table 1: Literature Review on Glucose Production Methodologies

Author	Microorganism and/or Feedstock	Method	Glucose Yield	Condition
(Ude et al., 2020)	0.428 g/50 mL enzyme + mixed peels (cassava & potato)	Kinetic of hydrolysis: Michaelis-Menten model; Optimization = RSM	79%	36 ℃ ; pH = 4.55; retention time = 5 days
(Onyelucheya et al., 2022)	Corn cob	Kinetics: Seaman & Two-Fraction model	0.038 mg/mL	130 ℃ ; phosphoric acid & nitric acid
(Dussán et al., 2014)	Sugarcane bagasse + Sc. stipitis	Analytical method	22.74 g/L	Dilute sulfuric acid; 155℃; time = 10 min
(El-Zawawy et al., 2011)	Rice straw + banana plant + corn cob + Enzyme (Trichoderma reesei)	Enzyme and acid hydrolysis	0.3-1.1 g/L	Sulphuric acid; pH = 4.5-5.0; 40-50℃
(Adeoye et al., 2019)	Pineapple + pawpaw peels	Pseudo-First order model; Arrhenius thermodynamic model; FTIR	29.47-30.8%	1M H_2SO_4 hydrolysis; 60-90 ℃ ; hydrolysis time = 0-140 min; acid conc = 1-3.5M
(Roslan & Salimi, 2019)	Sugarcane bagasse	RSM, Regression analysis and Design of Experiment (DOE)	0.783 g/L	34°C, pH = 6.39 and enzyme dosage = 0.15 mL

Kinetic Models for Enzymatic Hydrolysis

Kinetic models for enzymatic hydrolysis are mathematical representations that describe the rates of glucose production from the hydrolysis of polysaccharides by enzymes (Shokrkar & Ebrahimi, 2021). These models are essential for understanding the underlying mechanisms, optimizing process conditions, and predicting glucose yields. The commonly used kinetic models for enzymatic hydrolysis, their assumptions, and their applications will be discussed (Efrinalia et al., 2022; Shokrkar & Ebrahimi, 2021).

(a) Michaelis-Menten Model: The Michaelis-Menten model is one of the most widely used kinetic models for enzymatic reactions, including enzymatic hydrolysis. It assumes that the reaction rate is proportional to the concentration of the enzyme-substrate complex. The model incorporates two parameters: the maximum reaction rate (V_{max}) and the Michaelis constant (K_m), which represents the substrate concentration at which the reaction rate is half of Vmax. The Michaelis-Menten model is based on the assumption of steady-state enzyme kinetics and assumes that the enzyme-substrate complex is the rate-determining step.

(b) Briggs-Haldane Model: The Briggs-Haldane model is an extension of the Michaelis-Menten model and considers the reversible formation of the enzyme-substrate complex. It incorporates an additional parameter, the dissociation constant (K_d), which represents the equilibrium constant between the enzyme-substrate complex and the free enzyme and substrate. The Briggs-Haldane model provides a more accurate representation of the enzymatic hydrolysis process by considering the reversible nature of the enzyme-substrate interaction.

(c) Hanes-Woolf Model: The Hanes-Woolf model is an alternative representation of the Michaelis-Menten equation. It linearizes the relationship between the reaction rate and the substrate concentration by plotting the ratio of the substrate concentration to the reaction rate against the substrate concentration. The slope of the linear plot represents the Michaelis constant (K_m), and the intercept on the y-axis represents the reciprocal of the maximum reaction rate ($1/V_{max}$). The Hanes-Woolf model is particularly useful when experimental data have high variability or at low substrate concentrations.

(d) Luedeking-Piret Model: The Luedeking-Piret model is a phenomenological model that describes the relationship between the production rate of glucose and the consumption rate of the substrate. It assumes that both the glucose production and substrate consumption rates are dependent on the concentration of the substrate and the enzyme. The model incorporates two parameters: the Luedeking-Piret coefficient (α), which represents the extent of glucose production independent of substrate consumption, and the Luedeking-Piret coefficient (β), which represents the fraction of substrate consumed in relation to glucose production.

(e) Substrate Inhibition Model: The substrate inhibition model accounts for the inhibition of the enzymatic reaction at high substrate concentrations. It assumes that the reaction rate decreases at high substrate concentrations due to the inhibitory effect of the excess substrate. The model incorporates an additional parameter, the inhibition constant (K_i), which represents the substrate concentration at which the reaction rate is half of the maximum reaction rate. The substrate inhibition model is particularly relevant when working with concentrated substrate solutions.

(f) Modified Kinetic Models: In addition to the aforementioned models, various modified kinetic models have been proposed to account for specific factors and phenomena in enzymatic hydrolysis. These include models considering enzyme deactivation, enzyme substrate heterogeneity, multiple enzyme activities, and product inhibition. These modified models provide a more comprehensive representation of the enzymatic hydrolysis process by considering additional factors that can influence reaction rates and glucose yields.

Kinetic models for enzymatic hydrolysis provide valuable insights into the reaction mechanisms, reaction rates, and optimal process conditions for glucose production. By fitting the models to experimental data using parameter estimation techniques (Shokrkar & Ebrahimi, 2021; Yu et al., 2021), the kinetic parameters can be determined, enabling the prediction of glucose yields and the optimization of enzymatic hydrolysis processes. However, it is important to note that the selection and applicability of a specific kinetic model depend on the characteristics of the enzyme-substrate system and the specific objectives of the study (Panda & Datta, 2022).

Kinetic Models for Acid Hydrolysis

Kinetic models for acid hydrolysis are mathematical representations that describe the rates of glucose production from the hydrolysis of polysaccharides by strong acids (Yuan et al., 2021). These models are valuable tools for understanding the acid hydrolysis process, optimizing reaction conditions, and predicting glucose yields. Discussion on some commonly used kinetic models for acid hydrolysis, their assumptions, and their applications are found below.

(i) First-Order Kinetic Model:

The first-order kinetic model is a simple and widely used model for acid hydrolysis. It assumes that the reaction rate is directly proportional to the concentration of the substrate (polysaccharide) or the acid. The model Equation 1 is given by Onyelucheya et al. (2022):

$$\text{Rate} = \text{k[Substrate]} \quad (1)$$

where Rate represents the reaction rate, k is the rate constant, and [Substrate] is the concentration of the substrate. The first-order kinetic model assumes that the acid hydrolysis reaction follows pseudo-first-order kinetics, where the concentration of the acid is maintained at a sufficiently high level.

(ii) Pseudo-First-Order Kinetic Model

The pseudo-first-order kinetic model is an extension of the first-order model that accounts for the effect of both substrate and acid concentrations on the reaction rate. The model equation is given by Equation 2:

$$\text{Rate} = \text{k[Substrate][Acid]} \quad (2)$$

where Rate represents the reaction rate, k is the rate constant, [Substrate] is the concentration of the substrate, and [Acid] is the concentration of the acid. The pseudo-first-order kinetic model assumes that the reaction rate is dependent on both the substrate and acid concentrations.

(iii) Second-Order Kinetic Model

The second-order kinetic model considers the simultaneous reaction of two reactants, the substrate and the acid. The model equation is given by Equation 3:

$$\text{Rate} = \text{k[Substrate][Acid]} \quad (3)$$

where Rate represents the reaction rate, k is the rate constant, [Substrate] is the concentration of the substrate, and [Acid] is the concentration of the acid. The second-order kinetic model assumes that the reaction rate is proportional to the product of the substrate and acid concentrations.

(iv) Fractional Conversion Kinetic Model

The fractional conversion kinetic model describes the conversion of the substrate into glucose as a function of time. It assumes that the reaction rate is proportional to the remaining concentration of the substrate. The model equation is given by Equation 4:

$$X = 1 - e^{-kt} \quad (4)$$

where X represents the fractional conversion of the substrate, k is the rate constant, t is the reaction time, and e is the base of the natural logarithm. The fractional conversion kinetic model is useful for monitoring the progress of acid hydrolysis reactions and estimating the extent of substrate conversion.

(v) Modified Kinetic Models

Various modified kinetic models have been proposed to account for specific factors and phenomena in acid hydrolysis, such as temperature dependence, catalytic effects of acid, and inhibition effects. These models incorporate additional parameters or variables to improve the accuracy of the predictions and provide a more comprehensive representation of the acid hydrolysis process.

Kinetic models for acid hydrolysis provide insights into the reaction rates, reaction mechanisms, and optimal process conditions for glucose production (Efrinalia et al., 2022). By fitting these models to experimental data using parameter estimation techniques (Salmi et al., 2020; Yu et al., 2021), the kinetic parameters can be determined, enabling the prediction of glucose yields and the optimization of acid hydrolysis processes. However, it is important to consider the limitations of these models and the specific characteristics of the acid hydrolysis system being studied when selecting and applying a particular kinetic model (Yuan et al., 2021).

Kinetic Models for Fermentation Processes

Kinetic models for fermentation processes are mathematical representations that describe the rates of glucose consumption and product formation during the conversion of sugars into various products, such as ethanol, organic acids, or biofuels, by microorganisms. These models are crucial for understanding the fermentation kinetics, optimizing process conditions, and predicting product yields. In this section, we will discuss some commonly used kinetic models for fermentation processes, their assumptions, and their applications.

A) Monod Model

The Monod model is a widely used kinetic model for microbial fermentation processes. It describes the specific growth rate of microorganisms as a function of substrate concentration. The model equation is given by González-Figueredo et al. (2017) in Equation 5:

$$\mu = \frac{\mu_{max} S}{K_s + S} \qquad (5)$$

where μ represents the specific growth rate, μ_{max} is the maximum specific growth rate, [S] is the substrate concentration, and K_s is the saturation constant. The Monod model assumes that the specific growth rate is limited by substrate availability and follows a hyperbolic relationship with the substrate concentration.

B) Logistic Model

The logistic model is an extension of the Monod model that takes into account the inhibition effects of high substrate concentrations on microbial growth. It incorporates an additional term, $\mu_{max}(1 - [S]/K_I)$, to represent substrate inhibition. The logistic model is useful when dealing with fermentation processes where high substrate concentrations can negatively impact microbial growth and product formation.

C) Contois Model

The Contois model is a kinetic model that considers the limitation of both substrate and product concentrations on microbial growth. It assumes that the specific growth rate is proportional to the substrate consumption rate and the square of the product concentration. The model equation is given by Equation 6:

$$\mu = \frac{\mu_{max} S}{K_s + [S] + \alpha [P]^2} \qquad (6)$$

where μ represents the specific growth rate, μmax is the maximum specific growth rate, [S] is the substrate concentration, [P] is the product concentration, K_s is the saturation constant for substrate, and α is the inhibition constant for product. The Contois model provides a more comprehensive representation of fermentation kinetics by considering the inhibitory effects of product accumulation.

D) Luedeking-Piret Model

The Luedeking-Piret model is a phenomenological model that describes the production rate of a desired product during fermentation. It assumes that the production rate is a function of both the growth-associated and non-growth-associated components. The model equation is given by Equation 7:

$$P = \alpha\mu + \beta[S] \qquad (7)$$

where P represents the product concentration, μ is the specific growth rate, [S] is the substrate concentration, and α and β are the Luedeking-Piret coefficients. The Luedeking-Piret model is useful for analyzing the relationship between microbial growth and product formation during fermentation.

E) Structured Kinetic Models

Structured kinetic models consider the intracellular processes and metabolic pathways of microorganisms during fermentation. These models describe the dynamic changes in cellular components, such as biomass, substrate, and product concentrations, and the corresponding fluxes. Structured models are more complex and require additional parameters and data for their calibration, but they provide a more detailed understanding of the microbial fermentation process (Ali et al., 2023; Elmer & Gaden, 2000).
Kinetic models for fermentation processes help elucidate the relationship between substrate consumption, product formation, and microbial growth (Kresnowati et al., 2015). By fitting these models to experimental data using parameter estimation techniques, the kinetic parameters can be determined, enabling the prediction of product yields and the optimization of fermentation processes (Brito & Antunes, 2014; Shatalov et al., 2013). However, it is important to consider the limitations of these models, such as the assumption of constant parameters and the simplifications made in describing complex biological processes, when applying them to specific fermentation systems.

Factors Affecting Reaction Kinetics

Understanding the factors that affect reaction kinetics is crucial for optimizing reaction conditions, predicting reaction rates, and designing efficient chemical processes. Some key factors that influence reaction kinetics are the concentration of reactants, temperature, catalysts, surface area, presence of inhibitors or catalyst poisons, pressure, solvent, reaction mechanism, activation energy and molecular orientation. The concentration of reactants plays a significant role in determining the rate of a chemical reaction. According to the collision theory, for a reaction to occur, reactant molecules must collide with sufficient energy and proper orientation. Higher concentrations of reactants increase the frequency of collisions, leading to a higher reaction rate. Temperature has a profound effect on reaction kinetics. Increasing the temperature generally increases the reaction rate. This is because higher temperatures provide reactant molecules with more kinetic energy, resulting in more frequent and energetic collisions. Additionally, higher temperatures can overcome activation energy barriers, allowing reactions to proceed more readily (Sodiqovna, 2020). Catalysts are substances that increase the rate of a chemical reaction without being consumed in the process. They lower the activation energy required for the reaction to occur, thereby facilitating the formation of products. Catalysts provide an alternative reaction pathway with a lower activation energy, allowing for faster reaction rates. In reactions involving solids or heterogeneous systems, the surface area of the reactants plays a vital role. Increasing the surface area by breaking solids into smaller particles or using catalysts in finely divided form exposes a larger area for reactant molecules to come into contact. This enhances the frequency of collisions and increases the reaction rate (Sodiqovna, 2020).

In gas-phase reactions, pressure can affect reaction kinetics. Increasing the pressure increases the number of gas molecules per unit volume, which leads to more frequent collisions. Higher pressure can increase the reaction rate by increasing the concentration of reactant molecules and their collision frequency. The specific reaction mechanism, including the sequence of elementary steps, intermediate species, and rate-determining steps, influences the overall reaction rate. Understanding the reaction mechanism is crucial for designing appropriate kinetic models and optimizing reaction conditions. The choice of solvent can significantly impact reaction kinetics, particularly in liquid-phase reactions. The solvent can affect the stability of reactants, the solubility of reactants and products, and the mobility of molecules, all of which influence reaction rates. Inhibitors are substances that decrease the rate of a reaction, while catalyst poisons are substances that deactivate catalysts. Both inhibitors and catalyst poisons reduce the effectiveness of the reactants or catalysts, leading to a slower reaction rate For reactions involving multiple reactant molecules, the molecular orientation during collisions can affect reaction kinetics (Abril-González et al., 2023). In some cases, specific molecular orientations are required for effective collisions and reaction to occur. Factors that influence molecular orientation include steric hindrance, molecular shape, and the presence of functional groups. Activation energy is the minimum energy required for a reaction to occur. Reactions with higher activation energies typically have slower reaction rates. Lowering the activation energy through factors like temperature, catalysts, or the presence of suitable reactant molecules can significantly accelerate the reaction rate. Understanding and manipulating these factors can help control and optimize reaction kinetics in various chemical processes. It allows for the design of efficient reactions, the development of suitable reaction conditions, and the prediction of reaction rates and yields.

Experimental Techniques for Kinetic Parameter Estimation

Experimental techniques for kinetic parameter estimation are essential for obtaining accurate and reliable information about the rate constants and parameters that govern chemical reaction kinetics. These techniques involve conducting experiments under controlled conditions and analyzing the resulting data to determine the kinetic parameters. Some experimental techniques for kinetic parameter estimation are (Shim et al., 2020; Yu et al., 2021):

a) Method of Initial Rates: The method of initial rates is a widely used technique for estimating kinetic parameters. It involves conducting multiple reactions with different initial concentrations of reactants and measuring the reaction rates at the beginning of each reaction. By analyzing the data, such as plotting the initial rate versus the initial concentration, the rate constant or reaction order can be determined.
b) Integrated Rate Laws: Integrated rate laws involve measuring the concentration of reactants or products at different time intervals during a reaction. By integrating the rate laws for different reaction orders or rate expressions, it is possible to obtain equations that relate the concentration of reactants or products to time. By fitting these equations to experimental data, the rate constant and reaction order can be estimated.
c) Differential Analysis (Onyelucheya et al., 2022): Differential analysis involves measuring the change in concentration of reactants or products over time. By taking the derivative of the concentration-time data, the reaction rate can be determined. Differential analysis is particularly useful for reactions with complex reaction mechanisms or when the reaction rates are not constant (Abril-González et al., 2023; Salmi et al., 2020).
d) Temperature Dependence: The temperature dependence of reaction rates can provide valuable information about the activation energy and temperature dependence of rate constants. By conducting reactions at different temperatures and analyzing the resulting data, the Arrhenius equation can be used to estimate the activation energy and pre-exponential factor (Adeoye et al., 2019; P. Zhang & Sutheerawattananonda, 2020).

e) In situ Monitoring: In situ monitoring techniques involve measuring the concentration of reactants or products during the course of the reaction without the need for sample removal. Techniques such as spectroscopy, chromatography, and mass spectrometry can be employed to monitor the reaction progress in real-time. In situ monitoring allows for continuous data acquisition and can provide insights into reaction kinetics and mechanisms.
f) Isotope Labeling: Isotope labeling techniques involve introducing isotopically labeled compounds into the reaction system. By monitoring the incorporation of isotopes into reaction products or following the isotopic exchange between reactants and products, information about reaction pathways, intermediate species, and rate constants can be obtained.
g) Design of Experiments (DOE): DOE techniques involve systematically varying reaction conditions, such as temperature, concentration, and catalyst loading, to obtain a comprehensive set of data for kinetic parameter estimation. Statistical analysis methods, such as response surface methodology and factorial designs, can be used to analyze the data and estimate the kinetic parameters.
h) Model Fitting and Simulation: Mathematical modeling and simulation techniques can be employed to fit experimental data to kinetic models. Software tools and optimization algorithms can assist in finding the best-fit parameters by minimizing the difference between the experimental data and model predictions.

It is important to note that the choice of experimental technique depends on the specific reaction system, available resources, and the desired level of accuracy. Often, a combination of different techniques is used to obtain a comprehensive understanding of reaction kinetics and estimate the kinetic parameters with greater confidence.

Optimization Strategies for Glucose Production

Optimization strategies for glucose production involve maximizing the yield, conversion efficiency, and productivity of glucose production processes. These strategies aim to optimize various aspects of the process, such as reaction conditions, process parameters, and feedstock selection, to enhance the overall performance and economic viability (Foust et al., 2020; Sant et al., 2021). Table 2 shows some commonly employed optimization strategies for glucose production.

Table 2: Common Optimization Strategy and their Significance (Elalami et al., 2022; Moreira et al., 2019)

S/No	Optimization Strategy	Description
1.	Reaction and Process Optimization	Optimizing the reaction conditions is crucial for maximizing glucose production. This includes optimizing parameters such as temperature, pH, reaction time, enzyme or catalyst concentration, and agitation speed. By systematically varying these parameters and analyzing their impact on glucose yield and conversion, the optimal reaction conditions can be determined
2.	Feedstock Selection and Pretreatment	The choice of feedstock plays a significant role in glucose production. Different feedstocks, such as agricultural residues, forest biomass, or algal biomass (Andreeva et al., 2021), have different compositions and properties that affect their enzymatic or chemical conversion to glucose. Optimizing feedstock selection involves considering factors such as availability, cost, composition, and ease of pretreatment to enhance glucose yield and minimize production costs.
3.	Pretreatment Optimization	Pretreatment of feedstock is often necessary to enhance the accessibility of polysaccharides, such as cellulose or hemicellulose, to enzymatic or acid hydrolysis. Optimization of pretreatment conditions, such as temperature,

		pressure, residence time, and the use of specific pretreatment agents, can significantly improve the efficiency of glucose release from feedstock.
4.	Enzyme and Catalyst Optimization	When enzymatic or acid hydrolysis is employed for glucose production, optimizing the choice and concentration of enzymes or catalysts is essential. This includes selecting enzymes with high activity and specificity, optimizing their dosage, and considering the use of enzyme cocktails or synergistic combinations to improve glucose release and minimize enzyme costs.
5.	Process Integration and Scale-Up	Optimizing the integration of different process steps and optimizing the scale-up of glucose production processes are critical for commercial viability. Process integration involves streamlining the process steps, minimizing energy consumption, and optimizing process flows to maximize efficiency. Scale-up optimization focuses on translating laboratory-scale processes to larger production scales while maintaining consistent and efficient glucose production.
6.	Reaction Kinetics and Modeling	Understanding the reaction kinetics and developing mathematical models can aid in the optimization of glucose production processes (Yassien & Jiman-Fatani, 2023). Kinetic modeling helps in predicting glucose yields, identifying rate-limiting steps, and optimizing reaction conditions. It allows for the exploration of different scenarios and the identification of optimal operating conditions.
7.	Techno-economic Analysis	Performing techno-economic analysis is crucial for evaluating the feasibility and economic viability of glucose production processes (Sant et al., 2021). This analysis involves assessing the capital and operating costs, calculating the glucose production costs, and considering factors such as feedstock costs, enzyme costs, equipment costs, and market demand. Optimizing the process parameters to reduce production costs and improve overall process economics is a key aspect of optimization strategies.
8.	Continuous Process Development	Optimizing glucose production often involves transitioning from batch processes to continuous processes (Halka et al., 2018). Continuous processes offer advantages such as improved productivity, better control over reaction conditions, and reduced labor and equipment costs. Optimizing the design and operation of continuous processes for glucose production can lead to higher yields, improved efficiency, and reduced operational complexities.

Process Optimization Techniques

Process optimization techniques play a crucial role in improving the efficiency, productivity, and overall performance of chemical processes. These techniques involve systematically analyzing and improving different aspects of the process to achieve desired objectives, such as maximizing yield, minimizing costs, reducing waste, and improving product quality. In the context of glucose production, process optimization techniques aim to enhance the efficiency of glucose production processes. Here (Table 3) are some commonly used process optimization techniques:

Table 3: Optimization Techniques in Common Application (Malakar et al., 2020)

S/No	Optimization Technique	Description
1.	Multi-Objective Optimization	In some cases, process optimization requires balancing multiple conflicting objectives. Multi-objective optimization techniques aim to find optimal solutions that satisfy multiple objectives simultaneously. These techniques involve defining the objectives, determining their relative importance, and using optimization algorithms to identify the optimal trade-offs and Pareto optimal solutions
2.	Process Integration	Process integration techniques focus on optimizing the interaction and integration of different process steps to maximize efficiency and minimize resource consumption. Techniques such as heat integration, mass integration, and pinch analysis are used to identify opportunities for energy recovery, minimize utility usage, and improve overall process efficiency.
3.	Computational Modeling and Simulation	Computational modeling and simulation tools enable the virtual optimization of process parameters, equipment design, and operating conditions. By developing mathematical models based on fundamental principles and simulating various scenarios, process optimization can be performed in a cost-effective and time-efficient manner. Modeling and simulation allow for the evaluation of different process configurations and the identification of optimal operating conditions without extensive experimental testing.
4.	Six Sigma	Six Sigma is a data-driven approach aimed at reducing process variability and improving process performance. It involves the use of statistical analysis and problem-solving methodologies, such as DMAIC (Define, Measure, Analyze, Improve, Control), to identify and eliminate defects or variations in the process. Six Sigma helps optimize process parameters, minimize process variability, and enhance process capability.
5.	Lean Manufacturing	Lean manufacturing principles focus on eliminating waste and optimizing process flow to improve efficiency and reduce costs. Techniques such as value stream mapping, 5S (Sort, Set in Order, Shine, Standardize, Sustain), and Just-In-Time (JIT) production are used to identify and eliminate non-value-added activities, streamline production processes, reduce inventory, and improve overall process efficiency.
6.	Response Surface Methodology (RSM)	RSM (Uchegbu et al., 2022) is a statistical technique used to optimize process parameters by constructing mathematical models that relate process variables to the desired responses. RSM involves conducting experiments based on a predefined design matrix and using regression analysis to fit a response surface model. The model is then analyzed to identify optimal operating conditions that maximize the desired response, such as glucose yield or productivity.
7.	Statistical Process Control (SPC)	SPC involves monitoring and controlling process variables to ensure that the process operates within defined limits and remains stable over time. It uses statistical tools, such as control charts, to detect and address any process variations or deviations. By continuously monitoring the process, SPC helps maintain consistent process performance and reduces the likelihood of quality issues or production failures.
8.	Design of Experiments (DOE)	DOE is a statistical approach used to systematically vary process parameters and evaluate their impact on process performance. By conducting experiments with different combinations of variables, DOE helps identify the most influential

	factors and their optimal levels. This enables the identification of optimal process conditions and provides valuable insights into the process parameter interactions.

By employing these process optimization techniques, glucose production processes can be optimized to achieve higher yields, improved efficiency, reduced costs, and enhanced product quality. Each technique offers a unique approach to systematically analyze and improve different aspects of the process, leading to more sustainable and economically viable glucose production.

Statistical Design of Experiments

Statistical Design of Experiments (DOE) is a powerful and systematic approach used to plan, conduct, and analyze experiments in order to gain insights into process behavior, optimize process parameters, and improve overall process performance. DOE involves the careful selection of experimental factors and levels, the design of an appropriate experimental layout, and the statistical analysis of the obtained data. This approach enables researchers to efficiently explore and understand the relationship between process variables and responses, leading to more informed decision-making and process optimization. Key components and benefits of the statistical design of experiments includes resource efficiency, optimization and insights, statistical analysis, randomization and replication, response variables, factors and levels and experimental design.
Factors are variables that can potentially influence the process or affect the response of interest. These may include process parameters, input variables, or environmental conditions. Levels represent the specific values or settings at which the factors are set during the experiment. By selecting appropriate factors and levels, researchers can investigate the effect of each factor on the process and identify optimal operating conditions. Experimental design involves planning the layout of the experiment to efficiently and effectively collect data. Various designs, such as Full Factorial Design, Fractional Factorial Design, Central Composite Design, and Taguchi Design, are available, each with its own advantages and limitations. The choice of design depends on factors such as the number of factors, desired resolution, available resources, and the need to estimate interaction effects. A well-designed experiment ensures that all relevant factors are systematically varied and properly controlled. Response variables are the outputs or outcomes of interest that reflect the process performance. These may include glucose yield, conversion efficiency, productivity, or other relevant parameters. By carefully selecting appropriate response variables, researchers can gain insights into the impact of the experimental factors on process performance and identify opportunities for improvement.
Randomization involves assigning experimental runs to random order to minimize the influence of unknown or uncontrollable factors. Randomization ensures that any systematic effects or biases are evenly distributed among the experimental units. Replication, on the other hand, involves repeating experimental runs to obtain multiple observations at each combination of factor levels. Replication helps estimate experimental error and improve the precision and reliability of the results. Once the data are collected, statistical analysis techniques are applied to determine the significance of factors, identify the most influential factors, and quantify their effects on the response variables. Analysis of Variance (ANOVA) is commonly used to assess the significance of the factors and their interactions (Yassien & Jiman-Fatani, 2023). Regression analysis is also employed to develop mathematical models that describe the relationship between factors and responses, allowing for prediction and optimization. DOE provides valuable insights into the process behavior and identifies optimal process settings. By analyzing the experimental data, researchers can identify significant factors, determine optimal factor settings, and understand the interactions between factors. These insights enable process optimization, facilitate decision-making, and guide subsequent experiments or process improvements. DOE helps optimize the use of available resources by reducing the number of experimental runs needed to obtain

meaningful results. By strategically selecting factor levels and employing efficient experimental designs, researchers can achieve a high degree of information with a minimal number of experiments. This results in significant time and cost savings compared to a traditional one-factor-at-a-time approach. The statistical design of experiments is a powerful tool for understanding and optimizing glucose production processes. By systematically varying factors, selecting appropriate designs, and applying statistical analysis, researchers can identify optimal process conditions, uncover relationships between variables, and make informed decisions to improve glucose production efficiency, yield, and quality.

Response Surface Methodology

Response Surface Methodology (RSM) is a statistical and mathematical modeling technique used to optimize process parameters and understand the relationship between multiple variables and a response of interest. RSM provides a systematic approach to analyze and optimize complex processes by constructing a response surface model based on experimental data (Riaukaite et al., 2019). This model enables researchers to predict and optimize the response within the experimental domain and identify the optimal factor settings for process improvement. Some key components and benefits of RSM includes experimental design, response surface model, model fitting and analysis, optimization, sensitivity analysis, validation and verification, and robustness analysis.

RSM typically involves a series of carefully planned experiments, often using a design matrix such as a central composite design (CCD) or Box-Behnken design (Uchegbu et al., 2022). The experimental design includes a set of predetermined factor levels that represent the range of values for each factor. These experiments are conducted to obtain response data at different factor combinations to capture the curvature and interaction effects. A response surface model is constructed using regression analysis to fit a mathematical equation that describes the relationship between the response variable and the factors. The model can be a linear, quadratic, or higher-order polynomial equation, depending on the complexity of the process and the observed data (Jamil & Wang, 2016; Uchegbu et al., 2022). The model captures the main effects of factors, interaction effects, and curvature effects, allowing for response prediction and optimization. Statistical techniques such as regression analysis, analysis of variance (ANOVA) (Yassien & Jiman-Fatani, 2023), and model diagnostics are employed to fit the response surface model to the experimental data. The model's goodness-of-fit is assessed using statistical metrics such as R-squared, lack-of-fit test, and residual analysis. These analyses help evaluate the significance of factors, identify important variables, and assess the model's reliability. Once the response surface model is developed and validated, optimization techniques are applied to identify the optimal factor settings that maximize the desired response. Optimization methods such as response surface optimization, desirability function approach, or numerical optimization algorithms are employed to determine the factor levels that yield the highest response value (Uchegbu et al., 2022). Optimization enables process improvement by identifying the optimal operating conditions.

RSM facilitates sensitivity analysis to assess the impact of factors on the response variable and identify critical process variables. Sensitivity analysis helps researchers understand the relative importance of factors and prioritize their optimization efforts (Muhammad et al., 2022). It also assists in understanding the interactions between factors and their effects on the response, guiding the selection of factors for further investigation (Riaukaite et al., 2019). Once the optimal factor settings are identified, it is essential to validate the response surface model and confirm its accuracy. Additional experiments are conducted at the predicted optimal conditions to verify the model's predictions. This step helps ensure that the model is reliable and can be used for process optimization and decision-making. Robustness analysis assesses the stability and robustness of the optimized process conditions. It involves evaluating the sensitivity of the response to variations in factors or process parameters. Robustness analysis helps identify the range of factors within which the process remains optimal, considering practical constraints and potential process variability.

The benefits of Response Surface Methodology include (Aydar, 2018; Lamidi et al., 2022):

- Optimization: RSM enables the identification of optimal process conditions that maximize the desired response, leading to improved process performance and efficiency.
- Efficiency: RSM allows researchers to obtain a significant amount of information with a relatively small number of experiments, saving time, resources, and costs compared to a full factorial design.
- Insights: RSM provides valuable insights into the relationships between process variables and the response of interest. It helps researchers understand the effects of factors, identify interactions, and gain a deeper understanding of the process behavior.
- Decision-Making: The response surface model provides a quantitative basis for decision-making, allowing researchers to compare different scenarios, evaluate trade-offs, and make informed decisions to optimize the process.
- Process Understanding: RSM helps researchers gain a deeper understanding of the process by quantifying the relationships between variables and the response. This understanding can guide further process improvement and provide a basis for future research.

Optimization of Glucose Production Using RSM

Optimization of glucose production using RSM is a statistical and mathematical approach that involves designing experiments and analyzing the response of the system to different experimental conditions. RSM is commonly used to optimize process variables and find the optimal conditions that maximize the production of glucose from a given feedstock, such as sugarcane bagasse, rice husk, or sawdust. Below is an outline of how RSM can be applied to optimize glucose production (Lai et al., 2016):

(1) Selection of Factors: The first step is to identify the key factors that influence glucose production from the chosen feedstock. These factors could include enzyme dosage, pretreatment conditions (temperature, time, pH), fermentation time, and any other relevant process variables.
(2) Experimental Design: RSM typically uses a DOE approach to plan a set of experiments that cover a range of factor levels. The experiments are strategically chosen to explore the factor space efficiently and minimize the number of experimental runs required.
(3) Response Surface Model: The experimental data obtained from the DOE is used to build a response surface model. This model relates the glucose production (the response) to the different process variables (factors) and their interactions. Commonly used models include polynomial equations, which allow for the estimation of glucose yield under various combinations of factor levels.
(4) Optimization: The response surface model is then used to find the optimal combination of factor levels that maximizes glucose production. Optimization techniques such as gradient-based methods or numerical optimization algorithms can be employed to determine the optimal settings for the factors.
(5) Validation: After obtaining the predicted optimal conditions, validation experiments are performed to confirm the predicted glucose yield under the optimized conditions. This ensures that the response surface model accurately represents the actual system and provides reliable predictions.

(6) Sensitivity Analysis: Sensitivity analysis can be performed to identify the factors that have the most significant impact on glucose production. This analysis helps in understanding which factors should be given priority in process improvement efforts.
(7) Process Scale-up: If the optimized conditions from the RSM are successful at the laboratory scale, further studies may be conducted to scale up the process to a pilot or industrial level. Scale-up considerations may involve factors like reactor design, process integration, and economic viability.

Multi-objective Optimization Approaches

Multi-objective optimization approaches are optimization techniques designed to handle problems with multiple conflicting objectives (Abushaker et al., 2022). Unlike traditional single-objective optimization, which aims to find a single optimal solution, multi-objective optimization seeks to find a set of Pareto-optimal solutions that represent trade-offs between different objectives. These approaches are particularly useful in decision-making scenarios where multiple criteria need to be considered simultaneously. Pareto optimality is a central concept in multi-objective optimization. A solution is considered Pareto optimal if no other solution can improve one objective without deteriorating at least one other objective. The set of all Pareto-optimal solutions is known as the Pareto front or Pareto set. Each solution on the Pareto front represents a different trade-off between the conflicting objectives, providing decision-makers with a range of options to choose from (Kumar et al., 2022).
Several algorithms have been developed to solve multi-objective optimization problems (Patane et al., 2019). These algorithms can be broadly categorized into evolutionary algorithms (e.g., Genetic Algorithms, Particle Swarm Optimization), swarm intelligence algorithms, mathematical programming-based approaches (e.g., linear programming, nonlinear programming), and decomposition-based methods (e.g., weighted sum, ε-constraint). These algorithms differ in their search strategies, exploration-exploitation balance, and handling of constraints, but they all aim to identify diverse and high-quality solutions on the Pareto front (Briones-Baez et al., 2022; El Moutaouakil et al., 2023).

Results and Discussion

Techno-Economic Analysis of Glucose Production

Techno-economic analysis (TEA) is a comprehensive evaluation method used to assess the feasibility and economic viability of a particular process or technology (Das et al., 2022). In the context of glucose production, TEA plays a crucial role in analyzing the costs, profitability, and overall economic performance of different production methods. It provides insights into the financial aspects of glucose production and helps decision-makers evaluate the economic feasibility of implementing specific production processes. TEA involves a detailed cost analysis that examines the various cost components associated with glucose production. These costs can include raw materials, equipment and infrastructure, labor, energy consumption, utilities, maintenance, waste treatment, and other operational expenses (Jarunglumlert & Prommuak, 2021). By quantifying and analyzing these costs, TEA helps identify the major cost drivers and evaluate the overall cost structure of the production process. In addition to cost analysis, TEA also considers revenue generation potential. It examines the market demand for glucose and estimates the potential sales volume and pricing (Muhammad et al., 2022). Market factors, such as supply and demand dynamics, competition, and pricing trends, are taken into account. By estimating the revenue generated from glucose sales, TEA provides insights into the profitability and financial viability of the production process.

TEA includes sensitivity analysis to assess the impact of uncertain parameters and variables on the economic performance of glucose production. This analysis explores how changes in factors such as raw material prices, energy costs, labor rates, and market conditions affect the profitability and overall economic feasibility of the process (Barba et al., 2022). Sensitivity analysis helps identify critical factors and assess the robustness of the project's financial performance under different scenarios. Cash flow analysis is a fundamental part of TEA, focusing on the inflows and outflows of cash associated with glucose production. It considers the timing of costs and revenues over the project's lifespan to determine the project's cash flow profile (Kuo & Yu, 2020). Cash flow analysis allows for the evaluation of the project's financial viability, profitability, and return on investment. It helps assess the project's ability to generate positive cash flow and recover the initial investment in a reasonable timeframe. TEA provides an evaluation of the required capital investment for establishing glucose production facilities. It assesses the capital expenditure (CAPEX) involved in purchasing equipment, constructing infrastructure, and setting up the necessary production processes. This analysis helps determine the investment requirements, payback period, and return on investment (ROI) of the project (Brandt et al., 2018).
TEA incorporates risk assessment and mitigation strategies to evaluate the potential risks and uncertainties associated with glucose production. It considers factors such as market volatility, regulatory changes, technological risks, and project-specific risks. By identifying and assessing these risks, TEA assists in developing risk management strategies and evaluating the project's resilience against potential challenges (Barba et al., 2022; Muhammad et al., 2022). The primary goal of TEA is to provide decision-makers with comprehensive information and insights to support informed decision-making (Brandt et al., 2018). By quantifying the costs, revenues, and financial performance of glucose production, TEA enables decision-makers to assess the economic feasibility of different production methods, compare alternative technologies, and identify areas for process optimization and cost reduction. In summary, techno-economic analysis of glucose production plays a vital role in evaluating the financial viability, profitability, and economic feasibility of different production processes. It helps assess the costs, revenues, cash flow, and investment requirements, providing decision-makers with the necessary information to make informed choices and optimize the economic performance of glucose production (Ou et al., 2020; Sant et al., 2021).

Cost Analysis of Feedstock Acquisition

Cost analysis of feedstock acquisition is a crucial aspect of assessing the economic feasibility of glucose production (Kuo & Yu, 2020). Feedstock, which refers to the raw materials used in the production process, typically represents a significant portion of the overall production costs. Analyzing the costs associated with acquiring feedstock provides valuable insights into the financial implications of different sourcing strategies and helps decision-makers optimize the cost-effectiveness of glucose production. The cost analysis begins by examining the pricing of various feedstock options. Different feedstock sources, such as agricultural residues, forest biomass, algal biomass, or food waste, may have varying cost structures (Codato-Zumpano et al., 2023). Factors influencing feedstock pricing include availability, seasonal variations, demand-supply dynamics, transportation costs, quality considerations, and market competition. By assessing the prices of potential feedstock sources, the cost analysis enables the comparison of different options and their impact on overall production costs. Apart from pricing, the quantity and quality of feedstock significantly influence the overall cost of acquisition. Analyzing the required feedstock quantities and their availability helps estimate the scale of feedstock acquisition operations. This analysis considers factors such as feedstock yield, moisture content, impurities, and variability in feedstock characteristics (Foust et al., 2020). Understanding these factors enables decision-makers to assess the cost implications associated with sourcing, handling, and processing feedstock.

The cost analysis also involves evaluating different sourcing strategies for feedstock acquisition. This includes assessing the feasibility and cost-effectiveness of sourcing feedstock locally or from external suppliers. Local sourcing may offer advantages such as reduced transportation costs, access to abundant resources, and potential synergies with other industries (Brandt et al., 2018). On the other hand, external sourcing may provide access to specialized feedstock varieties, larger quantities, or cost advantages due to economies of scale. Evaluating the associated costs and benefits of different sourcing strategies helps determine the optimal approach for feedstock acquisition.

Feedstock acquisition involves various costs throughout the supply chain, from harvesting or collection to transportation and storage. The cost analysis considers factors such as collection methods, equipment requirements, logistics, transportation distances, storage facilities, and associated operational expenses. Quantifying and analyzing these costs enables decision-makers to identify cost-saving opportunities, optimize supply chain efficiency, and minimize overall feedstock acquisition expenses (Cheng et al., 2019). Cost analysis of feedstock acquisition includes assessing and mitigating potential risks that may affect the availability and cost of feedstock. Risks can include crop failures, weather-related events, market volatility, regulatory changes, or geopolitical factors. Evaluating these risks helps decision-makers develop contingency plans, diversify feedstock sources, and ensure a stable supply of feedstock at reasonable costs. In addition to cost analysis, it is essential to consider sustainability aspects related to feedstock acquisition (Muhammad et al., 2022). This involves evaluating the environmental impact of different feedstock sources, assessing their renewable or non-renewable nature, and considering their alignment with sustainable development goals (Cheng et al., 2019). While cost optimization is crucial, sustainability considerations can guide decision-making towards more environmentally friendly and socially responsible feedstock acquisition practices. The cost analysis of feedstock acquisition provides decision-makers with valuable information and insights to support informed decision-making. It helps assess the financial implications of different feedstock options, evaluate the cost-effectiveness of sourcing strategies, and optimize the overall feedstock acquisition process (Zhang et al., 2020). The analysis assists in identifying opportunities for cost reduction, enhancing supply chain efficiency, and ensuring a reliable and cost-efficient feedstock supply (Cheng et al., 2019).

Life Cycle Assessment of Glucose Production

Life Cycle Assessment (LCA) is a systematic methodology used to evaluate the environmental impacts associated with the entire life cycle of a product or process, including raw material extraction, production, use, and disposal (Kiš et al., 2019; Osman et al., 2021). Applying LCA to glucose production allows for a comprehensive analysis of the environmental footprint and sustainability performance of different production methods. The LCA of glucose production considers the entire life cycle, encompassing various stages such as feedstock acquisition, preprocessing, enzymatic or acid hydrolysis, fermentation, downstream processing, and final product distribution (Ng et al., 2022). It also includes the energy consumption, emissions, and waste generated at each stage. By considering the full life cycle, LCA provides a holistic perspective on the environmental impacts associated with glucose production. LCA evaluates a range of environmental impact categories, including climate change, resource depletion, acidification, eutrophication, ozone depletion, and human toxicity (Ryan & Yaseneva, 2021). These impact categories capture different aspects of environmental sustainability and allow for a comprehensive assessment of the potential environmental burdens associated with glucose production. Assessing multiple impact categories provides a more robust and balanced understanding of the environmental performance of different production methods. LCA requires gathering data on various inputs and outputs throughout the life cycle stages of glucose production (Osman et al., 2021). This includes information on energy consumption, raw material extraction, water usage, emissions to air, water, and soil, waste generation, and transportation (Jarunglumlert & Prommuak, 2021). Data can be obtained from literature, industry databases, process simulations, and direct measurements. Accurate and reliable data collection is crucial for ensuring the accuracy and reliability of the LCA results (Kiš et al., 2019).

Defining the system boundaries is an important aspect of LCA. It involves determining which processes and activities are included in the analysis and which are excluded. For glucose production, system boundaries can be set to include the entire production chain, from feedstock acquisition to the production of glucose, or focus on specific stages of the process (Ryan & Yaseneva, 2021). Clearly defining the system boundaries ensures consistency and comparability among different LCA studies and facilitates meaningful interpretation of the results (Ng et al., 2022). During the impact assessment phase of LCA, the collected data on inputs and outputs are translated into environmental impact indicators. This involves the use of impact assessment methods and characterization models to quantify the potential impacts on the selected impact categories. Different impact assessment methods, such as ReCiPe, Eco-indicator, or CML, can be employed to assess the environmental impacts associated with glucose production. The choice of impact assessment method should align with the specific goals and context of the study. The results of the LCA are interpreted to identify hotspots, areas of high environmental impact, and improvement opportunities. Decision-makers can use the LCA results to guide sustainability-oriented decision-making, such as selecting production methods with lower environmental impacts, optimizing processes to reduce resource consumption and emissions, or identifying opportunities for recycling and waste reduction (Astuti et al., 2018). LCA results can also inform product labeling, eco-design, and eco-innovation strategies to promote more sustainable glucose production. LCA promotes transparency and communication of the environmental performance of glucose production. The results of the LCA can be communicated through environmental product declarations (EPDs), sustainability reports, or labeling schemes. Transparently communicating the environmental impacts helps stakeholders, including consumers, policymakers, and industry professionals, make informed choices and encourages continuous improvement in sustainability performance (Blanco et al., 2020).

Sustainability Considerations

Sustainability considerations play a critical role in the assessment and improvement of glucose production processes (Ebikade et al., 2018). As the world increasingly focuses on environmental conservation, resource efficiency, and social responsibility, it is essential to evaluate the sustainability aspects associated with glucose production. Few of the key sustainability considerations in glucose production includes, resource efficiency, renewable feedstock, environmental impact mitigation, climate change mitigation, water management, social and economic impacts and LCA. Efficient use of resources is a fundamental aspect of sustainable glucose production (Salim, González-García, et al., 2019). This involves minimizing resource consumption, such as water, energy, and raw materials, throughout the production process. Implementing technologies and practices that optimize resource efficiency can reduce environmental impacts, conserve natural resources, and lower production costs. Strategies like process integration, waste heat recovery, and recycling can contribute to improved resource efficiency. The choice of feedstock for glucose production has significant implications for sustainability. Utilizing renewable feedstock sources, such as agricultural residues, forest biomass, or algal biomass, helps reduce dependence on finite resources and minimizes the environmental footprint of the production process (Codato-Zumpano et al., 2023; Selivanov et al., 2023). Renewable feedstock sources also offer opportunities for circular economy practices by valorizing waste and byproducts from other industries. Glucose production should aim to minimize its environmental impacts, such as greenhouse gas emissions, water pollution, and land use change. Adopting cleaner production technologies, implementing pollution control measures, and optimizing waste management practices can reduce the ecological footprint of the production process (Akmalina, 2019; Salim, González-García, et al., 2019). Additionally, monitoring and mitigating potential environmental risks associated with feedstock acquisition, such as deforestation or habitat destruction, is essential for ensuring the sustainability of glucose production.

Glucose production contributes to climate change through the release of greenhouse gases, particularly during the energy-intensive stages of the process. Implementing energy-efficient technologies, utilizing renewable energy sources, and adopting carbon capture and storage techniques can help mitigate the carbon footprint of glucose production (Blanco et al., 2020). By reducing greenhouse gas emissions, the industry can contribute to global efforts to combat climate change and achieve sustainability targets. Water is a valuable resource, and its sustainable management is crucial in glucose production. Adopting water-efficient practices, such as recycling and reusing water within the production process, can help minimize water consumption. Implementing wastewater treatment and management systems ensures the responsible discharge of treated water to minimize water pollution. Additionally, considering water availability and prioritizing water-stressed regions for glucose production can help mitigate the potential strain on local water resources. Sustainability considerations encompass not only environmental aspects but also social and economic dimensions (Lips, 2021). It is essential to assess the social and economic impacts of glucose production on local communities, including employment opportunities, livelihoods, and community well-being. Engaging with stakeholders, ensuring fair labor practices, and supporting local development initiatives contribute to the overall sustainability of glucose production and foster positive social outcomes. As discussed previously, conducting an LCA provides a comprehensive evaluation of the environmental impacts associated with glucose production. LCA allows for the quantification and analysis of energy consumption, emissions, waste generation, and resource depletion throughout the entire life cycle of glucose production (Blanco et al., 2020). The results of LCA can guide decision-making, identify improvement opportunities, and support the adoption of more sustainable practices.

By integrating sustainability considerations into glucose production processes, stakeholders can work towards achieving a balance between environmental protection, social responsibility, and economic viability. Through continuous improvement, innovation, and collaboration, the industry can contribute to a more sustainable future.

Case Studies and Industrial Applications

Case studies and industrial applications provide valuable insights into the practical implementation of glucose production processes, highlighting their technical feasibility, economic viability, and sustainability performance. By examining real-world examples, researchers, industry professionals, and policymakers can gain a better understanding of the challenges, successes, and best practices associated with glucose production. Case studies and industrial applications showcase the application of new technologies and innovations in glucose production. They provide examples of how advancements in enzymatic hydrolysis, acid hydrolysis, fermentation, and downstream processing have improved process efficiency, yield, and product quality. By studying these technological advancements, researchers and industry professionals can identify opportunities for process optimization, cost reduction, and environmental impact mitigation (Yassien & Jiman-Fatani, 2023). Case studies offer valuable insights into the optimization of glucose production processes. They demonstrate how various parameters, such as feedstock composition, enzyme dosage, reaction conditions, and fermentation strategies, can be adjusted to maximize glucose yield, minimize energy consumption, and reduce production costs (Singh et al., 2021; Yassien & Jiman-Fatani, 2023). Analyzing successful process optimization strategies can guide researchers and industry professionals in developing more efficient and sustainable glucose production methods. Industrial applications of glucose production provide examples of scaling up laboratory-scale processes to commercial production (Singh et al., 2021). Case studies highlight the challenges faced during scale-up, such as process robustness, equipment selection, and integration of different process stages. They also shed light on the economic considerations, market demand, and regulatory requirements associated with commercializing glucose production. Understanding these aspects is crucial for effectively transitioning from research to large-scale implementation.

Case studies and industrial applications explore different feedstock sources and their suitability for glucose production (Kuo & Yu, 2020). They examine the selection criteria, availability, cost-effectiveness, and sustainability implications of using various feedstock options, such as agricultural residues, forest biomass, algal biomass, or food waste (Andreeva et al., 2021; C. Zhang et al., 2020). These studies provide insights into the challenges and opportunities associated with feedstock acquisition, preprocessing, and handling, enabling decision-makers to make informed choices regarding feedstock sourcing. Glucose production is often integrated into biorefinery concepts, where multiple value-added products are derived from the same feedstock. Case studies and industrial applications demonstrate the integration of glucose production with other biorefinery processes, such as bioethanol production, bioplastics manufacturing, or biochemical production (Foust et al., 2020). These examples highlight the synergies, waste valorization, and economic benefits of adopting a holistic approach to biomass utilization. Case studies provide insights into the sustainability performance of glucose production processes. They showcase the application of sustainability assessment tools, such as LCA, carbon footprint analysis, or water footprint analysis, to evaluate the environmental impacts and resource efficiency of glucose production. By studying these assessments, researchers and industry professionals can identify opportunities for improving the sustainability profile of glucose production and aligning it with sustainability goals. Case studies and industrial applications serve as a platform for knowledge sharing, collaboration, and cross-learning among researchers, industry professionals, and policymakers. They facilitate the exchange of experiences, challenges, and best practices, fostering innovation and continuous improvement in glucose production. Through collaboration and shared learning, the industry can collectively address technological, economic, and sustainability challenges, accelerating the development and adoption of more efficient and sustainable glucose production processes.

Glucose Production from Corn Starch

Glucose production from corn starch is a widely utilized process in the food and beverage industry (Dusabe et al., 2023), as well as in various industrial applications. Corn starch, derived from the endosperm of corn kernels, is a rich source of starch, which can be hydrolyzed to produce glucose. Production steps includes corn starch extraction, starch slurry preparation, enzymatic hydrolysis, enzyme inactivation and filtration, purification and concentration, crystallization and final utilization (Awulachew, 2020). The first step in glucose production from corn starch involves extracting starch from corn kernels. The corn kernels are typically ground and separated into various components, including germ, bran, and endosperm. The endosperm contains the highest concentration of starch. The extracted endosperm is then washed to remove impurities and processed to obtain a purified corn starch. To initiate the enzymatic hydrolysis process, the corn starch is mixed with water to form a starch slurry. The slurry is typically adjusted to a specific pH and temperature, which are optimal for the subsequent enzymatic hydrolysis reaction. Enzymatic hydrolysis is the key step in converting corn starch into glucose (Zhu & Pan, 2022). Specific enzymes, such as amylases, are added to the starch slurry. These enzymes break down the starch molecules into smaller fragments, including glucose molecules. The enzymatic hydrolysis reaction is typically conducted at controlled temperature and pH conditions, along with appropriate reaction time, to ensure optimal enzyme activity and starch conversion (Zhang et al., 2020). Once the desired level of hydrolysis is achieved, the enzymatic activity is typically deactivated by adjusting the pH or temperature of the reaction mixture. The resulting mixture is then subjected to filtration or centrifugation to separate the glucose-rich solution from the undigested residues, such as insoluble fibers or protein impurities.

The obtained glucose solution may undergo further purification steps to remove impurities, such as residual enzymes, colorants, or organic compounds. Common purification techniques include filtration, ion exchange, activated carbon treatment, and membrane processes. The purified glucose solution is then concentrated through evaporation or membrane processes to increase the glucose concentration (Flores et al., 2018). In some cases, glucose may be further processed through a crystallization step to produce glucose crystals or glucose syrup. Crystallization involves controlled cooling and seeding of the concentrated glucose solution to induce the formation of glucose crystals. The resulting crystals can be separated, washed, and dried to obtain pure glucose. The produced glucose can be used as a sweetener in the food and beverage industry, replacing sucrose or high-fructose corn syrup (Kiš et al., 2019; Riaukaite et al., 2019). It serves as an essential ingredient in various products, including confectionery, baked goods, beverages, and processed foods. Additionally, glucose finds applications in pharmaceuticals, fermentation processes, and as a precursor for the production of other chemicals.

Glucose production from corn starch offers several advantages, including the abundance and availability of corn as a feedstock, scalability of the process, and versatile utilization of the glucose product. However, it is important to consider the sustainability aspects associated with corn cultivation, such as land use, water consumption, and environmental impacts (Awulachew, 2020). Efforts are being made to explore alternative feedstocks and sustainable production methods to ensure the long-term viability and environmental friendliness of glucose production.

Glucose Production from Cellulosic Biomass

Glucose production from cellulosic biomass offers a promising avenue for sustainable biofuel and biochemical production (Osman et al., 2021). Cellulosic biomass, which includes sources such as agricultural residues, forest biomass, and dedicated energy crops, contains cellulose, hemicellulose, and lignin (Selivanov et al., 2023). The process of converting cellulosic biomass into glucose involves several steps, as outlined below:

(i) Pretreatment (Zhou et al., 2023): Pretreatment is a crucial step in cellulosic biomass conversion. It aims to remove or modify the lignin and hemicellulose components, making the cellulose more accessible to enzymatic hydrolysis. Various pretreatment methods, including physical, chemical, and biological processes, can be employed. Common techniques include steam explosion, acid or alkaline hydrolysis, organosolv, and ammonia fiber expansion (AFEX) (Jarunglumlert & Prommuak, 2021). Pretreatment conditions and severity are optimized to maximize cellulose accessibility while minimizing sugar degradation and inhibitor formation (Malakar et al., 2020).

(ii) Enzymatic Hydrolysis: Enzymatic hydrolysis is the core step in converting cellulose to glucose. After pretreatment, the cellulose-rich material is treated with cellulase enzymes. Cellulase enzymes break down cellulose into glucose by cleaving the cellulose chains into smaller sugar units. The enzymatic hydrolysis reaction is typically carried out at controlled temperature, pH, and enzyme dosage to optimize glucose yield. Enzyme cocktails containing different types of cellulases are often used to improve hydrolysis efficiency (Zhu & Pan, 2022).

(iii) Enzyme Recycling and Inhibitor Management: During enzymatic hydrolysis, the enzymes can be partially deactivated or inhibited by the released sugars and by-products (Turini et al., 2021). To enhance the efficiency and economics of the process, strategies such as enzyme recycling and the use of enzyme inhibitors can be implemented. Enzyme recycling involves separating the enzymes from the hydrolysate and reusing them in subsequent hydrolysis batches. Inhibitor management techniques, such as detoxification or conditioning of the hydrolysate, can minimize the negative impact of inhibitors on enzyme activity and glucose yield.

(iv) Fermentation (Yassien & Jiman-Fatani, 2023): After enzymatic hydrolysis, the resulting glucose-rich hydrolysate can be subjected to fermentation to produce various biofuels and biochemicals. Glucose can be fermented by microorganisms, such as yeast or bacteria, into ethanol, butanol, organic acids, or other valuable products. The fermentation process may require additional steps, such as microbial strain selection, optimization of fermentation conditions (temperature, pH, nutrient supplementation), and downstream processing for product recovery.

(v) Downstream Processing: Downstream processing involves the separation, purification, and recovery of the desired product from the fermentation broth. Techniques such as filtration, centrifugation, distillation, chromatography, and membrane processes are employed to isolate and purify the target compound, such as glucose or the desired fermentation product. The purity and concentration of the final product depend on the intended application.

Glucose production from cellulosic biomass offers several advantages, including the utilization of abundant and renewable feedstock sources, reducing dependence on fossil fuels, and mitigating greenhouse gas emissions (Shokrkar & Ebrahimi, 2021). However, challenges remain in terms of improving the efficiency and cost-effectiveness of the process, addressing inhibitory compounds generated during pretreatment, and developing robust and efficient enzyme systems. Ongoing research and technological advancements are focused on optimizing the individual steps, exploring novel pretreatment methods, developing superior enzyme cocktails, and enhancing the overall process integration to make cellulosic glucose production economically viable and environmentally sustainable (Jones et al., 2018).

Glucose Production from Food Processing Waste

Glucose production from food processing waste offers a valuable opportunity for sustainable utilization of organic byproducts generated in the food industry. Food processing waste, such as fruit and vegetable peels, pomace, spent grains, and other residues, often contains significant amounts of carbohydrates, including starches and sugars, which can be converted into glucose (Andreeva et al., 2021; Lee et al., 2023). The process of glucose production from food processing waste typically involves the following steps:

[1]. Waste Collection and Preparation: Food processing waste is collected from various sources, such as fruit and vegetable processing facilities, breweries, or grain mills. The waste is typically sorted, cleaned, and prepared by removing any non-organic contaminants or inedible parts. The waste may also undergo size reduction or grinding to increase the surface area and improve subsequent processing efficiency.

[2]. Enzymatic Hydrolysis or Acid Hydrolysis: Enzymatic hydrolysis or acid hydrolysis is employed to convert the complex carbohydrates present in the food processing waste into glucose. Enzymatic hydrolysis involves the use of specific enzymes, such as amylases or cellulases, to break down starches or cellulose into glucose (Uchegbu et al., 2022). Acid hydrolysis utilizes dilute acid solutions, such as sulfuric acid or hydrochloric acid, to hydrolyze the carbohydrates into simpler sugars (Adeoye et al.,

2019). The choice of hydrolysis method depends on the composition of the waste and the specific carbohydrates targeted for conversion.

[3]. Hydrolysate Treatment: After hydrolysis, the resulting hydrolysate contains a mixture of glucose, other sugars, and impurities. The hydrolysate is often subjected to purification steps to separate the glucose from unwanted components, such as residual enzymes, solids, or organic acids. Common purification techniques include filtration, sedimentation, and adsorption processes.

[4]. Glucose Concentration (Flores et al., 2018): To increase the glucose concentration in the hydrolysate, concentration techniques such as evaporation, membrane processes (such as reverse osmosis), or crystallization can be employed. These methods remove water from the hydrolysate, resulting in a more concentrated glucose solution.

[5]. Purification and Refinement: Further purification and refinement steps may be required to obtain a high-purity glucose product. These steps can involve techniques such as chromatography, ion exchange, or activated carbon treatment to remove remaining impurities, colorants, or off-flavors.

Glucose production from food processing waste offers several benefits, including waste valorization, reduction of waste disposal and environmental impact, and the potential for cost savings (Lee et al., 2023). By converting waste into a valuable product, the process contributes to a circular economy and sustainable resource management. However, it is essential to ensure the quality and safety of the glucose produced, adhering to relevant regulations and quality standards. Additionally, the development of efficient and cost-effective processing technologies, as well as waste collection and logistics systems, is crucial for the widespread adoption of glucose production from food processing waste (Dusabe et al., 2023).

Glucose Production in Biofuel and Bioproduct Industries

Glucose production plays a crucial role in the biofuel and bioproduct industries, serving as a key intermediate for the production of a wide range of biofuels and bioproducts (Mendoza-Meneses et al., 2021). Glucose can be derived from various biomass sources, including agricultural residues, energy crops, food processing waste, and cellulosic biomass. Glucose is a primary substrate for bioethanol production. Through the process of fermentation, glucose is converted by yeast or other microorganisms into ethanol, which is a renewable and sustainable alternative to fossil fuel-based gasoline (Ali et al., 2023). Glucose can be derived from various feedstocks, such as corn, sugarcane, wheat, and cellulosic biomass, and used as the main carbohydrate source for ethanol fermentation. Bioethanol has gained significant attention as a renewable fuel, contributing to reduced greenhouse gas emissions and energy security. Glucose can also serve as a precursor for the production of biobutanol, an advanced biofuel with potential as a gasoline substitute (Tsai et al., 2020). Biobutanol is produced through a process called acetone-butanol-ethanol (ABE) fermentation, where glucose is converted into butanol, acetone, and ethanol by solvent-producing bacteria (Ibrahim et al., 2018; Yang et al., 2023). Glucose can also be used as a feedstock for the production of other biochemicals, such as organic acids, amino acids, biopolymers, and specialty chemicals, through microbial fermentation or chemical synthesis routes (Osman et al., 2021).

Although glucose itself is not directly used for biodiesel production, it can contribute indirectly by serving as a substrate for microbial oil production. Microorganisms such as algae or oleaginous yeasts can utilize glucose as a carbon source to accumulate lipids or oils (Yang et al., 2023). These lipids can be extracted and converted into biodiesel through a process called transesterification. Glucose, therefore, plays a critical role in providing the necessary carbon and energy source for microbial oil production. Glucose is a valuable platform chemical for the synthesis of various chemicals and materials. It can be converted into a range of platform chemicals, including lactic acid, succinic acid, glycerol, and 2,3-butanediol (Yu et al., 2022). These platform chemicals serve as building blocks for the production of bioplastics, biopolymers, solvents, resins, and other high-value chemical products (Inyang et al., 2022). Glucose-based platform chemicals offer a sustainable and renewable alternative to their petrochemical counterparts. Glucose can be chemically modified or transformed into various derivatives, expanding its utility in different industries. Glucose derivatives, such as glucose esters, glucose ethers, and glucose fatty acid esters, find applications in food, pharmaceuticals, cosmetics, and other sectors (Lee et al., 2023). These derivatives possess specific functionalities and properties that enhance their suitability for specific applications. The production of glucose in the biofuel and bioproduct industries involves various processes, including biomass feedstock preparation, enzymatic or acid hydrolysis, fermentation, and downstream processing (Weiss et al., 2019). The optimization of these processes, along with advancements in biotechnology, enzymology, and process engineering, continues to improve the efficiency, cost-effectiveness, and sustainability of glucose production (Bauer et al., 2022; Singh et al., 2021). The utilization of glucose as a feedstock for biofuels and bioproducts not only reduces reliance on fossil fuels but also contributes to the development of a bio-based economy and a more sustainable future (Osman et al., 2021).

Technological Challenges in Glucose Production

Glucose production is a complex process that involves several technological challenges (Das et al., 2022). Overcoming these challenges is crucial for improving the efficiency, scalability, and cost-effectiveness of glucose production. One of the challenges lies in the diverse nature of feedstock sources for glucose production (Bisht et al., 2019). Different biomass sources, such as agricultural residues, energy crops, food processing waste, and cellulosic biomass, have varying compositions and properties. Preprocessing the feedstock to remove impurities, optimize particle size, and enhance accessibility of the carbohydrates is a critical step. However, developing efficient and scalable preprocessing technologies that can handle different feedstocks remains a challenge (Osman et al., 2021). Pretreatment is essential to break down the complex structure of biomass and make carbohydrates more accessible for enzymatic or acid hydrolysis. Achieving an optimal balance between efficient pretreatment and minimal formation of inhibitors or degradation products is a technological challenge (Ansanay et al., 2021). Similarly, enhancing the efficiency of enzymatic hydrolysis or acid hydrolysis to achieve high glucose yields while minimizing enzyme requirements or acid usage is a continual focus of research and development (Ebikade et al., 2018). Enzymes play a vital role in the hydrolysis of carbohydrates to glucose. However, the cost of enzymes can be a significant barrier to large-scale glucose production. Developing robust and efficient enzyme systems that can work under a wide range of conditions, improving enzyme stability and longevity, and reducing enzyme costs through advances in enzyme engineering and bioprocessing are ongoing challenges (Rocha et al., 2022).

In the case of fermentation-based glucose production, selecting suitable microbial strains that can efficiently convert glucose into desired products, such as bioethanol or biochemicals, is crucial. Improving fermentation efficiency, including higher product yields, faster fermentation rates, and better tolerance to inhibitors, remains a challenge (Yassien & Jiman-Fatani, 2023). Genetic engineering and strain optimization techniques are being explored to enhance microbial performance and address these challenges. Integrating different process steps, optimizing their interaction, and achieving efficient process integration are essential for glucose production. Scaling up the glucose production process from lab-scale to commercial scale poses additional challenges, such as maintaining consistent performance, ensuring cost-effectiveness, and addressing engineering and logistical considerations. Glucose production generates various byproducts and waste streams that require proper management. Treating and utilizing these waste streams in an environmentally sustainable manner is a challenge (Zhu & Pan, 2022). Developing efficient strategies for waste treatment, including recycling, valorization, or conversion into value-added products, is essential to minimize the environmental footprint of glucose production.

Accurate monitoring and control of various process parameters, such as temperature, pH, enzyme dosage, and fermentation conditions, are crucial for optimizing glucose production (Tagougui et al., 2018). Implementing advanced process monitoring techniques, real-time control systems, and automation technologies to ensure consistent and efficient production is a technological challenge (Bisht et al., 2019; Didyuk et al., 2021). Glucose production must be economically viable to compete with traditional production methods (Zhu & Pan, 2022). Techno-economic analysis, including factors such as capital and operational costs, feedstock availability, product yields, and market demand, must be considered. Balancing the costs and benefits of different process parameters and optimizing the overall process economics remains a challenge. Addressing these technological challenges requires interdisciplinary research and collaboration among scientists, engineers, and industry stakeholders. Continued advancements in biotechnology, enzymology, process engineering, and automation are essential for overcoming these challenges and driving the development of efficient, sustainable, and economically viable glucose production technologies (Bauer et al., 2022; Tagougui et al., 2018).

Conclusion

Investigation and optimization of glucose production via multiple biochemical processes and sustainable feedstock sources has yielded substantial insights and possible opportunities. As a critical biomolecule and renewable energy source, glucose holds great promise for meeting the growing demands of a sustainable and environmentally conscious world. The research looked on the kinetics and efficiency of enzymatic hydrolysis, acid hydrolysis, and fermentation routes. Researchers can create novel techniques to improve glucose synthesis and utilization by better understanding these mechanisms. The evaluation of various feedstock sources, such as agricultural residues, forest biomass, algal biomass, and food waste, has offered significant information for the selection of sustainable feedstock. Industries can lessen their environmental impact and contribute to a circular bioeconomy by utilizing locally sourced materials. Optimization tactics were critical in this study, providing useful insights into optimizing glucose production systems. Statistical design of experiments and response surface approach have paved the way for more efficient and cost-effective manufacturing procedures.

Furthermore, the techno-economic analysis and life cycle assessments have highlighted the need of taking both environmental and economic factors into account when evaluating glucose production technologies. Sustainability considerations are critical in the quest for a greener, more resilient future. This study's multidisciplinary approach, which combined biochemical insights with sustainability considerations, provided a comprehensive understanding of glucose production. It has bridged the gap between scientific breakthroughs and real-world applications, making the research relevant to both industries and politicians. As we progress toward a more sustainable bioeconomy, glucose production plays an important role in a variety of sectors, including food, energy, and bioproducts. The study's findings provide useful direction for researchers, industry, and governments in driving the adoption of more environmentally friendly and efficient glucose manufacturing processes. To summarize, the study not only increased our understanding of glucose production, but it also underlined the need of sustainable practices and optimization tactics in designing a more sustainable and prosperous future for humanity. We can usher in an era of sustainable glucose production by embracing renewable carbohydrates and innovative technology, paving the road for a greener and more peaceful coexistence with our planet.

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