Integrating the New Age of Bioeconomy and Industry 4.0 into Biorefinery Process Design

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Manufacturing processes and their economy are dramatically evolving due to machinery and digital control improvements. Artificial intelligence, big data analytics, and the Internet of Things are key tools for this new industrial revolution era based on Industry 4.0. Bioeconomy and circular economy concepts have appeared in the forest, agriculture, food, pharmaceutical, pulp and paper, chemical, biotechnological, and energy areas, *etc.*, to achieve sustainable economic growth development *via* biomass valorization in a biorefinery platform. Biorefinery process development at an industrial scale requires the previous design and assessment of processes and technologies. Therefore, economic, environmental, and social factors should be evaluated to prevent the failure in one of these issues that could affect the performance of the others. With a growing interest in sustainable economic development, there is a need to incorporate new technologies early enough in the process design. This study aims to better understand how Industry 4.0 era tools can bring new solutions to the biorefinery process design, in terms of the technical, economic, environmental, and social factors. Thus, these tools could improve and revolutionize the process selection optimization, provide alternatives for biomass valorization, integration strategies, and the metrics selection for process evaluation, adding the approach toward sustainable economic development.

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INTRODUCTION

In the history of humanity, technology has evolved to satisfy the social-economic demand for materials, energy, food, and economic benefits, among others. The massive changes based on innovative industrial processes and production technology were considered Industrial Revolutions in contemporary history. These changes produced an unprecedented increase in prosperity, working ways, social-economic living, and significant societal transformation. During Industry 1.0 (1760 to 1840), the socio-economic changes were characterized by: (i) the conversion from human and animal labor into machinery technology; (ii) the development of new chemical processes and new material production (steel); (iii) the rise of new machines using water and steam power; (iv) transportation improvements; and (v) the use of coal as an energy resource. Industry 2.0 (1870 to 1970) produced huge technological advancements based on electricity, gas, and oil. It was characterized by: (i) revolutionary inventions such as the internal combustion engine, the telegraph, the telephone, computers, automatic operations, plastics, electricity, chemical synthesis, and the automobile, among others, and (ii) the design of automated assembly lines in industrial production, among others. Industry 3.0 (from 1970 to the present) was based on the revolutionary improvement and use of: (i) electronics, telecommunications, and computers; (ii) new research lines such as space expeditions, biotechnology, and nanotechnology, among others; (iii) new industrial technologies such as programmable logic controllers (PLCs) and robots to achieve high-level automation (Lee *et al.* 2018; Groumpos 2021; Javaid *et al.* 2022).

ASPECTS OF INDUSTRY 4.0 FROM A BIOREFINER CONTEXT

What is Industry 4.0?

Nowadays, Industry 4.0 is a revolutionary change based on disruptive technologies and trends integration (Internet, robotics, virtual reality, and artificial intelligence), which are changing people's lives and work. It is characterized by (i) the massive Internet use, the development of cheaper, smaller, and stronger sensors, (ii) rapid spread of information technology (IT), (iii) the development of a Collaborative Common, (iii) the transition from conventional fossil fuel-based economy to the renewable energy economy as circular economy and bioeconomy concepts, the spread of the newest IT, such as the Internet of Things (IoT), cyber-physical systems (CPSs), artificial intelligence (AI), machine learning (ML), artificial neural networks (ANN), and (v) the 3-D printer (Lee *et al.* 2018; Groumpos 2021; Javaid *et al.* 2022). The industrial revolutions and their main characteristics are illustrated in Fig. 1.

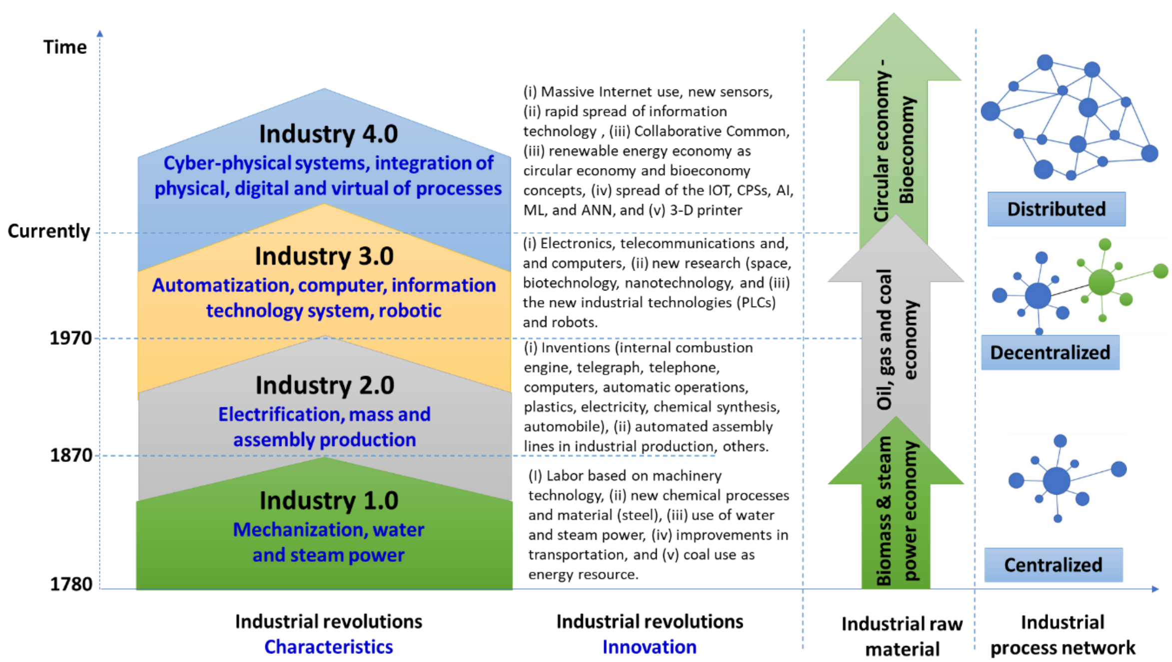

Fig. 1. Industrial revolutions and their main characteristics

Circular Economy

The Circular Economy (CE) concept has arisen in the current global economic system to attain more sustainable development. This concept responds to the growing social demand for renewable materials and energy, mainly by increasing resource efficiency and reducing generated waste, among other things.

A CE envisions achieving a more resource-effective and efficient economic system optimizing the materials and energy flows (Pieroni *et al.* 2019). In the same way, the bioeconomy (BE) concept appears as a strategy to act toward a sustainable future; it seeks to mitigate the effects of climate change by exploiting renewable carbon sources (biomass), and generating business and employment opportunities, mainly in rural areas (D'Amato *et al.* 2017; Ubando *et al.* 2020).

In this sense, a circular bioeconomy (CBE) has emerged based on CE and BE concepts, considering biomass an integral raw material to obtain a wide range of bioproducts, biochemicals, and bioenergy (Ubando *et al.* 2020). Furthermore, by closing the loop in the CBE framework, the sustainability and economic viability of bio-stream production processes are achieved (Carus and Dammer 2018).

Sustainability Assessement

Sustainability assessment allows the identification of which procedures are or are not feasible in terms of leading toward a sustainable process (Ruiz-Mercado *et al.* 2012). Knowing if a process could be sustainable is necessary to evaluate it in the process design step before implementation at a commercial scale.

In process design, the adverse circumstances could be prevented and (or) minimized by incorporating the sustainability criteria instead of performing corrective and costly modifications. However, one of the problems in measuring the sustainability of an industrial process and optimizing its performance is setting the right path (Veleva and Ellenbecker 2001; Tanzil and Beloff 2006). Many publications agree that sustainability should satisfy the following global aspects: environment, economy, and society (Ruiz-Mercado *et al.* 2012; Sadhukhan *et al.* 2014; Cardona *et al.* 2019). Therefore, sustainability indicators often are classified based on these aspects (Ruiz-Mercado *et al.* 2012). Several of these indicators could be used to measure the performance of developed processes.

In the biorefinery field, for economic assessment, the usual economic indicators are the net present value (NPV), the return on investment (ROI), the payback period (PBP), *etc.*, whereas the environmental indicators from a life cycle assessment (LCA) include emissions, resources consumption, and environmental pressures for products. Although social indicators have been studied in recent years, some methods seek to carry out studies in a comprehensive manner, *e.g.*, multi-criteria decision analysis (MCDA) (Ubando *et al.* 2020). In addition, other indicators based on a socio-economic framework have been proposed taking into account the territorial rooting of the regional economic activities; this method is called the social life cycle assessment (SLCA) (Rakotovao *et al.* 2018). However, economic, environmental, and social indicators are separately evaluated because it is difficult to quantify their relationships (Tuazon and Gnansounou 2017).

In addition to the usual methods, several alternatives to evaluate sustainability try to merge more than one of its aspects (Tuazon *et al.* 2013; El-Halwagi 2017; Shemfe *et al.* 2018; Meramo-Hurtado *et al.* 2020). A recent study showed that in a sustainability assessment, the process integration and environmental assessment are the greater assessed topics, followed by a techno-economic assessment. Finally, social assessment is an aspect that has undergone little analysis (Ubando *et al.* 2020).

Social analysis has been a restraint for the researchers due to the lack of or poor availability of methodologies or tools that allow precise assessment. The social impact assessment should involve, *e.g.*, job generation (at the land and process level), food supply, health, contribution to community development, minority inclusion, transparency, and end of life responsibility (Aristizábal-Marulanda *et al.* 2020). Due to the increasing demands of the social sector to have an active and enjoyable life, the current society is moving to a stage called Society 5.0, in which the economy is organized in a sustainable system based on a human-centered society that balances economic progress and resolves the social problems *via* digital and physical integration (Cabinet Office 2021). In this way, emerging technologies such as the Internet of Things (IoT), big data, artificial intelligence (AI) and its subsets, *i.e.*, machine learning (ML), and artificial neural networks (ANN), have great potential in terms of reducing energy consumption, environmental impacts, and several social concerns. Moreover, these technologies could be used to integrate the sustainability aspects and improve the global assessment of sustainability (Ghobakhloo 2020; Liao *et al.* 2021; Zengin *et al.* 2021). Figure 2 represents the relationship between the new technologies and how they could improve global sustainability. Future technologies could help to bring improvements in the process design and assessment, focusing on sustainable development.

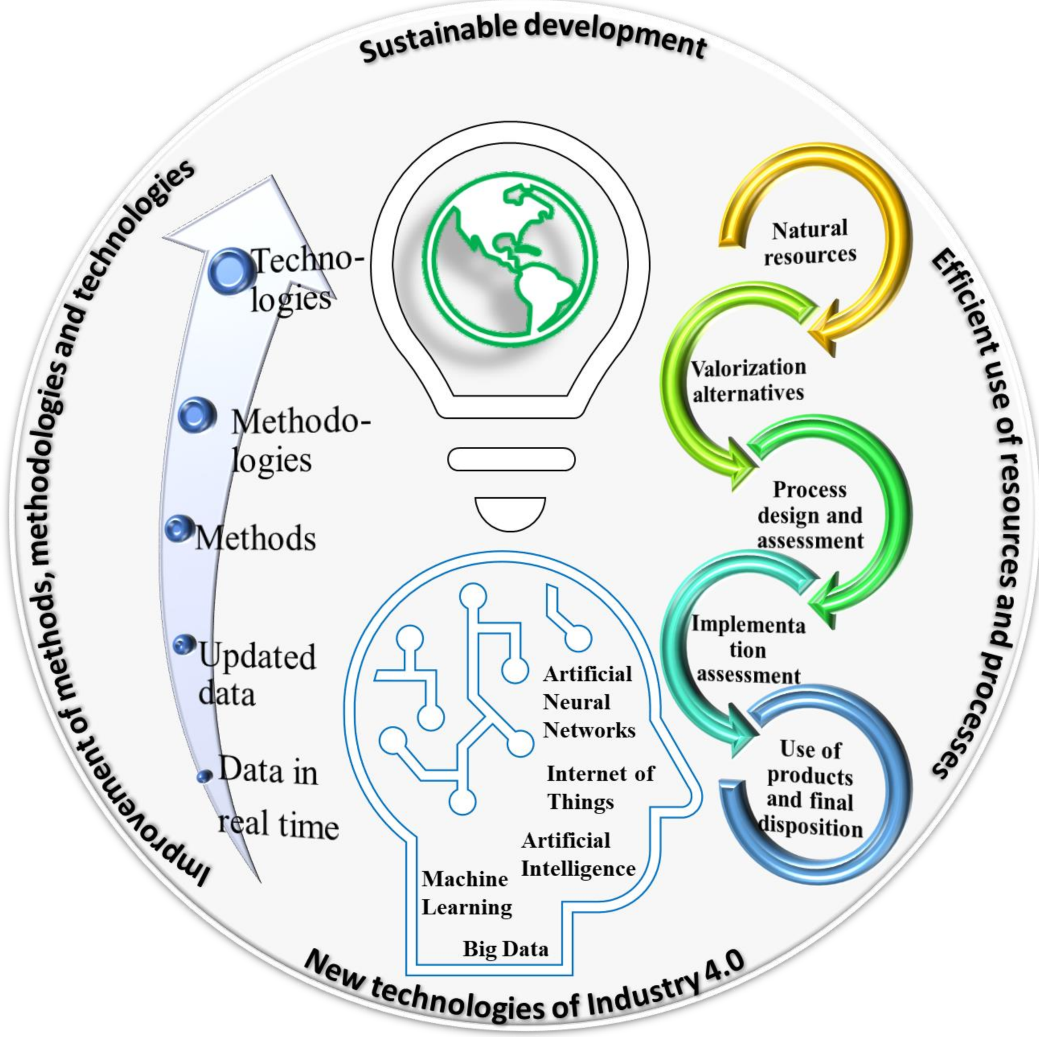

Fig. 2. New technologies improving global sustainability

Promising Technologies for Sustainability

The digital change in industries and companies is moving to the global systems toward the "Industry 4.0" level, which is generating a new innovative age (IoT, big data, and AI) (Dalenogare *et al.* 2018; Frank *et al.* 2019; Meindl *et al.* 2021). Recent tools support it (IoT, big data, and AI). These tools apply to several technologies, including product and process design systems, process and manufacture simulation, innovative robotics, *etc.* (Dalenogare *et al.* 2018; Meindl *et al.* 2021).

Industry 4.0 allows the construction of cyber-physical structures to interconnect all fields of the industry with more profoundly integrated processes (Benitez *et al.* 2020). The main goals for the application of Industry 4.0 associated technologies could be (i) increasing production efficiency, productivity, and quality; (ii) enhancing operational flexibility; (iii) integrating the production system with customers and the supply chain; or (iv) contributing to the safety of the workers and operational sustainability (Dalenogare *et al.* 2018; Meindl *et al.* 2021). In addition, it was estimated that Industry 4.0 technologies could reduce production, logistic, and management costs by up to 30% (Nahavandi 2019).

The smart manufacturing concept is gaining attention from both researchers and industries because it is a new tool that aims to connect unit operations and advanced computational intelligence by wireless networks using sensors to improve productivity and sustainability performance (Wang *et al.* 2018).

Digitalization provides unprecedented industry opportunities. Digital technologies, *e.g.*, AI, IoT, *etc.*, allow radical innovation strategies. Moreover, developing innovative technologies could make the industry more sustainable (Oztemel and Gursev 2018; Breque *et al.* 2021).

Implementing these technologies in today's industries requires economic resources, infrastructure, and labor, among others. Regarding this last one, industries in developing countries face problems mainly due to a lack of technical skills and poor financial conditions. In this sense, in developing countries, Industry 4.0 technologies implementation could be a challenge due to the high cost of sustainable practices, lack of skills and training, lack of standardized metrics and the lack of adoption of emerging technologies (Kumar *et al.* 2020). However, these technologies implementation can help the organization by reducing capital and operational cost, improving flexibility, and increasing revenue, especially among small and medium enterprises (SMEs) (Lim *et al.* 2021).

Industry 4.0 has shown remarkable potential for sustainable industrial value creation by improving resource efficiency (Khan *et al.* 2021). In addition, the common environmental goals can be achieved by incorporating new technologies and rethinking the production processes by considering their impacts (Sharma *et al.* 2020; Breque *et al.* 2021).

Due to the novelty of the applications of these technologies in biorefineries process assessment, a network map was generated using the papers published since 2016 to evaluate them. Approximately 40 articles were analyzed using the binary-counting method of the VOSViewer software (version 1.6.17, CWTS, The Netherlands) (as shown in Fig. 3). Regarding Industry 4.0 technologies, AI and its subsets (ML and ANN) were the most assessed topics. Other relevant terms in the network were related to biorefinery processes, economics, and the environment.

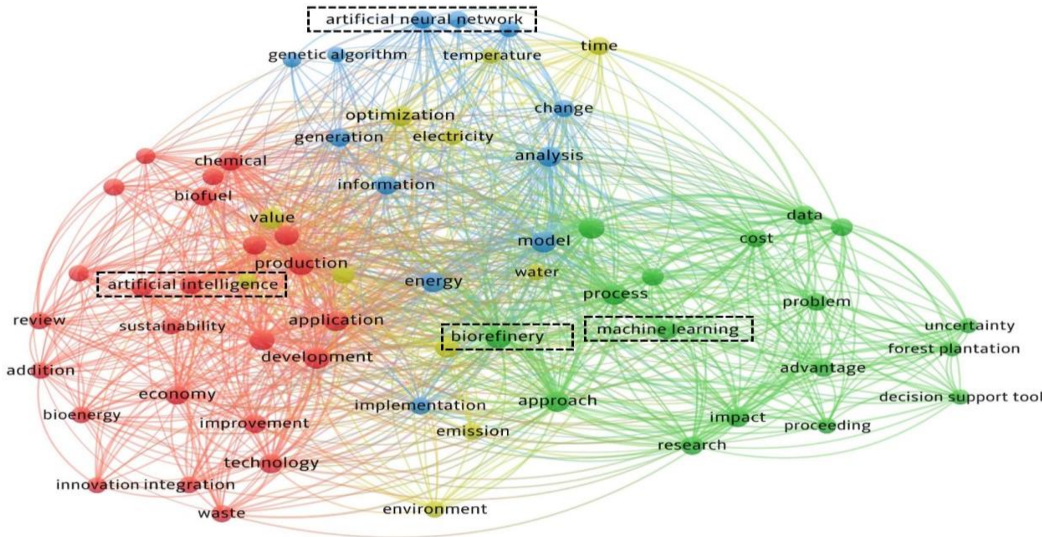

Fig. 3. Data collected from the Scopus database by consulting original articles, using the following search terms: Biorefinery AND Artificial Intelligence OR Artificial Neural Network OR Machine Learning OR Internet of Things OR Big Data Analytics

Artificial Intelligence (AI), Machine Learning (ML), and Artificial Neural Networks (ANN) in a Biorefinery Context

Artificial intelligence and its subsets (ML and ANN) could bring new solutions to biorefinery processes, from the first steps of process design, *e.g.*, literature review, to strategic steps, *e.g.*, allocation (as shown in Fig. 4). However, the application of these technologies requires necessary data collection (images, parameters, yields, *etc.*) and algorithm development. Potential applications of these technologies include data classification, optimization, pattern recognition, and prediction (Culaba *et al.* 2022).

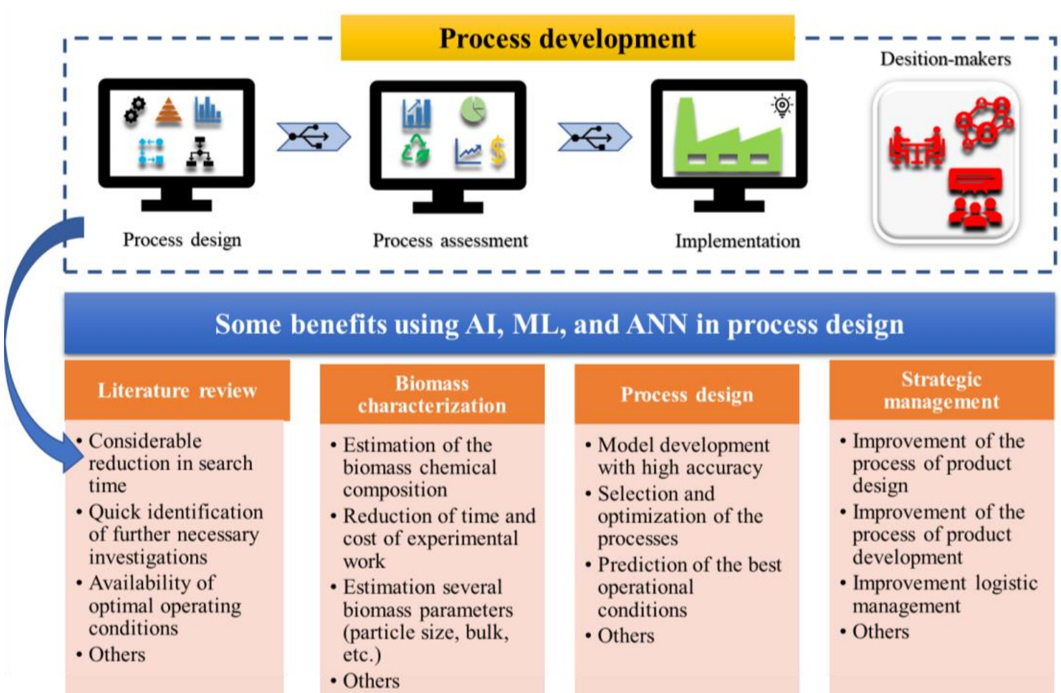

Fig. 4. Artificial intelligence, ML and ANN are becoming key players in biorefinery process design

Literature review

Usually, literature reviews consist of an overview of current knowledge, dates, and methods in the existing research. The operating conditions are commonly selected from updated bibliographies, patents, and experimental results based on the design, modelization, and optimization of biorefinery processes. In this step, it is possible to determine which process conditions fit better for the designed process in this study and whether it is possible to replicate them in this case study (Moncada *et al.* 2016; Clauser *et al.* 2021).

The usual review method is to screen thousands of studies by hand and determine which studies are feasible to include in the design. However, this process is inefficient and costly due to only a fraction of the screened studies being relevant. In this sense, it is possible to review the available literature using an ML-based method that would allow the filtering of the studies that could be adjusted to the studied process and the potential gaps to be evaluated and determined (Schoot *et al.* 2021).

Schoot *et al*. (2021) developed an ML framework to accelerate screening (titles and abstracts). It could help researchers realize a systematic review or meta-analysis. They demonstrate that systematic review could yield far high quality, more efficient, and transparent reviewing than manual reviewing. Regarding the Industry 4.0 field, ML-based systematic literature review methods have been recently developed, where approximately 5000 papers were evaluated and classified (Meindl *et al.* 2021).

Regarding biorefineries, its design starts with the available information about the processes, raw materials, products, *etc.* (Clauser *et al.* 2021). In these steps, the literature review is a crucial task for gathering knowledge about the topic, and the use of ML methods could bring a substantial improvement in this step.

Biomass characterization

Analysis and characterization of the lignocellulosic biomass are necessary to ensure consistent and uniform feedstocks for the subsequent conversion into several products and subproducts (Nag *et al.* 2021). Therefore, the critical parameters from the physicochemical characterization should be determined and assessed before designing any biorefinery conversion process, since these allow for evaluating possible treatments (thermochemical or biochemical processes). In addition, it allows for the evaluation of the initial chemical composition of the lignocellulosic biomass. Some of the parameters that should be considered in the design are as follows: the particle size, bulk density, moisture, ash, volatile, higher or lower heating values, the elemental composition, and chemical compositions (cellulose, hemicelluloses, and lignin contents) (Cai *et al.* 2017). However, the determination and quantification of these parameters consume resources and time. In addition, several types of analytical equipment are needed.

In this way, in addition to laboratory characterization, AI could be an alternative to minimize the cost and time of biomass characterization and offer a quick screening and selection of biomass species based on their properties (Liao and Yao 2021). Besides, studies on predicting higher heating values (HHV) compared AI-based models with empirical correlation, showing a higher fit (R^2) for AI models compared to the traditional approaches (Dashti *et al.* 2019; Xing *et al.* 2019b; Liao and Yao 2021). Another study developed a model to classify biomass for a pyrolysis plant, in which approximately 10 biomass types were selected using various raw materials, *e.g.*, pine, eucalyptus, sugarcane bagasse, *etc.* (Nag *et al.* 2021). In addition, the prediction of the chemical composition of biomass, *i.e*., cellulose, hemicelluloses, and lignin contents with a random forest model and the trained model showed high accuracy in one study using ultimate analysis data (144 samples) (Xing *et al.* 2019a). As shown, there are studies carried out to characterize different types of biomasses with good correlation results compared to experimental methods, showing that AI is a powerful tool for accelerating the characterization of raw materials. However, more research is needed for its application on a commercial scale.

Processes of the biochemical biorefinery

Biorefinery processes involve several steps, ranging from biomass fractionation to product recovery. A general scheme of a biorefinery process is presented in Fig. 5.

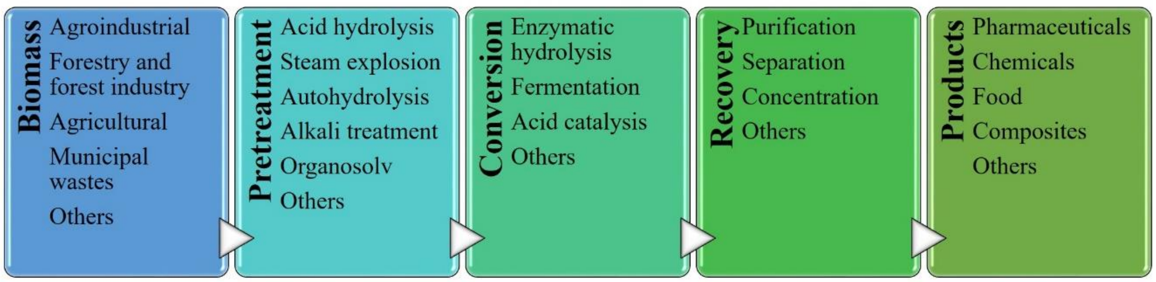

Fig. 5. Common steps involved in a biorefinery process

There are studies in which AI, ML, and ANN were used in biorefinery processes. Regarding biomass fractionation, Löfgren *et al.* (2021) developed a model-based ML framework to optimize lignin biorefinery based on hydrothermal pretreatment and solvent extraction. However, these predictive models fitted with data points within a margin of error similar to the experimental error, which could be used to determine optimal extraction conditions for applications in lignin valorization.

Vani *et al.* (2015) developed an ANN to predict the sugar yield of rice straw from enzymatic hydrolysis by utilizing biomass loading, substrate particle size, and hydrolysis time as the inputs. They carried out experiments for training (84), validation (18), and testing (18). The model presented excellent regression for glucose and xylose (R^2 of 0.97 and 0.96, respectively). Vani *et al.* (2015) concluded that sugar yields were significantly dependent on biomass loading. An optimized ANN model was developed based on hydrolysis conditions to maximize sugar yields. Gama *et al.* (2017) established an ANN applied to predict the best conditions to maximize glucose and reduce sugar yields from enzymatic hydrolysis of apple pomace using as inputs: temperature, pH, enzyme, and substrate loadings (Gama *et al.* 2017). In this case, the training and testing data set contained minimal fluctuations, which showed that enzymatic hydrolysis could benefit significantly from ANN technologies because it does not require specific feedstock composition details as input (Pomeroy *et al.* 2022).

Pappu and Gummadi (2016) examined the use of an ANN and a kinetic model as predictive tools for the xylitol production of a bioreactor. The influence of the pH, temperature, and volumetric oxygen transfer on the growth and xylitol production were evaluated. In addition, an ANN was developed to analyze the effect of the process conditions on the xylitol production process. It was determined that ANN is an efficient technology to predict the optimal time for microbial production of xylitol.

Meena *et al.* (2021) evaluated the potential of AI technologies with a focus on biofuel production. This study determined that it is possible to predict the energy from biomass and, with respect to the supply chain. AI could find the optimal available raw materials for a running system and sustainably utilize them.

Finally, in addition to production processes, there are studies developed using AI as a tool for wastewater treatment. Kamali *et al.* (2021) evaluated AI models used to treat different wastewater streams and showed that AI is useful for predicting the performance of technologies to treat polluted sources and recover clean water. Antwi *et al.* (2017) estimated the methane yields in an anaerobic reactor, and the results showed that ML is a promising technology for simulating wastewater treatment systems; the performance of the developed model ($R^2 = 0.979$) was better than the linear regression model ($R^2 = 0.926$). In the same way, Dach *et al.* (2016) developed a model that measured the level of methane emission during a fermentation process; the correlation of the ANN models was up to 0.99 for the methane emissions and methane produced. This study demonstrated that the ANN predictor served as an efficient tool for estimating the methane production during the fermentation processes.

For agro-industrial wastewater, another study evaluated the hydrogen production from the volatile fatty acids generated after the anaerobic acid phase in a biorefinery platform. With the proposed structure, the experiments showed that it is effectively possible to manage 10 years of data (Rodríguez *et al.* 2019).

As previously mentioned, AI tools could be used in several processes to improve process design and assessment.

Processes in thermochemical biorefineries

Seo *et al.* (2022) evaluated several studies developed for thermochemical processes to assess the use of AI, ML, and ANN in biorefinery platforms. Artificial neural networking modeling was used as an emerging tool to predict stability and conversion rates based on biodiesel properties and biodiesel blends in thermal conversion processes (De *et al.* 2007). ANNs tool can acquire mathematical models through experiences without determining the mathematical relationships that tie together interrelated solutions (Uzun *et al.* 2017). Machine learning is based on numerous techniques, *e.g.*, multilinear regression (MLR), random forest (RF), and support vector machine (SVM), among others, which can be successfully implemented in processes of biomass pyrolysis and gasification (Ullah *et al.* 2021). As a result, ML could reduce the time spent and experimental work needed for bio-oil and syngas production processes. In addition, it allows for the estimation of pyrolysis and gasification processes for various biomasses and improves bio-oil yields. Regarding environmental concerns, Olafasakin *et al.* (2021) evaluated the use of ML to analyze the emissions and costs of a pyrolysis biorefinery. They found the emissions ranged from 13.62 to 145 kg of CO_2 per MJ and the biofuel minimum selling prices ranged between $2.62 to $5.43 per gallon.

With the help of numerous experimental datasets, ML and AI could provide new insights into pyrolysis, hydrothermal treatment, gasification, and combustion (Seo *et al.* 2022). As such, AI and its subsets could considerably reduce the work needed for experiments.

Biorefinery allocation

Biorefinery operations are susceptible to several factors, *e.g.*, the changing nature of biomass properties, biomass feedstock supply, product demands, *etc.* (Clauser *et al.* 2021). In addition, allocation is a critical factor due to transportation costs and available raw materials being crucial factors for the success of the plant. In this sense, ML, AI, and

ANN could be regarded as novel and efficient tools (Ekşioğlu *et al.* 2009; Pournader *et al.* 2021).

Resource allocation optimization could contribute to an intelligent production process that responds swiftly to perturbations in raw material supply and product demand (Yuan *et al.* 2017).

One of the first steps of biorefinery process design is allocation and supply chain management. Chan *et al.* (2021) evaluated a resource allocation system based on a deep neural network (DNN) proposed for the biorefinery. The connection weights and topology of the DNN were optimized using the neuro-differential evolution (NDE) algorithm. It resulted in the DNN yield optimality (97.7%) and reduced the response time (99.5%) compared to the conventional nonlinear solver. During a smart resource allocation system synthesis, the proposed DNN-NDE framework accounts for both responsiveness and cost performance.

Sahoo *et al.* (2016) developed an integrated geographical information system (GIS) and ANN prediction model at a high spatial resolution to estimate sustainable raw material availability. This tool identified suitable biorefinery sites and selected optimal sites minimizing total transport distance. This study also determined that it is possible to develop 7 plants for cotton stalk valorization.

Supply chain assessments are commonly developed for specific regions and/or single and multiple biorefineries. They use different production scales and different temporal scales analyses, among other methods. These factors are complex to collect, determine, and evaluate; in this sense, various tools, *e.g.*, AI, ML, and ANN, could quickly solve the supply chain assessment and integrate several factors (Liao and Yao 2021).

Besides allocation, recent advances in computer vision, pattern recognition, and AI technologies have resulted in the development of new ML techniques, allowing the monitoring of forest ecosystems with higher accuracy. For example, recent studies reported that satellite data and machine-learning techniques were used for forest classification, obtaining higher accuracy (90% to 91%) (Lim *et al.* 2020). Another study used ANN to predict growing stock volume in forested areas (Astola *et al.* 2021). In addition, a recent study developed a method to prepare forest fire susceptibility mapping, considering numerous factors, *e.g.*, altitude, rainfall, wind effect, temperature, slope aspect, distances to roads and settlements, land use, and soil type, among others. The results showed an accuracy of up to 0.903 (Razavi-Termeh *et al.* 2020).

Product development

Finally, one crucial step for commercial process development is product selection. Specifically, no product design studies were found using AI strategies in the biorefinery field. Nevertheless, AI was used in other sectors, *e.g.*, the pharmaceutical industry, including for drug discovery and development (Paul *et al.* 2021). Artificial intelligence is being widely used to improve the time needed for drugs design and to develop new techniques that could be used in the design (Sahu *et al.* 2021). Each step of drug design could be improved using AI technologies. Besides, the integration of AI methods could mean a high success rate in the development of new compounds. In addition, AI is a powerful tool for developing clinical trial output prediction; this further decreases the clinical trials cost by improving the success rate (Sahu *et al.* 2021; Selvaraj *et al.* 2021).

From the above, AI technologies could be used in product design and development, which would decrease costs, decrease the number of product trials, and improve the amount of required development time.

From the above, these technologies appear to be promising implementation opportunities and can be used to improve the design and assessment of processes. However, these technologies should be carefully used. There is a need to consider the processes mechanisms and the factors that affect the operations.

Big Data Analytics and the Internet of Things (IoT) in a Biorefinery Context

4.1 Internet of Things (IoT)

The IoT is a technology that implies the sensing, transfer, and processing of information collected. This technology could be used to make decisions and process changes in real-time due to the inclusion of automation, ML, and sensors (Fabris *et al.* 2020). Devices and sensors are connected to an IoT platform. This platform integrates data from several devices and applies analytics to evaluate and share valuable information with applications developed to address specific tasks, reaching intelligent identification and management.

The IoT was also evaluated in agriculture in a biorefinery context for data collection and analysis to improve crop productivity and soil fertility (Patil *et al.* 2017). The IoT could improve several aspects, *e.g.*, land conditions, water utilization, pesticides, ecological condition, *etc*. Another recent study developed an IoT platform for microalgae biorefinery. Microalgae cultivation at competitive costs at a commercial scale is a challenge. In microalgae biorefinery, some drawbacks including cultivation strategies, extraction processes, efficient and effective monitoring, among others, require new developments. Its potential applications are in pharmacy, food, chemicals, composites, cosmetics, and bioenergy sectors (Khoo *et al.* 2020).

The new applications and possibilities of IoT technologies in biorefinery processes have promoted great efforts in research and development. The use of IoT for automatic processes control, monitoring, and evaluating process parameters for their optimization, and determining new factors for their evaluation, among others, make it a powerful technology to include in biorefinery processes (Wang *et al.* 2021).

From the reviewed literature, no studies have been found specifically in biorefinery processes applying IoT, which could be due to the novelty of this technology, thus becoming an interesting gap to fill up.

Big data analytics

Another relevant component of the new era of Industry 4.0 is Big Data Analytics (BDA), characterized by volume (referred to the enormous magnitude of data), velocity (related to the data generated and collected), and variety (referred to the formats of data) (Klein 2017). These concepts, combined with analytics, can create, analyze, and evaluate valuable knowledge. BDA could generate comprehensive knowledge for new biorefinery processes development as the connection of interdisciplinary and intersectoral datasets improves the decision-making process in each biorefinery process step (Dragone *et al.* 2020).

Regarding farming, the use of drones was recently evaluated to capture plant growth data to optimize the amount of nitrogen used for the fertilization of crops. As such, robots have considerably increased the ability of farmers to manage vast expanses of crops (Ciruela-Lorenzo *et al.* 2020).

In addition, big data and ML technologies facilitate collecting, analyzing, and generating data related to soil conditions. With big data implementation, it would be possible to find hidden characteristics from soil datasets and obtain information that allows identifying soil conditions, *e.g.*, pH levels, nutrients, and soil moisture (Hou *et al.* 2020; Rejeb *et al.* 2021).

Regarding biorefinery process design, a recent sustainability study analyzed big data used in pretreatment selection for agricultural waste valorization. This study shows that it is possible to use big data in process selection. The inclusion of new decision-making tools could improve the process design by producing a substantial time reduction (Belaud *et al.* 2019).

Besides, another valuable contribution is that BDA could significantly improve the product development process due to the use of simulation methods for lab tests (Dragone *et al.* 2020).

Application of Industry 4.0 in a Biorefinery Context

Regarding the biorefinery context, some industries have initiated projects to incorporate information technologies in their value chains, such as monitoring crops, increasing the efficiency in the fertilization process, designing fire prevention plans, and developing predictive maintenance plans (Teixeira *et al.* 2018). Also, it was determined that the use of BDA to improve crop harvesting could considerably increase industrial incomes (Dragone *et al.* 2020).

In farming, BDA could be used to analyze and evaluate characteristics of the soil conditions, weather, seeds, among others, bringing new solutions to the farmers to increase crop yields. BDA allows better decision-making regarding fertilizing, harvesting, and irrigation, among others, increasing the crops' yields (Chandran and Kasat 2019).

Regarding AI, researchers at the bioenergy program in Idaho National Laboratory have successfully tested an intelligence-based control system that could increase the reliability of the preprocessing equipment used in preprocessing feedstock by more than 50%. Combining automatic sensing with making manual adjustments ability allows a highly efficient process. The system maintained 97% reliability at 90% capability during this operation. It is an excellent advance in biorefinery processes since this parameter difficultly exceeds 20% operating capacity during the start-up (U.S. Department of Energy 2017). Various projects in the context of the biorefinery are presented in Table 1.

Table 1. Projects with Industry 4.0 Technology Applications in Biorefinery Context

Primary Technology	Description	Reference
BDA	Remote predictive maintenance. Improvement in fertilization efficiency. Upgrading in fire prevention action plans. Estimated cost reduction: 18 million dollars per year.	(Teixeira *et al.* 2018)
BDA	Increase of yields, producing less nitrogen, in precision farming. Increase incomes, providing the average farmer a $22 per acre return.	(Chandran and Kasat 2019)
AI	Increase of the reliability of the feedstock preprocessing equipment by more than 50%.	(U.S. Department of Energy 2017)
AI	Project to use AI for retrieval of forest biomass and structure.	(Aalto University 2018)

Large companies that are aiming to stay current with emerging opporunities are more prepared to implement Industry 4.0 technologies. Investing in process and product innovation may require a high level of investments. For this reason, several sectors are investing in Industry 4.0 technologies, including the pulp and paper industry, food products, pharmaceutical, energy, and chemical, among others (Dalenogare *et al.* 2018, Frank *et al.* 2019). Moreover, industries with an advanced implementation level of Industry 4.0 tend to adopt most of the technologies, whereas those with a low level tend to adopt specific technologies, such as AI, ML, ANN, and IoT, among others (Frank *et al.* 2019).

In this way, the new technologies in biorefineries could be through integrated processes in consolidated industries like pulp and paper, food (like sugar), and energy, among others, which could be a promising alternative to take advantage of the synergy between consolidated industries and the new technologies.

Improving Social Assessment Through Industry 4.0 Technologies

Finally, one of the sustainability factors that digitalization tools could revolutionize is the assessment of social impacts.

As previously shown, Industry 4.0 technologies could bring several solutions to biorefineries concerning sustainable development, *e.g.*, promoting sustainable farming, improving soil conditions, water utilization, pesticides, high growth yields, *etc.*, improving the economy in rural areas. Figure 6 shows several improvement opportunities using Industry 4.0 technologies.

Fig. 6. Sustainability opportunities in a biorefinery context

An increase in the efficiency of bioenergy systems increases the quality and decreases the cost of the energy produced, which could reduce the CO_2 emissions, increasing the efficiency of several processes. In addition, improving the production processes systems by implementing autonomous systems means better safety conditions for employees.

In addition, concerning social sustainability dimensions, smart and autonomous production systems can promote healthy and safe employment by taking over monotonous and repetitive tasks, improving employee satisfaction and motivation. However, Industry 4.0 technologies also bring many challenges and limitations; one of the primary concerns is employment reduction (Bai *et al.* 2020). In this sense, the concept of Industry 5.0 has recently emerged, and literature shows a lot of uncertainty about what it could bring as well as details of how it could disrupt business and its potential to break down barriers. Three core elements could define this new concept: human-centricity, sustainability, and resilience (Nahavandi 2019; Breque *et al.* 2021).

Promising Advances

Several efforts are developing in the biobased industry field to include new technologies. The Royal DSM and TU Delft have recently established the first AI Lab for Biosciences in Europe regarding academia. This laboratory could look to apply artificial intelligence (AI) to full-scale biomanufacturing (TUDelft 2021). In addition, the Bioenergy Technologies Office (EEUU) carried out the first workshop on “Predictive Models and High-Performance Computing as Tools to Accelerate the Scaling-Up of New Bio-Based Fuels,” in 2020, where diverse sectors and technology areas, including industry, academia, and government, attended the virtual meeting. More than one hundred participants provided inputs regarding AI and ML use and modeling tools across multiple scales to reduce technology uncertainty and accelerate the scaling-up of equipment used in biorefinery and chemical processes, optimizing its operation (Bioenergy Technologies Office 2020). In Europe, the Alan Turing Institute was awarded £38.8 million for 5 years since 2018 to develop research with a focus on AI in science and the government (The Alan Turing Institute 2018). The research has focused on several topics related to biorefineries.

Regarding industrial biorefineries, some promising start-ups offering biorefinery solutions with technologies related to BDA and AI have been recently reported. These start-ups focus on bioenergy production through pyrolysis, gasification, and torrefaction, among others, using raw materials like biomass and wastewater (StartUs Insights 2021a; StartUs Insights 2021b). In the same way, some companies were reelevated with a focus on energy optimization and efficiency using AI (StartUs Insights 2021c).

CONCLUSIONS

1. The applications of Industry 4.0 technologies in biorefineries are increasing, and their implementation is getting special attention. Artificial intelligence (AI), machine learning (ML), and artificial neural networks (ANN) are the most used technologies, but others like the Internet of things (IoT) and big data analytics (BDA) are gaining attention.

2. The current strategy for designing biorefinery processes could be considerably improved by using new technologies such as AI, ML, ANN, IoT, BDA, *etc*. In addition, these technologies could be applied to all steps of commercial process implementation, *e.g.*, design, operation, logistics, management, *etc*. The use of analyzed technologies could increase in quality in biorefinery implementations.
3. Artificial intelligence and its subsets (ML and ANN) are promising technologies that have great potential to improve several concerns, *e.g.*, reducing energy consumption, environmental burdens, and the operational risks of chemical production. In addition, the IoT and BDA are little explored technologies in the biorefinery field. However, they have shown great potential for improving and optimizing the assessment and monitoring of production processes.
4. Most studies about Industry 4.0 tools found in the bibliography were performed at lab and pilot scales; in this sense, large-scale applications of these technologies are still limited.
5. Another barrier is the lack of quantitative understanding of the potential benefits and risks of different applications of these technologies.
6. Applying these technologies in biorefineries processes design and assessment at the beginning could be developed as integrated biorefineries in consolidated industries such as pulp and paper, chemical, food industries, and energy to increase the opportunities of its successful implementation.
7. For a better understanding and consolidation of biorefineries on a commercial scale, considerable analysis, and development of these technologies are necessary for their application in the design step.
8. Circular economy and sustainable development concepts demand considerable commitment from all involved sectors (industry, society, academia, and government). Therefore, using Industry 4.0 technologies for biomass valorization through a biorefinery platform could be crucial for sustainable development.

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