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Review

Future trends in organic flour milling: the role of AI

Loïc Parrenin[1,2,3,*], Christophe Danjou[1,2,3], Bruno Agard[1,2,3] and Robert Beauchemin[4]

[1] Laboratoire en Intelligence des Données (LID), Montréal, QC, Canada
[2] Laboratoire Poly-Industrie 4.0, Montréal, QC, Canada
[3] Département de Mathématiques et génie industriel, École Polytechnique de Montréal, CP 6079, succursale Centre-Ville, Montréal, QC, Canada
[4] La Meunerie Milanaise, Saint-Jean-sur-Richelieu, QC J2X5V5, Canada

* **Correspondence:** Email: loic.parrenin@polymtl.ca.

Abstract: The milling of wheat flour is a process that has existed since ancient times. In the course of history, the techniques have improved, the equipment modernized. The interest of the miller in charge of the mill is still to ensure that a mill is functional and profitable, as well as to provide a consistent quality of flour. The production of organic flour means that methods of adding chemicals and unnatural agents are not possible. In organic flour production, it is necessary to work with the raw material. A grain of wheat is a living material, and its quality varies according to a multitude of factors. Challenges are therefore present at each stage of the value chain. The use of artificial intelligence techniques offers solutions and new perspectives to meet the different objectives of the miller. A literature review of artificial intelligence techniques developed at each stage of the value chain surrounding the issues of quality and yield is conducted. An analysis of a large number of variables, including process factors, process parameters and wheat grain quality from data collected on the value chain enables the development and training of artificial intelligence models. From these models, it is possible to develop decision support tools and optimize the wheat flour milling process. Several major research directions, other than constant quality, are to be studied to optimize the process and move towards a smart mill. This includes energy savings, resource optimization and mill performance.

Keywords: industry 4.0; organic wheat grains; flour milling optimization; flour quality; artificial intelligence; machine learning; data mining

1. Introduction

Organic agriculture is a specific method of food production using natural substances and processes. This type of agriculture is gaining in popularity and supported by people who are concerned by agri-food, environmental and health issues [1,2]. According to Willer et al. [3] global organic food sales grew by more than 15% between 2017 and 2019. They showed that in 2019 organic wheat was the most widely grown organic cereal in the world.

Flour milling refers to the industry of processing grains of cereal into flour. Wheat flour is produced by milling wheat. Milling is the process used to grind grains of cereal. This typically takes place in an industrial flour mill, which has replaced antique flour mills powered by wind or water. The objective of wheat flour milling is to separate the different parts of the wheat grain and reduce the grains into smaller particles. Various techniques and strategies have emerged over the years, two of which are still widely used today: stone milling and roller milling [4,5]. Both techniques have advantages and disadvantages. However, cylinder milling is the most often used because of its high yield. It also results in very white flour. By using cylinder milling, production parameters must be adjusted according to the quality of the grains of wheat.

Wheat flour milling is one of the oldest processes that is still in operation today [6]. The methods and tools have improved over the centuries [6,7]. The process of wheat flour milling follows a linear and continuous flow [8]. It can be broken down into 3 phases, as follows: cleaning, tempering and milling. The cleaning process eliminates all impurities and foreign materials present in a wheat batch that can degrade the quality of flour or, at times, damage equipment. Then, the tempering process takes place to condition the wheat for optimal performance in the milling process. Finally, the grains of wheat are milled in a multistage environment that takes place successively until flour is obtained. The wheat milling process can generally be separated into 2 operations: breaking the grain into particles and reducing the particle size. At each stage, the particles are sifted through several sieves. The particle size will classify the particle as flour. According to FAO [9] flour should have a particle size less than 212 μm.

Although equipment for the wheat flour milling process has been modernized and some parts are now semi-automated, the miller is responsible for controlling the entire process. He starts by selecting the right kind of wheat to produce a specific quality of flour. A mix can be made with different qualities of wheat if necessary to balance and obtain the desired quality of flour. The wheat mix is then processed following the three operational phases, described previously, in the mill. During each phase, the miller adjusts the right process parameters to manufacture the quality of flour required, while reaching the highest achievable yield of flour. The choices and adjustments made by the miller during those procedures are often described as an art. The miller applies his accumulated knowledge and experience to make decisions and changes in the wheat flour milling process.

The industrial production of organic flour differs in some regards from the conventional flour production method. In conventional flour production, volumes are significantly greater. From the vast availability of different types of wheat and the use of improvers, fewer wheat mixtures are required. The use of improvers helps maintain a stable level of flour quality throughout the year. Among the improvers available, it is possible to use chemical agents such as chlorine for flour bleaching to improve the visual aspect of the flour, ascorbic acid to improve baking quality of the flour and enzymes to improve rheological performance of the wheat dough [7,10,11]. In contrast, organic wheat flour is produced from organic wheat, only natural ingredients explicitly authorized by organic norms and in certain proportions may be used. For those reasons, two main levers of action are possible, in addition to the use of natural ingredients, to improve and reach the organic flour quality desired: organic wheat mixing and adjustment of the production parameters. These levers of action exist in conventional flour production. However, the miller must deal with a greater variety of organic wheat from different regions compared to conventional. Moreover, the quantities of protein are lower but offer better protein quality than those present in the conventional environment [12]. Mixtures and adjustments must be constantly readjusted by the miller to reach a certain level of organic flour quality. This adds complexity to the production process.

As wheat is a living raw material, every grain of wheat that is cultivated has unique, intrinsic properties. The intrinsic properties vary according to the variety of wheat, climate where it was grown, weather, harvesting period and crop rotation [13–15]. Because of the variations in wheat quality, there is an impact on flour yield and flour quality if the same process parameter is applied to the same type of wheat mix. The miller's goal is to reduce this variability in the process to produce the best yield with the desired flour quality. By relying on his knowledge and experience, the miller learns through trial and error to select the right wheat mix and to adjust it to the right process parameters. However, many variables exist along the value chain that can affect the flour yield and quality of the flour output. For this reason, it is difficult to fully understand and measure the impact of each variable and its impact on the output.

This is where artificial intelligence can come in. Artificial Intelligence (AI) is a part of computer science. Many have tried to broadly define AI. The most recent definitions describe AI as computer programs or algorithms that imitate intelligent human behavior [16,17]. Machine Learning (ML) is a sub-filed of AI. Kelleher [18] explains that ML involves "the development and evaluation of algorithms that enable a computer to extract (or learn) functions from a dataset (set of examples)". From the available data, it is then possible to identify and discover patterns that accurately associate relationships between different system variables without any prior knowledge of the system [19].

This paper intends to review the state of the art of analytical tools and methods (such as AI algorithms) that could be applied to the organic flour industry sector to improve the quality and yield of organic wheat flour.

This paper is organized into four sections. Section 2 describes organic wheat flour milling more in depth and the different AI techniques used to improve flour quality and yield output based on the literature review. Section 3 covers the future direction that deserves to be studied to improve the flour milling process. It explores aspects other than flour quality and yield output, such as energy savings, resource optimization and mill performance. Section 4 concludes the paper.

2. State of the art

The production process of wheat flour has existed for a long time and still applies to organic wheat flour milling. This section focuses on explaining the key steps in the value chain of wheat flour milling. An overview of the challenges regarding flour quality and yield are presented across the value chain at specific steps. Research that has been conducted to overcome those challenges using AI techniques and statistical tools is then outlined.

Figure 1 illustrates the workflow of the wheat flour milling process. In this diagram, the key steps of the processing of grains of wheat are shown. It begins with the quality of wheat selected by the miller. It ends in either a manufacturing process of an end-product made from the wheat flour, or by selling the wheat flour that is produced to wholesalers and grocery stores. Between those two starting and ending points in the value chain, the diagram details the different steps that the wheat grains follow in a factory mill.

The grains of wheat received at the mill experience the transformation process illustrated in Figure 1. The objective of this process is to extract the maximum quantity of wheat flour at a desired quality level. The different steps numbered in Figure 1 will be explained in the following subsections.

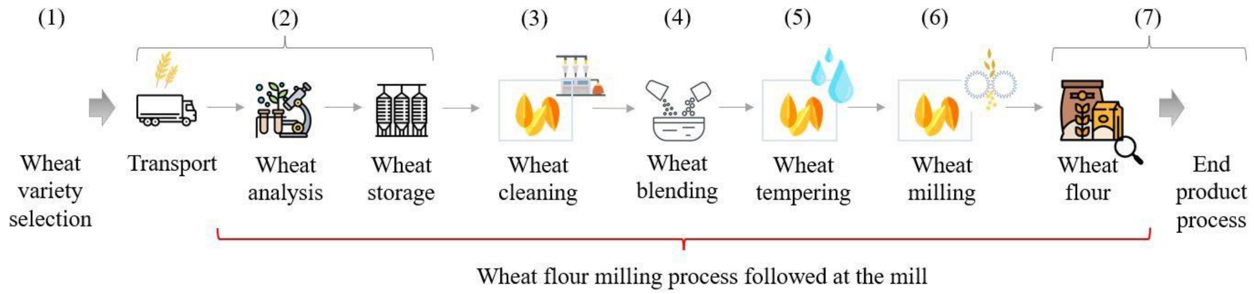

Figure 1. Diagram of the wheat flour milling production value chain.

2.1. Selection of the wheat variety

The selection of the wheat variety involves choosing the right quality and quantity of wheat to order from a mill. Different types of wheat varieties and levels of quality exist. A grain of wheat, as pictured in Figure 2, is located in a wheat ear. It is composed of four distinct parts: the germ (3% of the total mass of the grain), the endosperm (84%), the bran (13%) and the brush (negligible mass).

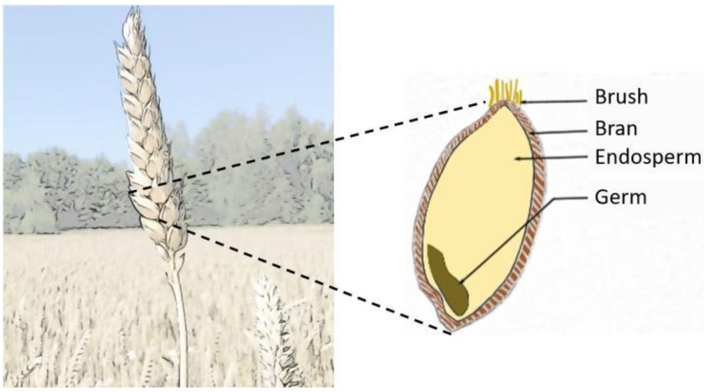

Figure 2. The anatomy of a grain of wheat (longitudinal section).

The *germ*, which is rich in fat and vitamins, represents the future plant. The *endosperm* contains mainly carbohydrates (starch) and proteins (including gluten). The starch is a complex carbohydrate (slow sugar) that is useful for the growth of the new plant. Gluten is a protein that forms a viscoelastic dough and gives dough sufficient elasticity to ensure that it will rise. The elasticity and the tenacity of the dough are explained by the creation of the gluten network, which is formed during the process of hydration and kneading dough made from wheat flour. network provides unique rheological properties to the wheat dough, allowing it to be stretched and deformed without breaking up with a certain level of force. The *bran* protects the components inside the wheat grain. It is rich in fiber, but nutritionally poor compared to the endosperm [6]. The *brush* at the top of the grain is characterized by thin and short bristles and contains no nutrients.

Depending on the quantity and quality of wheat available at the mill, the miller must select and order the appropriate quality of wheat to produce and deliver the desired quality of flour to customers. As previously explained, each batch of wheat that is cultivated at a certain time in a specific geographic area has unique intrinsic and physical properties. Those properties vary according to genetic factors, variations in environmental conditions and crop rotation [13,20–22]. The knowledge of those properties is therefore important, as it influences the adjustments made in the following steps at the mill and affects the final quality of the flour [23]. The miller wants the farmer to grow varieties of wheat that produce good flour. Depending on the kind of flour desired by the client, the miller will analyze the intrinsic and physical properties of the wheat grains that are the most suitable to mill. The intrinsic properties inform the chemical composition of the wheat grain. For example, *protein content* and *moisture content* are two main intrinsic properties among others, that are analyzed. The physical properties are more related to the appearance and texture of the wheat grain. A few examples of the physical properties of wheat grains are *hardness*, *dimension*, *shape* and *color*.

2.1.1. Challenges

In wheat fields, the quality of wheat (intrinsic and physical properties) fluctuates from one geographic area to another, as well as from one portion of a field to another. Climate change accentuates those variations resulting from more abrupt and less predictable changes in weather conditions. The variation in the quality of wheat grains from wheat fields affects the flour quality and yield produced at the mill. In addition to the fluctuating quality of wheat, there are many more varieties of wheat in the organic sector than in the conventional sector. This makes it more difficult to control and produce consistent quality flour throughout the year.

2.1.2. Progress of work research

To address these issues, some research focuses on improving the selection of wheat variety that will offer the best quality of wheat according to a miller's needs. To this end, some research has studied the physical properties of grains of wheat and its impact on the yield of flour milling. Aydin et al. [24] have developed an artificial neural network model (ANN) capable of predicting the flour yield based on four physical properties of wheat grains. Their study showed that wheat grain hardness plays an important role in determining flour yield. Dowell et al. [25] have studied Near-Infrared Spectroscopy (NIRS) data from wheat grains to predict the quality of wheat grains, flour quality and flour milling yield. The results showed that NIRS data, such as intrinsic properties, were useful in predicting the quality of wheat. Today, most analysis of the intrinsic properties of wheat is conducted by NIRS as it is a reliable, quick and non-destructive method to test the quality of wheat [26]. However, NIRS analysis has shown mixed results for identifying flour quality and flour milling yield. Assadzadeh et al. [27] focused on predicting flour milling yield. They proposed a Gaussian process regression model based on grain image data and NIRS data. Image data allows physical properties to be described and interpreted, such as grain shape, color and morphology. This model was able to explain the variation of the milling yield variable better than previous work based on a multiple linear regression model [28]. The Gaussian process regression model reached a R-squared equal to 0.61.

More recently, deep learning algorithms have been used to classify wheat grains from images. Unlersen et al. [29] proposed a Convolutional Neural Network (CNN)-base model to classify four different wheat varieties from images of wheat lot samples. Zhu et al. [30] developed CNN models to classify slightly sprouted and sound wheat kernels from hyperspectral images. The use of sprouted grains in wheat milling reduces flour quality and yield. Both techniques can be used to monitor grain quality and sort grain varieties based on images. Although these techniques are applied to a small number of wheat varieties, they show promise in selecting wheat grains to purchase for wheat milling.

Table 1. Summary of existing AI research on wheat selection.

Author(s)	Objective type	Model	Parameters	Output
Dowell et al. [25]	Predict flour quality and yield	PLS (Partial least square) regression	Near-Infrared Spectroscopy (NIRS)	*Wheat quality*, *flour quality* and *flour milling yield*
Delwiche et al. [28]	Predict flour yield	Multiple linear regression model	NIRS and physical grain properties	*Flour milling yield*
Aydin et al. [24]	Predict flour yield	ANN (Artificial neural network)	Physical grain properties	*Flour milling yield*
Assadzadeh et al. [27]	Predict flour yield	Gaussian process regression model	NIRS and physical grain properties	*Flour milling yield*
Unlersen et al. [29]	Classify wheat varieties	CNN-SVM (Support Vector Machines)	Wheat grains images	*Wheat variety class*
Zhu et al. [30]	Classify sound wheat kernels and slightly sprouted wheat kernels	CNN (Convolutional Neural Network)	Hyperspectral images of wheat grains	*Wheat kernels class*

Table 1 highlights some representative AI research on wheat selection. The studies relied on intrinsic and physical properties to predict the yield and quality of flour. The intrinsic properties are collected by NIRS. Physical properties are collected from physical tests and images. From the parameters studied, we may note that no author analyzed both the intrinsic properties and the hardness of wheat. Yet, Aydin et al. [24] showed through his prediction model that wheat hardness is an important factor in predicting flour yield. Moreover, no author has taken into account the variety and locality of wheat in flour yield prediction. Finally, the gluten quality of wheat grains measured from the rheological behavior of the dough deserves to be explored to improve the prediction results of the studies performed [31].

2.2. Transport/wheat analysis/wheat storage

After wheat grains are selected by the miller, they are transported from the farmer's land to the mill. Depending on the quantity ordered, batches of wheat are received at the mill throughout the year. After it is received, a sample test is conducted to analyze and measure the quality of the wheat grains received. The results of the analysis help to decide in which specific silos (storage tanks) they will be stored, according to their quality level. This grouping allows a homogeneity to be maintained in the quality of the grains in each silo. Before wheat grains are stored in silos, pre-cleaning is conducted to eliminate big pieces of waste (stones, mud, dirt, and so forth) as well as metallic objects that could damage production equipment [10].

2.2.1. Challenges

The main challenges at this stage of the value chain are related to transportation time and conditions, as well as storage time and condition. Depending on initial location departures and circumstantial events (political, economic, etc.), the transport time varies. This makes it necessary to have a stock of wheat grains that can handle long transportation lead time (TLT) before replenishment. In addition, as wheat is harvested during summer and delivered throughout the year in lots, wheat grains can be stored in a farmer's silo for several months or years. In this context, several problems can arise. First, if wheat is stored for a long period of time in silos in an uncontrolled environment, the quality can fluctuate and deteriorate [7]. This deterioration causes issues in terms of flour quality and yield once the wheat is milled. Second, in terms of stock, as wheat storage is limited by the number of silos, it is necessary at times to load different wheat lots together in a silo due to space constraints. This loading mixture of different quality of wheat lots impacts the resulting flour quality and yield. According to Boudreau et al. [7], the grouping rule of wheat lots followed are based on wheat class, wheat grade and wheat protein content. A wheat class regroups wheat varieties. A wheat grade informs the quality of wheat and its overall visual quality. Based on these three pieces of information, a decision is made to store wheat in a specific silo. However, this raises questions about the relevance and appropriateness of these attributes. With today's rapid analysis of intrinsic and physical properties of grains of wheat, additional information could improve decision-making on the grouping of lots of wheat and, consequently, improve the flour manufacturing process.

2.2.2. Progress of work research

The aim of wheat storage is to preserve the quality of a wheat harvest until it is processed. Wheat grains are a living raw material. This means that their quality is affected by environmental factors that can stimulate the presence and growth of microorganisms and insects [32]. According to Jia et al. [33], storage temperatures lower than 15 degrees can prevent insect development. Mite and microorganisms such as fungi can be controlled by reducing wheat moisture content and relative humidity [33]. In regard to wheat moisture, Campbell [6] specifies that a moisture content lower than 14% allows the wheat grains to be stored for a long period of time. However, it is not always possible to store wheat in a controlled environment or to dry wheat to reduce the moisture content of wheat. This would lead, in most cases, to an increase in the cost of wheat storage. To overcome this, several studies have examined the effects of wheat properties under different storage conditions. Campbell [6] and Kibar [34] showed that a combination of high temperatures and relative humidity during wheat grain storage had a significantly decreasing effect on potential flour yield, leading to economic loss. In addition to the flour yield performance metrics, they showed mixed results in terms of dough quality in the bread-making process. However, Posner et al. [35] showed, contrary to recent studies, an improvement in milling performance and flour quality based on storage time in a stable environment (relative humidity = 68% and temperature = 21 degrees) for the Hard Red Winter (HRW) wheat variety. The study shows that wheat goes through a "sweating process" after harvest that tends to change its intrinsic properties and improve milling and baking qualities. An increase in flour extraction of 2-5% has been realized when milling HRW wheat after the first five months. As most wheat is not stored in a controlled environment, additional research must be done to evaluate the possibility of increasing the wheat quality for milling by taking into account wheat variety, wheat properties, storage time and fluctuation in environmental conditions.

Other research focuses on developing a method to improve the selection and separation of wheat batches to store in silos. The method is based on the physical properties of the wheat grains. Physical properties are important characteristics that directly influence the production yield and the quality of the flour [36–38]. The knowledge of these characteristics is useful for the adjustment of the production parameters. A large dispersion of grain sizes from one silo implies a longer processing time, a higher energy cost and eventually a degradation of the quality of the flour produced [38]. Therefore, Yoon et al. [38] used mathematical tools and a clustering technique to better sort the different batches of wheat based on their physical properties such as grain size, hardness and shape. Three cluster groups are used based on wheat grain size: small, medium, and large. The cluster analysis enabled an improvement in the flour yield by 0.13%, which represent a 5% increase in milling income per day, on average.

Table 2. Summary of existing AI research on wheat transport and storage conditions.

Author(s)	Objective type	Model	Parameters	Output
Posner et al. [35]	Predict flour yield and quality	Regression analysis	*Storage time*	Milling characteristics and flour quality
Yoon et al. [38]	Improve flour yield	Clustering – KNN	*Grain size*	Wheat lot assigned to a cluster
González-Torralba et al. [39]	Study input parameters on wheat quality and flour quality	PCA (Principal component selection) and ANOVA (Analysis of Variance)	*Temperature*, *relative humidity*, *time of storage*	Wheat quality and flour quality
Kibar [34]	Study input parameters on wheat quality	ANOVA and PCA	*Relative humidity* and *temperature*	Wheat quality

Table 2 provides a summary of existing AI research on wheat transport and storage conditions. It shows that research has focused on variables that consider storage time, environmental conditions, and grain quality during wheat storage. However, there is a noticeable lack in studies on the conditions of wheat grain transportation. Environmental conditions during transport could impact wheat quality. Moreover, the mix of wheat batch made at a grain terminal or in cargo storage to optimize space is another approach to take into consideration to improve flour yield and quality.

2.3. Cleaning

At the cleaning stage, a wheat recipe is created to select the different grains of wheat needed according to the miller for flour production. A milling run can begin. The milling run starts with a cleaning process with the purpose of eliminating all foreign materials and impurities remaining with the wheat grains, such as broken grains, dust and straw. Four different machines are usually set up in a flour mill to efficiently eliminate all kinds of waste present in a wheat grain batch [10;40]. One cleaning machine is dedicated to eliminating foreign material according to its size. A second aims to sort foreign materials that have a mass density that is significantly different than wheat grains. A third seeks to sort broken grains and cereal grains from grains of wheat by their shape. Finally, a fourth uses aspiration to eliminate thin materials that are bonded to the grains of wheat, such as brush and dust. Sometimes, a fifth could be added in addition to the one already presents at the pre-cleaning stage (occurring at the step 2.2 in the value chain), to ensure that metal objects are properly eliminated.

2.3.1. Challenges

The main challenge in the wheat cleaning process is ensuring that no residual material remains with the grains of wheat. One control lever at the miller's disposal is to regulate and balance the airflow according to the percentage of foreign materials and impurities present with the wheat grains. The greater the quantity of foreign material and impurities, the more the air flow needs to be increased to efficiently clean the grains of wheat. However, this adjustment is done manually and is approximated by visualizing a sample of wheat grains. This can lead to a fluctuation in the quality in the wheat flour milling process depending on a miller's expertise. Additionally, the miller can decide, by visualizing the output result of the cleaning stage, to start a second cleaning cycle if necessary. However, an additional cycle is time consuming and implicates additional energy costs.

To the best of our knowledge, no research paper has addressed those issues using artificial intelligence techniques to improve flour quality at the mill. The studies about cleaning grains of wheat are limited to being evaluated by a series of tests, according to particular interest in using a specific cleaning machine or a method for wheat cleaning [41–43]. Therefore, some ideas will be discussed in section 3 for research perspectives.

2.4. Wheat blending

Wheat blending is the process of mixing different qualities of wheat. During this process, grains of wheat that have been cleaned are mixed. Wheat blending acts as a lever action to improve the quality of the flour produced [6]. It is necessary when the desired quality of wheat is not directly available. It enables the use of low-grade wheat as a compensating material in response to baking demand when the supply of wheat is insufficient [44]. To this end, a wheat mixture or wheat recipe is created at the beginning of a milling run. A milling run covers the main production process required to make flour. It includes the cleaning process, the tempering process and the milling process described in the following subsections 2.3, 2.5 and 2.6. The wheat blending is done between the cleaning and tempering stages. For each milling run, production parameters must be adjusted. The parameters are adjusted not only according to the quality of the selected wheat grain when mixing, but also according to the type of flour desired by the customer. The wheat mixes and the adjusted production parameters together form a production recipe.

2.4.1. Challenges

Wheat mixing is a good lever action for improving and reaching the quality of the flour desired [6]. According to Posner et al. [37], it is estimated that 75% of flour quality is determined by the quality of the wheat and 25% by the milling technology, adjustment of mill parameters and environmental conditions in the mill. This makes wheat blending a necessary step in reaching the quality of flour desired. Many factors influence the decision of making one specific wheat mixture at a specific time. Those factors include wheat grain price, wheat grain quality, wheat grain availability and the type of flour desired. It is difficult to determine the best blend and mix ratio to use to produce the right quality of flour at the best output yield. The blend of certain types of wheat could negatively impact the flour quality and yield if, for example, certain grains of wheat need different treatment conditions. The miller, using their knowledge and expertise, is in charge of creating the right blend taking into consideration the different factors that were stated. The miller will adjust the milling parameters by trial-and-error during the mill run. This trial-and-error process occurs through the analysis of a machine's performance.

2.4.2. Progress of work research

The price of organic wheat grain varies according to quality and demand. Wheat recipes are therefore a variable unit production cost ($/Ton) for a company. To improve the profitability of a company, wheat recipes are the subject of scientific research. Hayta et al. [44] worked on a wheat recipe optimization model. The objective of their model is to minimize the cost of wheat recipes while respecting a satisfactory quality level of flour production adapted to the bread-making process. For this purpose, they build a linear optimization model. In their model, they select the volume of the bread as the variable measuring the bread quality. Depending on the volume of the bread, they perform a multiple linear regression analysis to select the variables that can best explain the volume of bread. To do this, they use the best subset regression method. Among the 8 possible explanatory variables describing characteristics of the quality of the wheat grains, 3 are selected. The 3 variables selected explain the bread volume relatively well, with an R-square equal to 0.77. More recently, Steffan [11] focused his research on building an optimization model for blending wheat and additives that both meet the needs of its customers, while being the least expensive. His study is limited to minimizing the production cost of a single type of flour, intended for the manufacture of French-style bread (baguettes). Since additives are present, this study only concerns the production of conventional flour. In his method, several linear regression models are used to predict different output variables that are associated with flour quality, which are specific to bread production and bread volume. The R-square value obtained by the linear regression models fluctuates between 0.41 and 0.93 depending on the variable output to predict. The linear regression equations will then be used as constraints in the optimization model to respect the quality of flour to be produced for baguettes. Finally, Elevi et al. [45] seek to optimize the cost of wheat recipes for all types of flour. They estimate flour quality by calculating the weighted average of each wheat grain quality measurement based on the wheat ratios used in a future recipe. For example, the moisture content of the flour is estimated by the weighted average of the moisture content of the different batches of wheat grains used. However, they do not specify the performance or accuracy of their mathematical model to estimate the quality of the flour produced. Elevi et al. [45] and Steffan [11] studied wheat blending and flour blending. Milling wheat separately and mixing the final flour at the end of the process is a possibility. This method benefits the miller by responding quickly in a "just-in-time" mode for customer orders [6]. However, according to Campbell [6], blending flour requires additional space and investment in equipment. He also explains that, in practice, it is much easier to blend wheat than flour.

Table 3. Summary of existing AI research on wheat transportation and storage conditions.

Author(s)	Objective type	Work frame	Model	Parameters	Output
Hayta et al. [44]	Minimizing cost (predict flour quality)	Flour for bread	Linear regression model	*Particle size index*, *dough volume* and *falling number*	*Bread volume*
Steffan [11]	Minimizing cost (predict flour quality)	Conventional flour for baguette	Linear regression model	*Quantity of soft wheat*, *hard wheat*, *gluten*, *ascorbic acid* and *enzyme mixes*	*Flour quality* and *bread volume*
Elevi et al. [45]	Minimizing cost (estimate flour quality)	All types of flour	Average	*Moisture content*, *gluten*, *gluten index*, *sedimentation*, *delayed sedimentation*, *falling number*	Cost of wheat recipe

Table 3 highlights existing AI research on wheat transportation and storage conditions. It shows that studies have focused on minimizing the cost of wheat blending while resulting in a satisfactory flour quality. However, none of these studies included the adjustment of parameters at each step in a mill run. Those adjustments must be made according to the wheat blend.

2.5. Tempering

The milling run continues with a tempering process. Tempering is the process in which water is added to the grains of wheat, followed by a period of rest in an empty silo to let the water penetrate the wheat [10]. The tempering process takes place in two and sometimes three cycles for some types of grains. The number of cycles depends on several factors, such as wheat grain quality and environmental conditions. The tempering aims to moisten the wheat to facilitate the separation of the endosperm from the rest of the grain component in the milling process. This is explained by the fact that water absorption by wheat grains will increase wheat bran flexibility and soften the endosperm [7]. When manufacturing white flour, the goal is to extract as much endosperm as possible from the grain without any bran contamination. Tempering during milling helps separate the endosperm from the bran, which as a result, improves flour quality. Moreover, tempering helps compensate for the loss in moisture that occurs during milling operations. As flour prices are fixed according to quality and weight, there is an economic interest in increasing the final flour moisture content.

Before milling, it is suggested that the wheat moisture should be raised to about 16% [6]. A tempering stage is thus necessary as the moisture content of wheat grains is mostly kept below 14% during storage for shelf life reasons [6]. However, an increase in the moisture con- tent of wheat grains is not proportional to the water quantity or water flow used. Depending on the quality of wheat, its specific variety and environmental conditions, grains of wheat do not all absorb water the same way. Therefore, adjustments must be made during the tempering process to reach the moisture content desired.

2.5.1. Challenges

The adjustment of the tempering process parameters is difficult as they are influenced by many factors. According to IAOM [10] those factors include: wheat properties, ambient moisture, ambient temperature, resting time and tempering bin space available. Furthermore, the wheat mixes made before the tempering stage add complexity to the control of the process. The miller, according to his experience and knowledge, is in charge of adjusting tempering parameters. Depending on the type and quality of flour desired, the miller sets a target moisture content. This is the desired moisture content that needs to be reached by the end of each tempering stage. The target moisture content is used to calculate (by a mathematical formula) the water flow rate required to temper the wheat grains according to the wheat grain flow rate and the initial wheat moisture content [10]. Other parameters controlled by the miller are the flow of wheat grains, quantity of wheat, the duration of the resting time and the number of tempering stages.

In this context, many different factors must be considered to adjust the tempering parameters efficiently and to reach the wheat moisture content desired. Depending on the wheat moisture content reached at the end of the tempering stage, flour yield and flour quality are impacted during the milling process. If wheat grains are not sufficiently moistened, the wheat grains are crumblier during the milling process. This results in bran contaminating the flour at the end of the milling process. On the contrary, if the grains are too humid, the wheat grains are stickier. This will make flour extraction difficult as wheat grains will not flow well and will be inefficiently sifted [10]. Thus, an optimal wheat moisture content must be reached to efficiently extract quality flour with high yield.

2.5.2. Progress of work research

Several studies have investigated the wheat tempering stage to better understand the variables of interest in this stage. [46–48] have studied different wheat properties and process parameters to evaluate their influence on flour yield and flour quality. Their method relies on statistical analysis to evaluate the influence and interaction of several independent variables on a single dependent variable. Using this method, they showed, for example, the existence of a relationship between moisture content and flour quality as well as flour yield. When the moisture content of the wheat increases, the yield decreases while the flour quality increases. Therefore, a good compromise has to be found, especially for the production of white flour which should not be contaminated with bran. Moreover, Hook et al. [48] show that hard wheat is more tolerant to the addition of water, which results in less of a decrease in flour yield compared to soft wheat. In addition to the impact of wheat tempering on flour quality and yield, Warechowska et al. [47] show that an increase in wheat moisture content for hard wheat softens the wheat, but leads to more energy required during the wheat flour milling step. This results in higher production costs. This variable must be considered in order to optimize a mill's profitability.

There is research that is limited to the production of whole wheat flour. Whole wheat flour differs from white flour because of its higher proportion of bran residue. Bran residue is made up of particles of wheat grains that come from the bran and the germ. In this context, Doblado-Maldonado et al. [49] studied the relevance of the tempering stage, when there is no real interest in efficiently separating the different wheat components. To this end, a two-way ANOVA (analysis of variance) is used to compare and measure the effect of different tempering treatments and wheat varieties on the wheat particle size distribution obtained from the milling process. In this study, the flour quality is based on particle size distribution. Significant differences are noted as a result of the tempering treatments prior to milling. Much larger particles are produced after one milling step when wheat grains have undergone a tempering stage. According to Doblado-Maldonado et al. [49], a higher quantity of thin particles is related to good bread quality, which is explained by a higher bread volume. If wheat is tempered, it is necessary to reduce those large particles to produce whole wheat flour for bread-making by performing additional milling steps. Milling wheat grains without any tempering could avoid those additional milling steps that are time and energy consuming. Furthermore, the study showed that flour milled from wheat grains that did not undergo a tempering stage had the same level of quality as expected in commercially milled flour. However, the study is limited to one milling step, while in industrial wheat flour milling, several milling steps exist. Moreover, Noort et al. [50] explains that a higher quantity of thin bran particles is not always related to good bread quality. Bread quality is influenced by the intrinsic and physical properties of wheat, wheat mixing and bread baking procedures [50]. Additional research needs to be done to compare flour quality produced from wheat tempered grains that follow several milling steps in an industrial mill.

Other research has focused on the stone milling process, which is a different method of wheat milling. In this context, Cappelli et al. [51] studied the effect of two parameters, which include stone milling speed and wheat moisture, on the operative milling performance, flour quality and bread quality. A two-way ANOVA is used to measure the influence of the two parameters with four grades of moisture and three grades of rotational speed. They show that wheat tempering had a significant effect on flour quality and bread quality. However, wheat mill productivity decreases as the moisture content of wheat increases. They found that a 13% wheat moisture content is the best compromise between milling overall performance and flour quality for bread-making. On the other hand, at moderate or high moisture content, they found that rotational speed did not significantly influence flour yield, although it is maximized by the lowest rotational speed grade.

To support operators in conditioning wheat grains and achieving required wheat grain moisture contents for milling, decision support tools can be used. In this context, Parrenin et al. [52] developed an ElasticNet regression model based on wheat properties, tempering process conditions and tempering process parameters to predict the percentage increase achieved in wheat moisture content at the end of the first tempering stage. From the model equation, by scaling the different feature variables, it is possible to measure the influence of each feature on the output variable. This provides operators with a sensitivity analysis of the controllable parameters on the percentage increase in wheat moisture content. This tool allows to keep and consolidate knowledge within the organization that is useful to help new operators adjust the parameters of the soaking process.

Table 4 highlights the existing AI research on wheat tempering. The research shows that wheat tempering has an impact on the milling process on flour yield and quality. This impact is reduced when milling whole wheat, as there is no need to efficiently separate the different wheat components. Whole wheat flour yield is therefore not affected but the quality is. This is explained by the fact that wheat tempering tends to produce large bran particles and small endosperm particles when milled [6,53]. The particle size dimension is a key characteristic of flour quality that will influence the product quality after baking or bread-making [54,55].

Although every research shows interest in tempering wheat grains for flour yield and quality, none of the research has studied the process itself. None of the studies addressed the control of tempering process parameters, which depends on several factors such as environmental conditions and input quality. Moreover, additional research has to be done concerning the relationship between the particle size dimension of wheat bran and whole wheat flour quality as several research studies have had contradictory results [49,50].

Table 4. Summary of existing AI research on wheat tempering.

Author(s)	Objective type	Model	Parameters	Output
Hook et al. [48]	Study the effect of added water on milling performance for different levels of wheat hardness	Multiple regression analysis	*Wheat hardness*, *wheat moisture content*	*Flour yield* and *flour color*
M. Kweon et al. [46]	Study the variable effect on flour yield and flour quality	Statistics: Full factorial design	*Initial wheat moisture*, *tempered wheat moisture*, *tempering temperature*, *tempering time*	*Flour yield* and *flour quality*
Doblado-Maldonado et al. [49]	Study the impact of omitting tempering stage for wholegrain flour	Two-way ANOVA and One way ANOVA	*Wheat variety*, *tempering treatment (dried, as is, tempered)*	*Particle size distribution*, *flour quality* and *baking quality*
Warechowska et al. [47]	Study the variable effect and pattern between input and output variable	Analysis of variance	*Initial wheat moisture*, *tempered wheat moisture*, *wheat variety*	*Energy milling*, *flour yield* and *flour quality*
Cappelli et al. [51]	Study the effect of stone milling speed and wheat tempering on milling efficiency, flour and bread quality	Two-way ANOVA	*Stone rotational speed* and *wheat tempering*	*Operative milling performance*, *flour quality* and *bread quality*
Parrenin et al. [52]	Predict the percentage increase in wheat moisture content at the end of first tempering stage	ElasticNet regression model	*Water quantity*, *initial wheat moisture content*, *target wheat moisture increase*, *wheat temperature*, *water flow*, *wheat quantity*, *resting time*	*Percentage wheat moisture content increase*

2.6. Milling

The milling run ends in the milling process. The milling process breaks the grains, separates the different parts of the grain and reduces the endosperm into flour. The milling process is divided into 4 stages: grinding, sifting, sizing and reduction. The *grinding operation* is always the first stage of the milling process. It aims to break the grain into large particles by using fluted rolls. These large particles are called semolina. At the end of the grinding operation, the particles go to the *sifting operation*. At this stage, the particles are separated and sorted according to their size using several sieves located in a machine called a plansichter. The objective of sorting the grain is redirecting the different particles to a new milling operation or to silos that store flour and bran. The *sizing operation* is to reduce the white semolina (large particles of the endosperm). The *reduction operation* aims to reduce the size of coated semolina. The coated semolina is described as large particles where most of the endosperm is still attached to the bran. The last two operations are realized by smooth cylinders. The particles created at the end of each grinding, sizing and reduction operation go once again to a new sifting operation. The operations follow one another until the entire set of particles is converted into flour or bran residue. The 4 stages are carried out successively, which is why several machines are present in the mill. The process follows a progressive reduction approach to extract the maximum amount of endosperm particles and to reduce them into flour.

The objective of wheat milling, as mentioned previously, is to extract the maximum quantity of flour of a specific quality from the wheat grains. *The quantity of flour extracted from the wheat grains represents the production yield*. It is most often referred to as the extraction rate in the flour industry. Formula (1) explains the method of calculating the production yield:

$$Production\ yield = \frac{Flour\ Weight * 100}{Weight\ of\ clean\ and\ conditioned\ wheat} \tag{1}$$

Maximum production yield is sought to maximize profits due to a higher price of flour compared to its by-products, such as bran geared toward the animal industry [56]. Endosperm extraction reaches its theoretical maximum at around an 81–84% grain extraction rate as endosperm represents about 84% of the wheat grain weight. However, the variation in wheat grain quality and operating conditions make it difficult for the miller to achieve this extraction rate [10]. The yield generally achieved in the flour industry is actually around 72% [10]. Above this percentage, the flour becomes increasingly contaminated with bran residue. Therefore, a trade-off between flour production yield and quality exists to ensure the economic profitability of the mill.

2.6.1. Challenges

Based on the production equipment installed and the quality of the grain, production parameters must be controlled and adjusted according to terms of wheat mixture, cleaning, tempering, and milling process to produce organic flour. The adjustments ensure optimal production yield and quality when there is variation in the quality of the raw material. However, the number of parameters and their influence on the whole manufacturing process make each adjustment complex.

2.6.2. Progress of work research

Some authors have analyzed the production systems present in the flour mill [36,57–63]. Production parameters influence the quantity and quality of flour extracted from wheat grains [6]. Among flour production operations, milling operations are at the heart of the production system. Most mills use rollers to grind wheat grains in order to achieve higher yields. However, rollers need to be well-configured. To this end, Campbell et al. [57] analyzed the operation of roller mills and their parameters. They group the input factors and parameters affecting the grinding process into 3 sets. The 3 sets include: raw material properties, roll design and roll operation. The raw material properties explain the quality of the wheat grains. The roll design is defined at the time of purchase and is considered to be fixed production parameters. Roll operation factors account for the current state or settings of the rolls during production. They include roll arrangement, roll speed, roll speed differential, roll gap distance and roll wear.

The flour particle size distribution generated by the roller is an indicator of the flour quality and performance of the milling process [10]. To predict the particle size distribution at the first grind, Campbell and other co-authors developed a mathematical model [57,58,64]. The equation calculates the particle size distribution of the particles generated at the end of the first grinding operation according to the wheat grain size and the roll gap distance. Fang et al. [53];Campbell et al. [65] then improve the equation to take into account the moisture and the hardness of the wheat grains, which affect the flour particle size distribution and, consequently, the flour quality [61].

Dal-Pastro et al. [61] goes further and takes an interest in several crushing rollers as well as the plansichter. They seek to predict the particle size distribution of the flour obtained after milling operations, reduction operations and sorting operations. The prediction models are based on a partial least square regression method. They are based on 3 inputs: roll gap distance (μm), wheat grain flow (kg/h) and the moisture content of the wheat grains (%). The data is obtained using a factorial design of experiment 23 (DOE—Design of Experience) including the 3 parameters mentioned. Dal-Pastro et al. [61] show from their results that the roll gap distance is the parameter with the greatest impact on the particle size distribution followed by moisture content and wheat grain flow.

Work has shown the relevance of using a neural network model to predict the quality of wheat particles produced after the first milling operation [62]. Fang et al. [62] confirm the importance of the 3 explanatory variables used by Dal-Pastro et al. [61] for the prediction of flour particle size distribution. Furthermore, they show that average kernel size, average kernel weight, and average kernel hardness are important variables for accurately predicting the quality of wheat particles obtained after the first milling. According to their results, the neural network model is able to correctly predict the average particle size at the first milling stage (R2 > 0.99).

Table 5 highlights existing AI research on wheat milling. Several prediction models have been developed to predict the quality of particles generated at the output of production equipment. However, most authors only try to predict the quality of the flour particles generated from milling experiments in a laboratory. They rely on simulation data [62] or experimental data [57,61,64]. Analyzing real production data on the whole process to improve the quality of the flour would be an interesting approach in addition to the studies done. The quality of the flour could be influenced not only by the milling process, but also by the previous production steps including the wheat blending step, the cleaning step and the tempering step. Moreover, operating conditions and equipment wear have been infrequently studied in flour quality prediction studies. These fluctuating conditions in the mill have an impact on the quality of the flour and the yield of the production. Hook et al. [66] showed, by performing a series of milling experiments, an increase in flour yield as roll temperature increases due to successive millings. The use of data describing environmental and production constraints could provide additional and relevant information to the flour quality prediction model. The prediction models would therefore learn from real experiences and be able to adapt production parameters according to current operating conditions.

Table 5. Summary of existing AI research on wheat milling.

Author(s)	Objective type	Model	Parameters	Output
Fang et al. [62]	Predict the ground wheat quality (flour particles) and milling performance	ANN	*Wheat moisture content*, *hardness*, *size*, *weight*, *feed rate*, *roll speed*, *roll speed differential*, *roll gap*	*Geometric mean diameter*, *specific surface area increase* and *break release*
Fang et al. [67]	Predict the power and energy requirements for size reduction of wheat (milling)	Stepwise regression	*Class of wheat*, *moisture content*, *feed rate*, *fast roll speed*, *roll speed differential,* *roll gap*, *wheat hardness*, *wheat weight*	*Fast roll speed*, *slow roll speed*, *net power*, *energy per unit mass* and *specific energy*
Campbell et al. [57] ; Campbell et al. [58]	Predict particle-size distributions from First Break milling of wheat	Breakage function	*Roll gap* and *wheat size particle*	*Particle-size distributions of flour*
Fang et al. [64]; Fang et al. [53]	Predict the outlet particle-size distributions from first break milling of wheat	Breakage function	*Roll gap*, *wheat size particle*, wheat *varieties* and *roll disposition*	*Particle-size distributions of flour*
Campbell et al. [65]	Predict the outlet particle-size distributions from first break milling of wheat	Breakage function	*Roll gap*, *wheat size particle*, wheat *varieties*, *roll disposition* and *wheat hardness*	*Particle-size distributions of flour*
Dal-Pastro et al. [60]	Predict the particle size distribution of the milled material at the end of the second break stage	Partial least squares (PLS) regression	*Roll gap*, wheat *flow rate*, *wheat moisture content*, *ambient humidity* and *ambient temperature*	*Particle-size distributions of flour*
Dal-Pastro et al. [61]	Improve process understanding and predict the particle size distribution of the milled material	Multivariate statistical models	*Roll gap*, wheat *flow rate* and *wheat moisture content*	*Particle-size distributions of flour*
Kalitsis et al. [68]	Optimize the process to produce flour to maximize flour yield while meeting quality constraints	Response surface methodology (RSM)	*Wheat conditioning level*, *first break roll gap* and *second break roll gap*	*Ash content*, *protein content*, *moisture content* and *flour yield*

2.7. Organic wheat flour end products

Different types of flour are available on the market. Each type of flour manufactured has specific qualities sought after by a client to produce a specific end product. A list of possible end-products is presented in Figure 3.

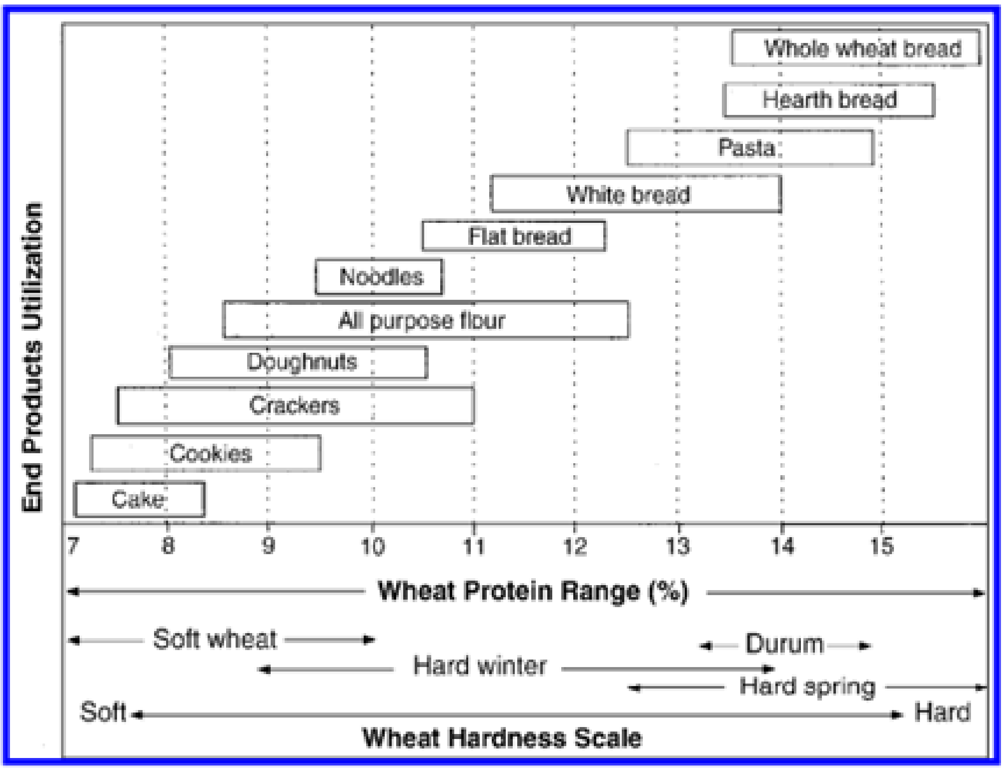

Figure 3. Different end-product utilization, depending on type of wheat, protein percentage, kernel hardness [37].

Figure 3 illustrates in a graph the different type of wheat and quality that are suitable for producing a specific food product. Depending on end product utilization, it is important to select wheat grains based on their intrinsic and physical properties such as protein and hardness. Then, from the selected grains, the production parameters will influence the types of flour that can be made.

Figure 4 illustrates in a diagram the different types of flour produced according to their ash content. The classification of wheat flour as described in Figure 4 extends from T45 to T150 flour. This number scale indicates the ash percentage of the wheat flour. It informs of the amount of mineral matter in the flour and influences its color [69]. A low ash content indicates a white flour, mainly composed of endosperm particles. As the ash content increases, the flour becomes more like integral flour, which includes all of the particles from the wheat grains. This becomes more nutritionally rich.

To ensure the client receives the right quality of flour as desired, a flour sample is collected and analyzed at the end of the milling stage. The result of the analysis will control the quality and bring additional information about the behavior of the future wheat dough. This information is useful to the client when adjusting the fermentation and bread-making process to produce a final product that has constant quality.

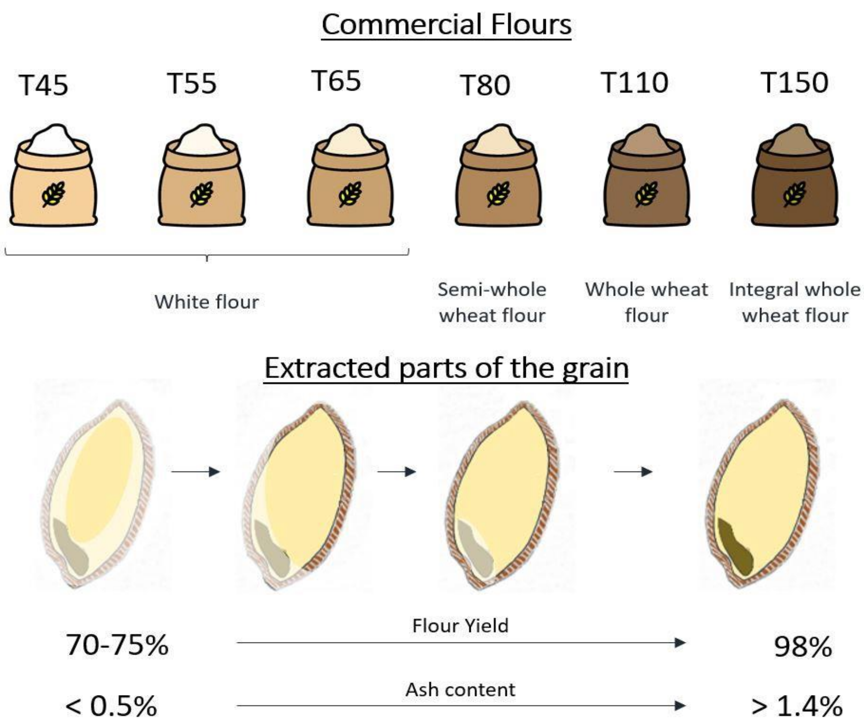

Figure 4. The types of wheat flour according to ash content.

2.7.1. Challenges

Most of the tests are conducted at the end of the wheat milling process to measure wheat flour quality. By following the wheat flour milling process that was previously described, it is often too late and difficult to make changes to the production process to achieve the desired level of flour quality. In this context, data analysis approaches using AI tools have been used to improve the bread-making process and to produce an end product that has consistent quality.

2.7.2. Progress of work research

The flour is used as a raw material in many processing operations. The flour quality has an effect on the quality of the final processed product, especially in bakery products. Several studies have focused on the process of bread-making. They studied the quality of flour and its impact on the quality of bread manufactured [70–74]. The quality of the flour influences the fermentation process as well as the rheological properties of the bread dough, which are specific to each customer [75]. Studies on enzymes that act as flour improvers will not be covered in this article. Although ingredients or improvers could be added during the bread-making process to improve the dough quality, we limit our field of study to the production of organic end products made from wheat flour.

To optimize the bread making process, some research focuses on the prediction of bread quality based on rheological quality measurement data of dough [71,76,77]. From the predictions made, flour mixture and bread making process methods seek to be improved to reach a consistent and higher quality of flour used. Three models use a regression method to evaluate the relevance of variables. Dowell et al. [71]; Ktenioudaki et al. [76] based their regression model on flour properties and dough properties to predict the bread quality, which depends mainly on the volume of the loaf and crumb hardness. Their models reach a good predictive accuracy of bread quality with a R-square of 0.8. From their model, they were able to identify certain influential variables of flour properties, such as: *protein content*, *falling number* and *ash content*. Among dough properties, they found that *dough tenacity* and *dough extension* were highly relevant as well. Apart from the regression model, Abbasi et al. [78] built a neural network model to predict dough properties based on seven input variables that describe flour properties. The artificial neural network (ANN) is optimized by a genetic algorithm. The model tires to reproduce the same results obtained from a Farinograph instrument. This instrument provides valuable information about flour quality and dough properties to the baker, who seeks to optimize production control parameters and the final product quality [10]. Their model obtains satisfactory results with a R-squared value higher than 0.96 and a normalized squared error lower than 0.09. Their work would allow flour manipulations to be avoided, and thus save time in the manufacturing process. Finally, Cappelli et al. [75] limited their study to whole wheat bread. Whole wheat flour is nutritionally rich but leads to rheological problems such as: lower loaf volume and increased crumb density. To solve these issues, Cappelli et al. [75] analyzed the bread making process. They conducted an analysis of variance to measure the effect of two controlled parameters during the bread making process on the dough and bread quality. The parameters included the percentage of bran and middling content added, and the time it was added during the process. They found that the addition of bran and middling to white flour at different times in the process influences wheat dough and bread quality. From their results, the delayed addition of bran and middlings during the bread making process showed improvements. It led to better dough extensibility and a greater loaf volume of the bread. This is a good solution for bakers who need to improve their organic end product quality.

Table 6. Summary of existing AI research on organic wheat flour end product.

Author(s)	Objective type	Model	Parameters	Output
Dowell et al. [71]	Predict bread quality	Regression model	Wheat, flour and dough properties	Bread properties
Ktenioudaki et al. [76]	Predict bread quality from different varieties of wheat	Stepwise multiple regression	Wheat varieties and rheological properties	Baking quality
Różyło et al. [79]	Predict bread quality	Stepwise multiple regression	Wheat flour and dough properties	Bread properties
Abbasi et al. [78]	Predict dough quality	Artificial Neural Network (ANN)	Wheat flour properties	Dough properties
Cappelli et al. [75]	Improve wheat dough and bread quality from kneading methods	ANOVA	Bran content and addition times	Dough and bread quality

Most of the studies base their mathematical model on either flour or dough properties as input variables. Only Dowell et al. [71] take into consideration the wheat quality selected. Further research could be conducted to analyze the relationships between manufacturing process parameters, including wheat blends and their effect on wheat flour, dough and bread quality. According to Dowell et al. [71], milling can affect dough and baking properties. Although the studies presented in Table 6 are useful in addressing variations in the rheological properties of wheat flour dough, it would be interesting to find solutions upstream in the value chain to achieve consistent and satisfactory flour quality from the milling process. Customers would then no longer have to mix different flours or adapt their bread making process each time.

2.8. Discussion

The literature review demonstrates that several authors have studied different parts of the wheat flour production value chain to improve quality or yield. The studies were grouped according to their intervention point in the value chain. We note that little research has focused on the impact of several processes in the value chain on flour quality and yield. Only Dal-Pastro et al. [61] take into account several milling steps (grinding and sieving) in a data-driven approach. Moreover, Cappelli et al. [51]; Kalitsis et al. [68] are the only ones to consider both tempering and grinding parameters. Yet the parameters and factors of one process affect the next. Moreover, most research that focuses on milling operation is conducted using experimental data in a specific environment. Little research has been conducted considering environmental and production constraints as inputs to better control and improve flour yield and quality at the end of the wheat flour milling process.

From the literature review, it is possible to note that most authors limit their work to statistical analysis or prediction algorithms. The objective of their work is to better understand each process and the importance of specific parameters on the quality and yield of the flour. However, none have proposed decision support tools that could help the miller and operators control and improve flour quality and yield according to the configuration and factors present in the mill. Only three research studies were interested in proposing decision support and optimization tools. These studies that focus on wheat blending are found in section 2.4. They develop tools for suggesting the best wheat blend ratio at minimum cost while meeting the customer's desired quality. Further studies are still necessary as these models do not take into account the production process of a milling run that includes cleaning, tempering and milling. As a result, the expected quality and yield of the flour cannot be guaranteed.

With regard to the number of studies conducted on organic wheat flour milling at each point of the value chain, two processes are relatively unstudied, if at all. They include wheat blending and wheat cleaning. Both of these areas should be explored as they both impact flour quality. Wheat blending, which is considered a major lever for improving flour quality as well as mill profitability, is even more important.

Given the analysis conducted on quality and yield in this section, section 3 will address other aspects of optimizing the wheat milling process.

3. Research areas towards smart wheat milling

The aim of this section is to propose several research directions that combine AI and the organic wheat milling sector to optimize the wheat flour milling process. In the milling process, there are other dimensions besides flour quality to ensure optimal mill operation and profitability, such as energy savings, resource optimization and mill performance. Each dimension includes key objectives that can be achieved and solved using AI to optimize the milling of organic wheat flour. These key objectives are identified based on the literature review, observations and experiments conducted in an organic flour mill over a two-year period and inputs from wheat milling experts. Figure 5 shows a mind-map constructed from the 4 dimensions and the key objectives identified.

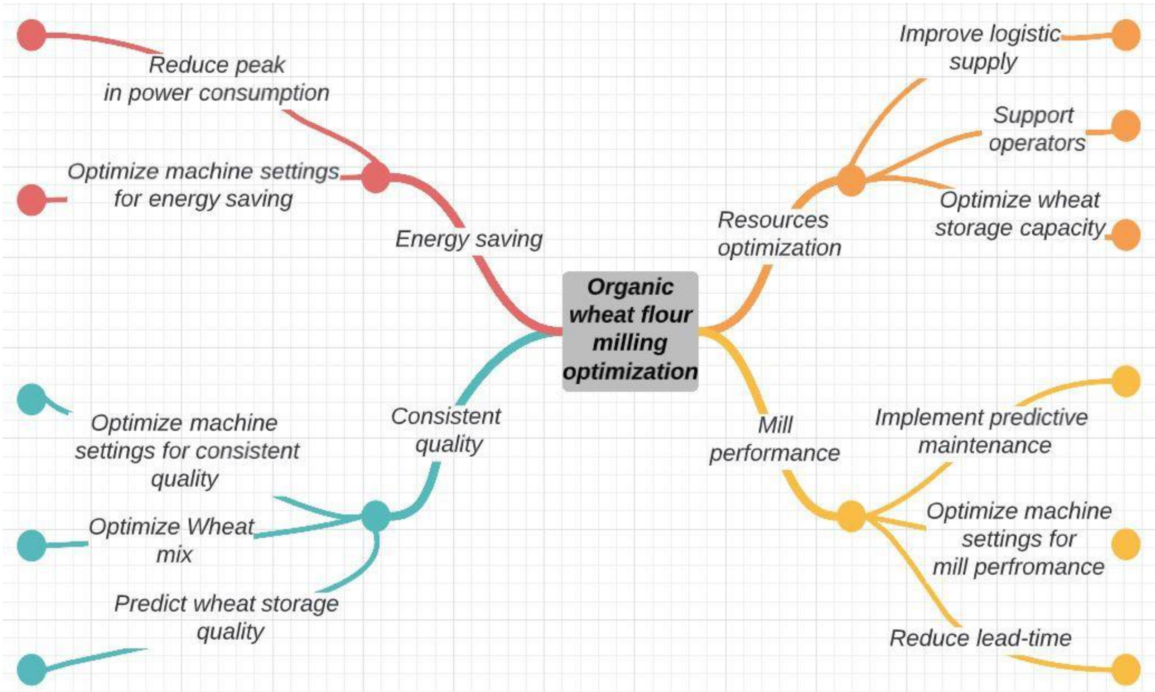

Figure 5. Mind map for future topics research centered around the optimization of organic wheat flour milling.

Four dimensions are represented in Figure 5, illustrated by the different color branches. The sub-branches represent the key objectives to be addressed in a specific dimension. To ensure the consistent quality of organic flour, it is important to properly adjust machine parameters, wheat recipes and to know the quality of the raw material stored in inventory. To save energy and in- crease mill profitability, the reduction of peak consumption and the adjustment of machines are avenues to explore. Resource optimization is possible through improved logistical efficiency, decision support for operators and better management of wheat inventories. Regarding mill performance, the implementation of a preventive maintenance approach based on data collected in real time, the adjustment of production parameters and strategies to reduce operating time using AI techniques offer solutions to optimize this dimension. The actions of the key objectives can be involved in several dimensions, depending on the final objective set. This is, for example, the case for the optimization of the machine set-up, in which we try to find the best parameters to meet our objective. Each of the four dimensions will be explained in more detail in the following subsections.

3.1. Energy savings

In order to reduce production costs and improve mill profitability, the authors have explored ways to optimize energy requirements to efficiently grind wheat grains [47,67,80]. The authors all rely on linear regression models to predict the energy consumption of the roller mill based on process parameters and wheat properties. Among the input variables studied, Fang et al. [67] notice that wheat hardness is the most useful variable from the physical properties variable to predict energy requirements for grinding. On the other hand, the feed rate of wheat grains and the roll gap are the most significant process parameters. In addition to those input variables, Warechowska et al. [47] showed that the tempering process also influences the energy used for grinding. An increase in moisture content of the wheat grain results in a higher energy requirement. This is explained by the fact that a change in moisture content implies a change in wheat grain hardness. Although moisture content has been shown to influence yield and quality, no study has taken into account the energy required, yield and quality together to optimize the milling process. Moreover, no study has been done on the energy used according to the seasons and the external environments that influence the properties of wheat grains. Based on energy input, weather data and process parameter settings over time, AI can detect patterns and provide a decision support tool to optimize machine settings to efficiently grind grains of wheat and save energy. In addition, there are energy peaks in the wheat mill when the grinding equipment starts. This causes significant energy consumption. With a better estimation of the operation time and the amount of flour required from AI models, it would be possible to schedule the production in order to reduce peaks in energy consumption. Finally, high energy consumption could be explained by poorly adjusted parameters or by equipment wear. This could be a good indication for preventive maintenance and should be explored further.

3.2. Consistent quality

Consistent wheat flour quality is the most overarching facet of the wheat flour milling process. It has a direct impact on a client's needs. Through the literature review, however, we note the absence of research on the wheat cleaning process. AI computer vision models could provide a solution to detect the percentage of foreign material and improve the cleaning process parameters and the number of cycles required. We also note that there are currently no decision support tools for either the milling process or the tempering process to assist the miller and operator in achieving their flour quality goals. One of our research objectives will be to develop a support tool from AI models to adjust the tempering parameters and to efficiently achieve the desired wheat moisture. Furthermore, none of the studies have attempted to predict flour quality based on both wheat blend ratio and process parameters. From historical production data, AI models could be trained to predict wheat flour quality at the end of milling. The objective would be to optimize and suggest a wheat mix to reach a specific quality of flour depending on the factors and parameters present at the mill. This will mark our second research axis. Similarly, AI models would provide solutions to optimize milling parameters based on grain quality, surrounding factors and desired quality while maximizing yield. In this context, our objective will be to develop a decision support tool that maximizes both the quality and yield of flour production. For the optimization of the milling process, other optimization models taking into account resources and energy related to quality would also be relevant to develop. Finally, a more accurate estimation of the quality of wheat grains stored for several days, weeks or months in a silo would offer more precision when blending wheat for a specific milling run and thus on the flour quality produced. In addition to the work already done on the subject, it would be interesting to analyze and predict the quality of the grain stored in a silo using an AI model by taking into account wheat variety, the storage time and the indoor environmental conditions.

3.3. Resource optimization

One of the least discussed aspects is resource optimization. Resources include time, material, as well as labor. These resources must be optimized to reduce production cost and waste. To do this, several avenues can be explored. One is to examine how to properly set the equipment parameters for each milling run. This would save production time and material. A second is to look at the supply chain in order to transport the right amount and quality of wheat grains to produce a certain type of flour. This would reduce lead time production and optimize wheat storage capacity. Another research axis is to look at how to support workers. Workers' knowledge and skills are needed to handle this equipment and manage the mill operations. The technical nature of the operations makes the profitability of the mill dependent on expert and vulnerable to high worker turnover. AI could help optimize the different resources. Based on data collected, it could offer decision support tools. It would then help workers make better decisions to optimize resources. The AI models developed and used at the mill would help retain the knowledge within the mill. the data automatically acquired to feed the AI models would reduce the number of manual data collection tasks performed by workers to make decisions. This would optimize the time and number of workers managing milling operations. By analyzing travel times, economic and weather events, estimates of wheat grain supply could be made from AI models to better schedule production and improve logistic supply. Finally, with a better forecast of the demand for flour, information on inventories, information on wheat quality and estimates of grain arrivals, solutions to optimize wheat storage capacity at the mill would be possible.

3.4. Mill performance

Mill performance is primarily related to flour yield based on milling parameters and wheat properties. However, while the extraction rate is a good indicator of the mill's production performance, it is important to look at the mill's overall operation efficiency through the OEE (Overall Equipment Effectiveness) performance indicator. The OEE indicator provides insights into machine availability, operation performance and production quality. The interest would then be to maximize the OEE indicator and use an AI model for this purpose. Another point is that the studies have been conducted in a controlled environment. No research has been done on how to optimize parameters to minimize operation time without affecting the quality. This would offer an opportunity to reduce production lead time. Also, to our knowledge, no research has been done on equipment maintenance. The equipment degrades after each wheat milling. This influences the adjustments of production parameters and can cause un- planned production stops. AI models could be used to learn optimal adjustments based on the condition of the tools and perform predictive maintenance. Finally, the limits on laboratory experimental data are that they do not take into account environmental conditions that impact flour yield. They influence the optimal parameters in producing a specific flour.

4. Conclusions

This paper reviews the state of the art of AI techniques applied in the organic flour industry to improve quality and yield. It aims to identify future trends to optimize the milling process. Some authors have focused their work on wheat flour milling. With the popularity of organic products among consumers and the emergence of data science over the past several years to address industrial issues, it seems important to review the literature on the use of AI techniques in the flour manufacturing process applicable to the organic sector. In view of the literature review, the tools used in AI are mainly centered around statistical analysis and regression models. Their models focus on understanding the system and their parameters in order to have better control. Deep learning models could offer good perspectives on optimizing several processes that no longer have linear relationships. Deep learning techniques are beginning to be used in grain image analysis, providing tools to quickly detect and classify wheat grains based on variety and visual appearance. These tools are relevant for grain quality control and wheat blending that influence the quality of flour produced. In order to optimize the wheat milling process, four major research areas emerge: energy savings, consistent quality, resource optimization and mill performance. The new research areas identified in this paper are promising and future work will focus on these leads. This research will enable the development of wheat mills that are more connected and smarter through the use of AI in optimizing the process for a specific purpose.

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Conflict of interest

The authors declare that they have no conflicts of interest.

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