Post-roast Moisture Process Improvement of Fish Sheet Production Process

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วัตถุประสงค์หลักของโครงงานในวิทยานิพนธ์เล่มนี้คือการควบคุมความชื้นของแผ่นปลาที่ผลิตในโรงงานผลิตอาหารในประเทศไทย การควบคุมความชื้นของแผ่นปลามีความสำคัญต่อผู้ผลิตเนื่องจากแผ่นปลาดังกล่าวเป็นวัตถุดิบหลักของผลิตภัณฑ์ของผู้ผลิต และความชื้นของแผ่นปลาหลังการปิ้งเป็นมาตรวัดคุณภาพที่สำคัญ ทั้งนี้เดิมทีทางผู้ผลิตใช้วิธีการปรับค่าในสายการผลิตในการควบคุมระดับความชื้นในแผ่นปลาตามวิจารณญาณของผู้ปฏิบัติงาน ซึ่งทำให้ความชื้นของแผ่นปลาหลังการปิ้งมีความแปรปรวนสูง จึงจำเป็นต้องมีการพัฒนากระบวนการผลิตเพิ่มเติม ทั้งนี้ค่า C_{pk} ของความชื้นของแผ่นปลาหลังการอบไล่ความชื้นและแผ่นปลาหลังการปิ้งก่อนการพัฒนากระบวนการผลิตคือ 0.19 และ 0.04 ตามลำดับ

ในวิทยานิพนธ์เล่มนี้จะนำเสนอและประเมินผลวิธีการพัฒนากระบวนการผลิต 2 วิธี วิธีการที่ 1 ทำการเปลี่ยนขั้นตอนการตีผสมวัตถุดิบเพื่อปรับปริมาณของน้ำภายในส่วนผสมตามความชื้นของปลาบดแช่แข็งที่วัดได้ โดยปลาบดแช่แข็งเป็นวัตถุดิบหลักในขั้นตอนการตีผสมนอกเหนือจากน้ำ วิธีการที่ 2 ทำการเลือกค่าที่ใช้ในกระบวนการผลิตหลังการตีผสมที่เหมาะสมที่สุด โดยการใช้วิธีการพื้นผิวผลตอบ จากข้อมูลที่ได้จากการออกแบบการทดลอง หลังจากการพัฒนากระบวนการผลิตด้วยวิธีทั้งสองแล้ว ค่า C_{pk} ของความชื้นของแผ่นปลาหลังการอบไล่ความชื้นและแผ่นปลาหลังการปิ้งเพิ่มสูงขึ้นเป็น 0.75 และ 0.46 ตามลำดับ

ภาควิชา	ศูนย์ระดับภูมิภาคทางวิศวกรรมระบบการผลิต	ลายมือชื่อนิสิต ....
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The primary concern of this thesis is moisture control of fish sheets produced in a Thai factory. The moisture control of fish sheets is important because these fish sheets are primary work-in-process products used in the factory, and the sheets' post-roasting moisture is a key quality metric for fish sheets. The factory initially used ad-hoc subjective procedures to control moisture level. However, it is found that variation of fish sheets' moisture at all stages of production remains high, making it a subject of process improvement in this thesis. The C_{pk} index of post-air-drying and post-roasting fish sheets, measured at the start of the project, are 0.19 and 0.04 respectively.

This report will present and evaluate two process improvement methods implemented in the factory. The first method modifies ingredient mixing procedures such that the quantity of water in ingredient mixture are adjusted based on measured moistures of frozen minced fish which is the primary non-water ingredient in the mixture. To avoid subjective adjustment of control parameter values, the second improvement finds an optimised set of values for post-mixing processes' parameters, using response surface generated with regression analysis on data collected in a design of experiments. After improvement, the post-air-drying C_{pk} index and the post-roasting C_{pk} index were improved to 0.75 and 0.46 respectively.

Department:	Regional Centre for Manufacturing Systems Engineering	Student's Signature	....
		Advisor's Signature	....
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CHAPTER I

INTRODUCTION

I.1 Background of the Research

I.1.1 Product Overview

The problem of interest concerns the manufacturing of fish sheets which is a work in process produced by a Thai snack manufacturer. Examples of fish-based snacks in the Thai market that also use dried fish sheets as their WIPs are shown in Figure I.1. These dried fish sheets use minced fish as the key base ingredient. Only significant differences among these products are their flavouring and cut sizes.

Figure I.1: Examples of products made from dried fish sheets

The fish sheet is used as a base WIP for many products sold by the factory and are produced in two main varieties: the thick variety (average 1.25 mm) and the thin variety (average 1.00 mm.) Differences in flavouring among these final products have little consequence to the operation. The company has six fish-based final products: A, B, C, D, E and F. Products A and B use thick fish sheets as its WIP, while the rest of the products use thin fish sheets. However, it is the thick-sheeted products that account for 64% of the sales in the product line. In fact, product B, the top product of the company, alone accounts for 52% of the sales. The share of fish sheet production in the company is shown in Figure I.2.

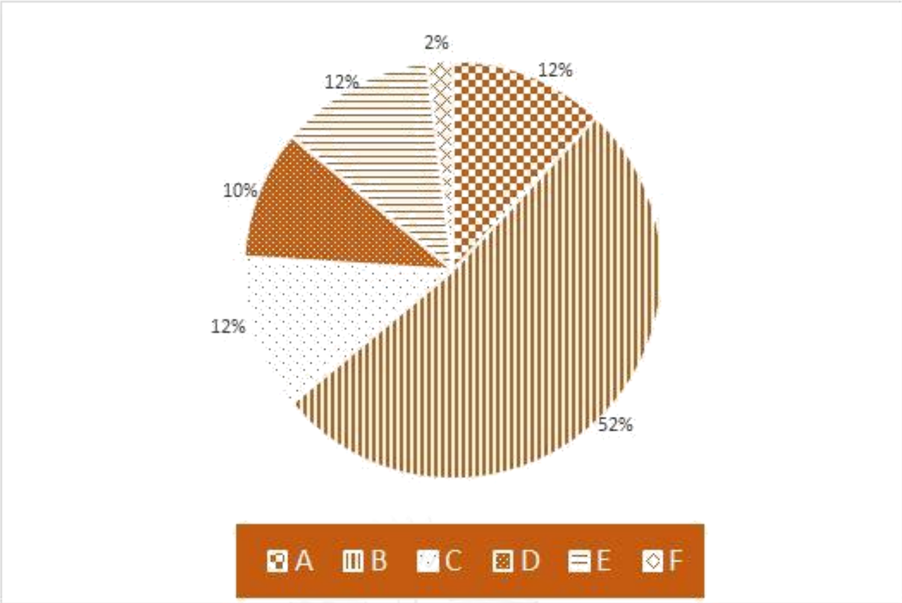


Figure I.2: Proportions of fish-based final products sold by the manufacturer

I.1.2 Production Overview

In the fish-based product manufacturing in the factory can be split into two stages. The first stage mass-produces fish sheets as WIP for later process. The second stage specialises fish sheets into many kinds of products (highlighted in yellow and blue in Figure I.3 respectively).

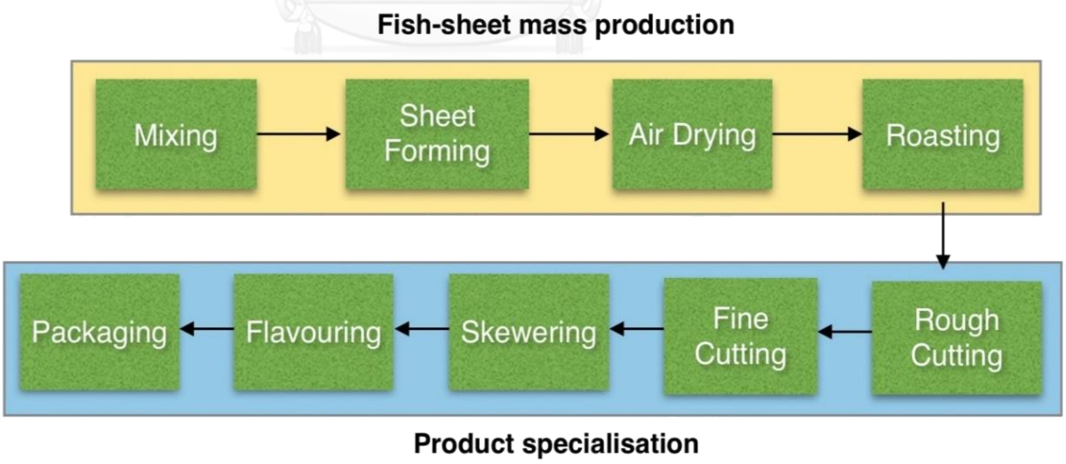


Figure I.3: Process flow diagram of the fish sheet production

If only the fish sheet manufacturing is concerned, there are four key processes: mixing, sheet forming, air drying and roasting. The fish sheet's base ingredients including minced fish, flavouring ingredients and water are first weighed according to the recipe provided by the R&D department and mixed into a thick liquefied solution batch for half an hour. Then, the solution is poured into a heated roller (Figure I.6) that heats and forms fish sheets using natural gas. Most of the excess moisture is then taken out by passing the fish sheet through the air-drying oven (Figure I.7) for one hour on a conveyor belt, exposing the fish sheet to low heat for extended amount of time. Finally, the fish sheet is given roasted texture using the roasting machine (Figure I.8).

The specialisation production process, happening afterwards, differ across multiple products in terms of size of cutting, flavouring and packaging. The post-roasting process consists of five processes including rough-cutting, fine-cutting, skewering, flavouring and packaging. After roasting, the fish sheet is roughly cut into smaller sheets (with approximate dimension of 60 by 20 centimetres) to make it easier to be piled and stored in buckets. The produced fish sheet is then either moved to the next production station or stored in the storage space for production on later dates. When the factory is ready for further production, the roughly cut fish sheet is then cut to the size of final products, skewered with bamboo sticks and flavoured with seasoning or dipping sauces. Finally, the flavoured products is packaged in plastic bags and shipped to customers.

The nine key processes are illustrated in Figure I.3. These processes can be divided into two key stages: mass manufacturing of the WIP fish sheet and specialisation of the fish sheet, drawn in yellow and blue frames respectively. Because the project's focus is on the fish sheet production, more detailed process flow chart of the current practice is illustrated in Figure I.4. Based on the process flow chart, it is notable that the roasting stage engages in feedback-styled moisture correction whose details will be discussed in the statement of problem section (Section I.2.) The key ingredient of the process, the minced fish, is shown in Figure I.5. Prior to the fish sheet production, the frozen minced fish must be thawed, flavoured and mixed with additional water to liquefy into fish paste that can be heated and rolled into sheets. Generally, there are multiple suppliers for the minced fish.

There are two production lines in the factory (henceforth referred to as Production Line 1 and Production Line 2.) Production Line 1 exclusively produces thick fish sheets, while Production Line 2 primarily produces thin fish sheets but is sometimes scheduled for production of thick fish sheets. The manufacturer can easily switch the fish sheet's thickness in a production line by adjusting the gap between the heated roller in the sheet forming stage.

Each of these production lines have a capacity to process 900 kg of mixture of fish and flavouring ingredients per day. The manufacturer mixes the solution in eight batches using a recipe provided by the R&D department. Quantities of each ingredients are weighed before being added to the mixture. As the previous batch is about to be used up, the new batch is poured into the input bucket for the sheet forming process to avoid disrupting the production line. The conveyor belt between the sheet-forming stage and the air-drying oven are also integrated. Therefore, except for lunch breaks, the production line up to the air-drying process can be run continuously.

The production uses natural gas for heating in the heated roller, the air-drying oven and the roasting machine. Only air-drying oven's temperature can be precisely adjusted with a digital controller. Natural gas supplies for the heated roller and the roasting machine are controlled with non-digitised gas valves. As such, the amount of gas supplied to these machines cannot be precisely controlled and, as a result, their temperatures cannot be precisely controlled. However, the roasting machine has a thermometer that can measure the current temperature in the machine.

It is possible to make adjustment to conveyor belt speeds in both the air-drying oven and the roasting machine. However, because the belt speed in the air-drying oven is difficult to adjust, the speed is left constant. In the current practice, the speed of the roasting machine's belt is frequently adjusted as part of the moisture-correction scheme to be described fully in Section I.2.

In the current quality control practice, the manufacturer takes moisture measurements at various stages of the production as lag indicators for evaluation of the production's performance in previous days. Because any formal moisture measurement takes up to 30 minutes, these measurements are not typically used to alter parameters and practices in the production line on the day of measurement.

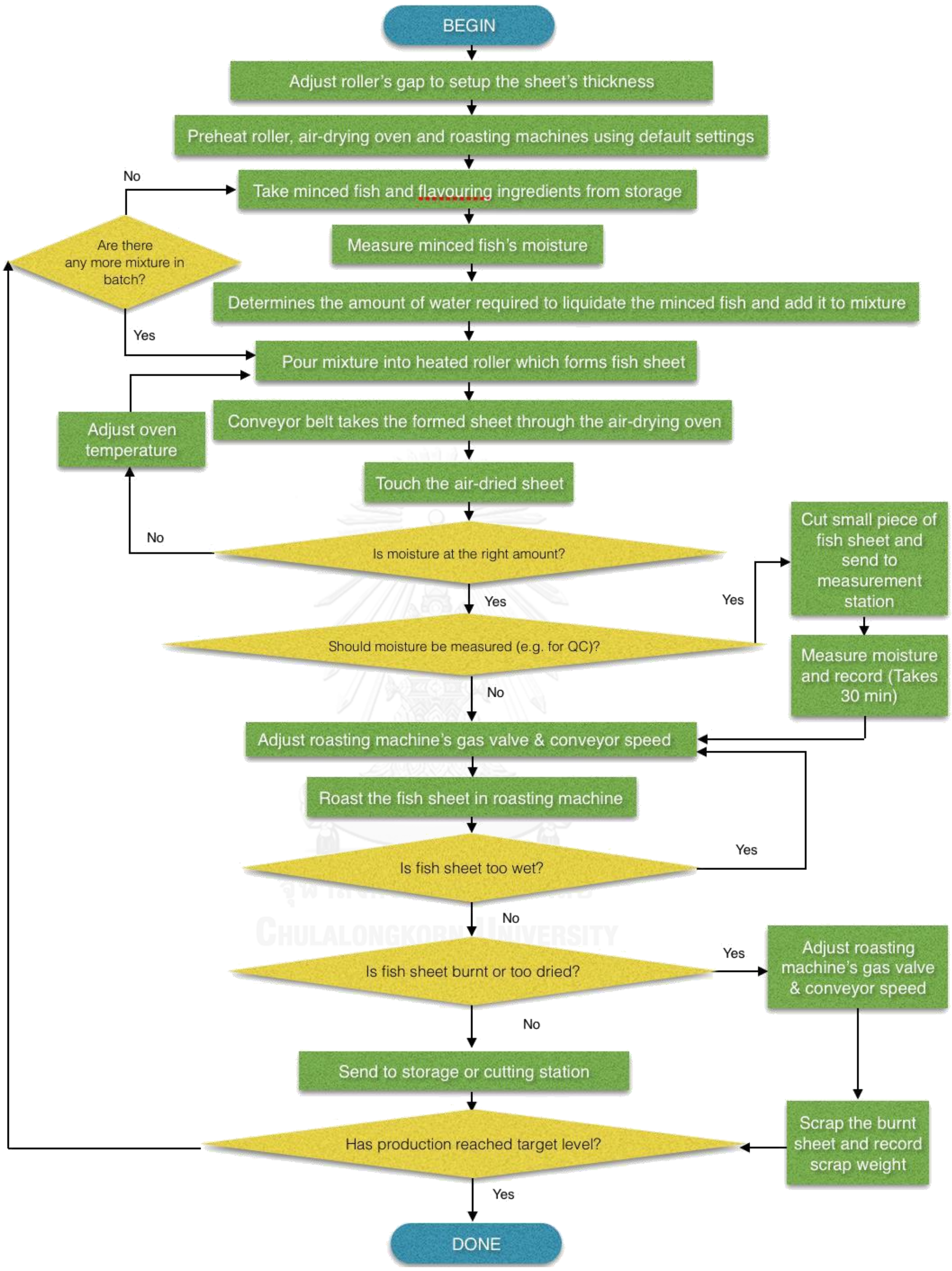


Figure I.4: Detailed process flow chart of the fish sheet mass production

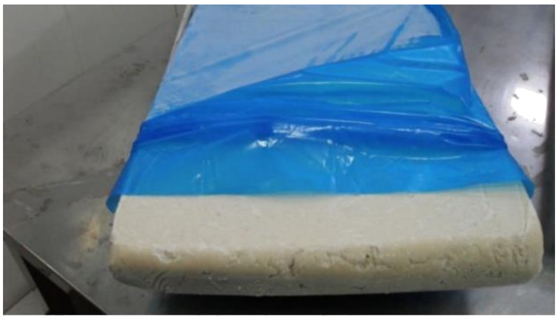


Figure I.5: Frozen minced fish

Figure I.6: Heated roller

(a) The Air-drying Oven Temperature's Controller

(b) The Air-drying Oven Speed's Controller

(c) The Conveyor Belt

Figure I.7: Air-drying oven and its control panels

(a) The Roasting Machine Speed's Controller (b) The Conveyor Belt Flow Rate Lever (c) The Roasting Gas

Figure I.8: Roasting machine and its control panel

I.2 Statement of Purpose

I.2.1 <u>Overview of Problem</u>

According to the manufacturer, there is a variation in its end products' shelf life. The production team determined that the shelf life of the products got significantly decreased due to higher than intended moisture, resulting in 3-5% of the products getting recalled due to premature change in texture, colour and molding. A brainstorming session also determined that the most likely root cause of the problem is due to the WIP fish sheet having higher moisture than intended. The hypothesis is confirmed by the collected moisture statistics which will be discussed in detail later in Section I.2.4.

In short, the post-airdrying and post-roasting moistures of fish sheets have high variation with their means significantly shifted from the target means. Because fish sheet moisture is the most likely target and can affect multiple types of products, this project will focus process improvement on processes in the fish sheet mass production stage. The processes include mixing, sheet-forming, air-drying and roasting (shown in the yellow box of Figure I.3.)

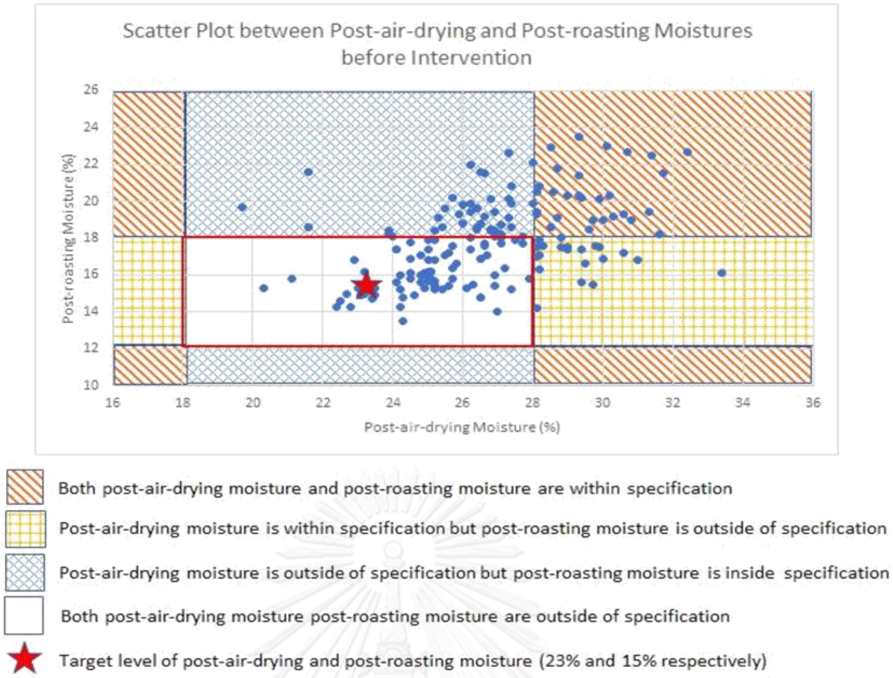


Figure I.9: Scatter plot between post-air-drying and post-roasting moistures of samples before intervention

A noticeable problem in the process is the inappropriate use of feedback control in the roasting process. Although the roasting process is only meant to give a finishing touch to the fish sheet, the process is abused into a moisture correcting station. To cope with variations in post-air-drying moisture, the roast machine operators adjust both the amount of natural gas used, to alter roasting temperature, and the conveyor belt speed. There are no formal procedures for this adjustment and the operators rely on their experiences to gradually make adjustment. If fish sheets still have too much moisture after roasting, the sheet is then roasted again. Because of such manual adjustment and rework, the roasting machine currently cannot be integrated into a continuous production line like the other three processes.

It is also found that despite their experience, the machine operators do not always give out consistently good moisture results. The scatter plot of post-air-drying and post-roasting moistures, collected from the production line in which the above moisture correction procedure is applied is shown in Figure I.9 (with raw data listed in Table A.1.) Samples within the white panel with red borders are those with moistures within specification. The figure illustrates how well machine operators can adjust fish sheet moisture such that its post-roasting moisture converges to acceptable ranges in the specification. In an ideal case where the operators are perfect in correcting moisture, the slope of the linear relationship between post-air-drying and post-roasting moistures should be close to zero and the post-roasting moisture's standard deviation should be very low. Although the operators can successfully adjust samples with lower post-air-drying moistures (between 24%,) they are less successful on samples with higher post-air-drying moistures, implying that operators have less consistent results for samples with larger post-air-drying moisture.

Table I.1: Matrix of the number of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits prior to any interventions

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	43	30
	Inside specification	77	21

Table I.2: Matrix of distribution of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits prior to any interventions

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	25.15% (43/171)	17.54% (30/171)
	Inside specification	45.03% (77/171)	12.28% (21/171)

More importantly, most of the samples lie outside of specification ranges for both post-air-drying and post-roasting. The information in Tables I.1 and I.2, which are derived from the data in Figure I.9, support the above observation. Given that the post-air-drying moisture is between 20% and 28%, operators can adjust the moisture so that 43 out of 120 samples (64.17%) lie within the post-roasting moisture's specification limits (between 12% and 18%). On the other hand, if the post-air-drying moisture is outside of the specification limits, the operators are less successful in tuning the moisture back within the post-roasting moisture's specification limits. Operators succeed in adjusting only 21 out of 51 samples (41.18%) that have out-of-range post-air-drying moisture to have post-roasting moistures within the specification limits.

Overall, the standard deviation of the post-roasting moisture is 2.19% which is relatively large compared to the target mean at 15%. The information points out that even with experience, human operators still have rooms for improvement in moisture correction.

The inconsistent performance in the described feedback-styled moisture correction can be explained as a result of the operator's inability to objectively measure moisture in a timely manner. According to the factory's production manager, moisture measurement for a sample takes up to 30 minutes. Therefore, it is impractical for machine operators to objectively assess the fish sheet's moisture in real time using formal tests. Instead, operators rely on their experience to subjectively assess the sheet's moisture by touching the sheet and by observing other visual characteristics.

While the ineffectiveness of real-time moisture correction procedures could help explain why samples have post-roasting moistures outside of specification limits, there are under-lying causes of moisture variation will be discussed in details in Chapter III and IV. Based on fish-bone diagrams and consultation with experienced operators in the production, key causes of variations would include high moisture variation in raw material, subjective adjustment of post-mixing production parameters as part of feedback-styled moisture correction, inability to control temperature in the roasting process and variation in the factory's temperature and humidity. As it will be discussed later in this chapter and in Chapters III and IV, this project will focus on the first two key problems.

Variation and the lack of precise control on the roasting temperature can also be an obstacle to real-time moisture correction. Even when the natural gas valve is always set to the same setting, the measured temperature can vary significantly. A preliminary experiment shows that the roasting temperature at a specific gas supply setting is 163:97 6:94 C. Moreover, there will always be a lag between when the natural gas supply is adjusted and when the temperature reaches the desired level, making it difficult to make real-time adjustment as the fish sheets are fed into the roasting machine.

Regardless of how successful the operators can control the moisture with the current method, the procedure is labour-intensive and its success heavily depends on individual operators' experiences and skills. Unfortunately, the manufacturer has long had problems with ageing labour pool. According to the factory manager, the current workforce's average age is now over forty years old. Although there are some younger workers who join the company, it is hard to retain these workers due to intensely competitive labour market. As a result, it is expected that a great majority of current workers will retire within twenty years and the company will struggle find replacement. Considering this imminent labour shortage, the manufacturer has set up a strategy to reduce reliance on human expertise and to automate or standardise as many parts in the process as possible.

Moreover, to improve labour efficiency in the factory, there have been initiatives in the factory to train its operators so that they can be stationed in various departments across the factory. Therefore, reducing the number of employees to be stationed in a process can increase production capacity and flexibility in other departments.

The described intensive intervention for moisture correction runs counter to this strategy. Ideally, as the factory manager put it, it is preferable for the roasting process to be integrated into the main production line and eliminate the intensive human intervention. However, it is impossible due to moisture variation in the process that warrants correction before the fish sheet can be cut up and be used in later processes.

I.2.2 Project Requirement and Constraints

Based on the above discussion, the overarching goal of this project is to find better practice in moisture control for the manufacturer such that the roasting process can eventually be integrated into the production line and such that minimal human intervention is required to control the fish sheet's moisture. Therefore, any moisture-control procedures that this project will recommend to the manufacturer should have the following characteristics.

1. The procedure should be able to control variation of post-roasting moisture within specification provided by the manufacturer.
2. The procedure must not involve complicated adjustment that would heavily rely on personal skills of machine operators and extensive training sessions.
3. The procedure must not significantly disrupt the provided production process.
4. If possible, the procedure should be operable with minimal number of operators.
5. The conveyor belt speed should be synchronised across the production line. If it is not possible with the current setting, the conveyor belt speed at each stage should remain constant.

These procedures also have to be operable under the following constraints.
1. Due to technological limitations, each formal moisture measurement will take 30 minutes.
2. These measurements can only take place only during 8-hour work time on each production day.
3. There is currently only one moisture measuring device although it is possible to purchase more devices if sufficient justification can be provided.
4. Because the sheet forming and the air-drying processes has an integrated conveyor belt, it is not possible to intervene on specific parts of the fish sheet during these processes unless the whole production line is stopped.
5. Because fish sheets are passed through the air-drying oven for one hour using a conveyor belt, it is not possible to apply treatment to a specific portion of fish sheets during the air drying process.

I.2.3 Focus of the Project

Because products that use the thick variety of fish sheets account for 64% of the company's sales (as shown in Figure I.2), this project will focus on the production of the thick fish sheet. It will also only concern about the Production Line 1 which exclusively produces the thick fish sheet.

I.2.4 Initial Production Statistics

According to preliminary data gathered from the factory and the moisture specification for the thick-variety of fish sheet, the statistics of various stages in the production line is provided in Table 1.3, whose raw data can be found in Section A.1. Please note that, to acquire more accurate data on roasting when no human intervention is applied to correct moisture, the manufacturer was asked not to make moisture-correction intervention and fix the roasting machine's conveyor belt speed and temperature to default values. For visualisation, histograms of observed moistures are shown in Figure I.10 (for moisture of minced fish from each source) and Figure I.11 (for moisture of intermediate products after each key process).

The key specification that the production should fulfil is the moisture level after roasting (lower and upper specification limits are 12% and 18% respectively and a target mean at 15%. Because of the moisture correction practice at the roasting machine, the manufacturer also set up moisture specification for moisture after air-drying process. The manufacturer never sets target moisture for post-mix and post-sheet-formed stages.

In the mixing stage, the manufacturer uses minced fish from two sources that are mixed in equal proportions. Together, the minced fish accounts for more than 40% of the mixture by weight and water accounts for another 30%, according to the production manager. Moisture of minced fish from each source are listed separately in Table I.3. Other dried ingredients (specified as having moisture less than 3%) and water are weighed according to the recipe before being added to the mixture. Therefore, they are omitted from Table 1.3. The specification of the minced fish's moisture is based on the specification that manufacturer gives to its suppliers.

The target C_{pk} value for the process improvement would be set to 1.33. According to Montgomery (2009), the recommended minimum process capability for two-sided specifications in an existing process is 1.33. To the best of our knowledge, there is no known benchmark of C_{pk} index for the fish sheet manufacturing. Likewise, there are also no indication that food manufacturing adopts different standards for C_{pk} index than the threshold suggested by Montgomery (2009). Process improvement in a medicated sweet manufacturing process, as discussed in Knowles, Johnson et al. (2004), succeeded in improving the process's C_{pk} index from 0.5 to 1.6. In addition, Leiva, Marchant et al. (2014) which derives capability indices of Birnbaum-Saunders processes in electronic and food industries use the C_{pk} benchmark from Montgomery (2009). It is notable, however, that not all efforts in improving C_{pk} index of food manufacturing processes could achieve the targeted level of 1.33. For example, Wonganawat (2016), which applies the Six Sigma methodology on ready-to-eat rice packaging process, could only improve the index from 1.04 to 1.17. Therefore, although the benchmark of 1.33 should be used as the target of process improvement, it is challenging for food manufacturing processes to achieve high values of C_{pk} index.

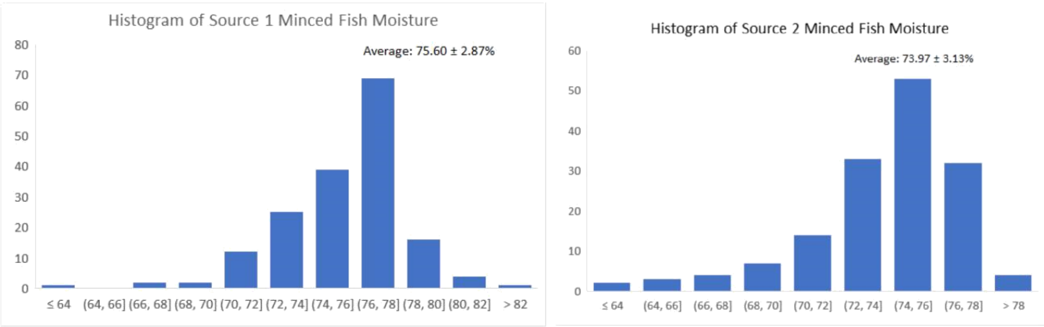
Based on the above benchmark for the C_{pk} index, the available data suggests that there are rooms for improvement for the production process. The information in Table I.3 shows that all processes' process capability indices are well below the target level. It is also evident that the observed means deviate from the target mean especially the post-air-drying moisture and the post-roasting moisture.

Based on the data, the minced fish ingredients do not have significantly large moisture variations. However, the suppliers cannot provide them with satisfactory process capability either. The process capability indices, C_p and C_{pk}, only have values between 0.4 and 0.5. The distribution of the minced fish's moistures from each source are shown in Figure I.10. In the histograms, while the mean is close to the specification (75.6% and 73.97% for source 1 and 2 respectively), the variability of moisture of fish from both sources are significant with many measurements lying significantly outside of specification. Because the factory cannot directly control the suppliers' production, finding measures to cope with this source of variability will be a part of the research in this thesis.

According to Figure I.11, it is unsurprising that the ingredient mixture's moisture would have significant variation, given the large standard deviation of the minced fish's moisture as discussed earlier. However, it is rather peculiar that the moisture variation is noticeably reduced after the fish sheet is pressed and rolled in the sheet-forming process. A hypothesis given by the production manager is that the heated roller used in the sheet-forming process would squeeze out more moisture from the viscous mixture with more initial moisture. As a result, the moisture level of fish sheets after the sheet-forming process become more uniform. Afterwards, the moisture variation then increases again after air-drying and roasting, most likely due to adjustment of product parameters across the time of data collection, especially in the air-drying process.

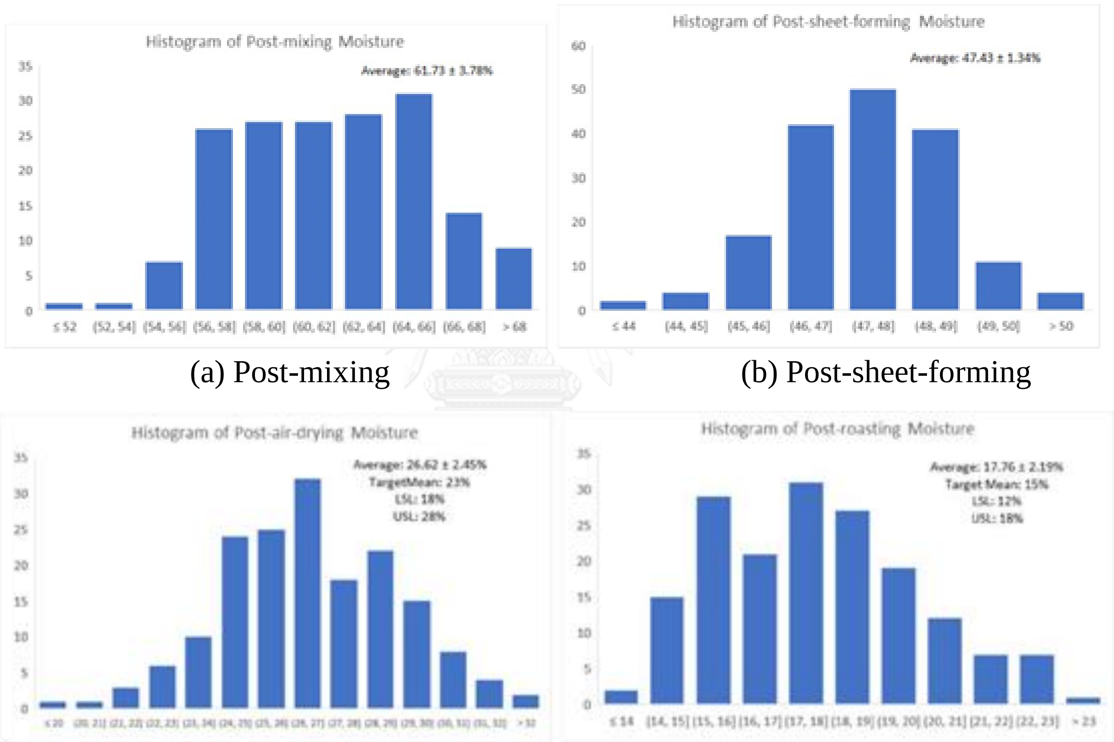
Table I.3: Production statistics prior to intervention

	LSL	**USL**	**Target Mean**	**Observed Mean (Sample Size)**	**Observed Stdev. (Sample Size)**	**C_p**	**C_{pk}**	**C_{pm}**
Minced fish moisture (Source 1)	70%	78%	74%	75.60% (171)	2.87% (171)	0.46	0.28	0.41
Minced fish moisture (Source 2)	70%	78%	74%	73.97% (171)	3.13% (171)	0.43	0.42	0.43
Post-mixing moisture	N/A	N/A	N/A	61.73% (171)	3.78% (171)	N/A	N/A	N/A
Post-sheet-forming moisture	N/A	N/A	N/A	47.43% (171)	1.34% (171)	N/A	N/A	N/A
Post-air-drying moisture	18%	28%	23%	26.62% (171)	2.45% (171)	0.68	0.19	0.38
Post-roasting moisture	12%	18%	15%	17.76% (171)	2.19% (171)	0.46	0.04	0.28



(a) Source 1 (b) Source 2

Figure I.10: Histograms of moisture of frozen minced fish from various sources before intervention



(a) Post-mixing (b) Post-sheet-forming

(c) Post-airdrying (d) Post-roasting

Figure I.11: Histograms of moisture of fish sheet at various points in the process before intervention

I.3 Objective of the Thesis

This thesis's objective is to improve the process capability index of fish sheet production process using process improvement, such as finding the best production parameters with design of experiments, that concurs with the requirements and constraints listed in Section I.2.2.

I.4 Scope of the Thesis

As mentioned in Section I.2.3, this thesis will focus on the following areas.

1. Improvement of the process capability index of the production of thick variety of fish sheets which are WIP of products in the factory especially the post-roasting moisture.
2. The production process of Production Line 1 which exclusively produces thick fish sheets
3. The approach that will be used for this quality improvement project will be limited to process improvement such as finding the best parameters using design of experiments.

Technological improvement will not be the focus of the thesis. Determination of production specifications will also not be a focus of the project. The specifications will be given by the manufacturer although additional specifications can be refined and acquired through further collaboration with the manufacturer.

I.5 Expected Outcome and Benefits

The project is expected to provide the following contributions:

1. The project will help lower the moisture variance in the air-drying and the roasting processes in the factory's fish-sheet drying process.
2. The success in controlling both the pre- and post-roasting moisture will allow the factory to integrate the roasting machine into a continuous production line and pave ways for further automation of the process.
3. The standardisation of production procedure will reduce reliance on skilled opera-tors that need to be stationed to closely monitor the roasting process. As a result, the operators can be deployed elsewhere to increase production capacity and flexibility in other processes in the factory.

I.6 Structure of Thesis

The structure of this thesis consists of six chapters. This chapter has provided an overview of the production processes, current problems, and objectives of process improvement. In Chapter 2, various topics in the literature are reviewed. Chapters 3 and 4 will discuss about methodologies used for each of the two phases of process improvement. Results of both phases of experiments are then discussed and evaluated in Chapter 5 to determine significance of improvement after each phase of intervention. Finally, Chapter 6 provides a discussion, a conclusion for this report, as well as future directions of the project.

CHAPTER II
LITERATURE REVIEW

II.1 Review of Literature on Process Control and Improvement in Food Industry

II.1.1 Process Improvement Techniques in Food Drying Processes

A review of process improvement techniques specific to the control of food drying process in the literature will be reviewed in this section. The focus of process improvement in literature diverge into two main areas. The first group of works focus on finding optimal production parameters or conditions that allow manufacturers to produce the most desirable end products with the most reliable and economical process possible. The second group of literature seeks to establish control of production process according to specification, mostly by using automatic controller systems.

Works that focus on parameter and process optimisation typically resort to mathematical modeling of the production system, properties of material and thermodynamic conditions of the process which are then simulated to find optimal drying processes. In Imre and Környey (1990), temperature, concentration and stress fields in salami drying process are expressed as a function of time, and a proper drying schedule is derived based on this system of equation. In Cristea, Irimita et al. (2012), the process of forced convective drying is simulated and validated with experimental data on carrot slabs. Based on this simulator, the researchers can simulate temperature and velocity of water in the system and to improve the drying operation with goals in minimising the duration of the drying process and reducing energy cost. Temple, Tambala et al. (2000) models fluidized-bed tea drying and simulates the model in MATLAB, allowing the researchers to study effects of various control strategies prior to implementation. Petersen, Poulsen et al. (2013) models multi-stage spray drying process to predict the temperature, residual moisture, and the particmoisture,in each of three stages in the process.
An alternative approach to mathematical modeling described above is to rely on experimental data to optimise the production process. Gowen, Abu-Ghannam et al. (2008) conducts an experiment to find relationship between inputs, including microwave levels and air temperatures, and outputs, including drying kinetics, rehydration kinetics and colour change, and predictive models of dehydrating and rehydrating are created. In the study, a combination of experimented inputs with the best result is selected as optimal. In Poonnoy, Tansakul et al. (2007), a two-hidden-layered artificial neural network model was trained to determine temperature and moisture content of the non-homogeneous food that undergoes microwave vacuum drying from inputs such as microwave power, vacuum pressure and other physical properties of the product. The study's goal is to generate a model to find optimal values of input parameters for a microwave vacuum drying operation.

On the control side of the literature, it is generally agreed that controlling a drying process can be challenging because of the process's non-linearity. According to Mujumdar (2014), all drying processes involved in dryers, even basic ones, are highly non-linear. The same concerns are voiced in literature which focuses on control of drying processes. For example, according to Li and Mao (2006), Liu and Bakker-Arkema (2001) and Cárdenas, Moya et al. (2009), grain drying procedure is a non-linear process with long delays, making it difficult to control. Likewise, Ma, Zhang et al. (2015), which primarily concerns with meat drying process, states that temperature and relative humidity are coupled and therefore creates humidity to fluctuate. Moreover, the fluctuation of humidity is a non-linear process due to non-linear thermodynamic law.

As a result, works that focus in control aspects of process improvement usually depend on the use of automatic controllers such as feedback controls which adjust the system's parameters based on outputs' deviation from targeted levels. A class of control tool commonly used in the literature are PID control (shortened from "proportional, integral and derivative" control) and its variants. It is noted in Araki (n.d.), that more than 90% of controllers used in process industries in Japan are PID controllers and their more advanced variants. PID control is a feedback control that uses PID controller at its core. In its most basic concept, PID controllers consist of three main components as its name implies including P element, I element and D element which calculate various aspects of errors that the system tries to correct. In brief, the P element's output is proportional to the observed error at instant t. The I element's output is proportional to the accumulation of past errors up to instant t, while the D element's output is proportional to a derivative of error at instant t. As Araki (n.d.) states, it can be interpreted that outputs of these components provide information about the present, the past and the future state of the system's error to the PID controller so that it can provide the right feedback to the system. Works that use PID controllers based on these basic concepts on food drying processes include Li and Mao (2006) and Cárdenas, Moya et al. (2009) which both focus on industrial grain drying. Ma, Zhang et al. (2015) applied fuzzy PID controllers, which is a variant of the PID control that depends on fuzzy logic, to a meat-drying process.

Another class of control used in the literature is model-predictive control. According to Bemporad (2010), a model-predictive control derives the system's control strategy based on a system model which allows the controller to predict inputs and outputs over finite future horizon of N time steps. In other words, the controller optimises based on projected performance of the system over the future N time steps and implements the optimised parameters in the current time step. The predictive element makes it different from PID controllers which use error information only up to the current time step. Liu and Bakker-Arkema (2001), which applies model-predictive control on a grain-drying process, states that the technique's main advantages include applicability to a non-linear process with long delays and ability to optimise performance online as the system's model improves and is less susceptible to changes in the process condition. Moreover, Bemporad (2010) states that the technique can be applied to a wide range of problems and can reduce training, reduce cost and simplify design maintenance. This technique is without drawbacks. According to Bemporad

(2010), the technique requires higher computational power com-pared to PID controllers because of the future prediction. Similar performance can be attained using PID controllers in the case of single-input/single-output control loops with constraints. Therefore, for simpler use cases, PID controllers are more economical choices. Examples of food drying process literature that uses model-predictive control are Liu and Bakker-Arkema (2001) mentioned above, Bremner and Postlethwaite (1997) which uses a fuzzy relational model as a model for prediction for grain drying process in whiskey distillery, and Zhao, Chi et al. (2007) which uses recurrent fuzzy neural network as a model in model-predictive control for controlling grain drying process.

To address issues of complex and inexact measurement found in many systems, various works adopt fuzzy logic into its control implementation. According to Lee (1990), fuzzy logic controller allows for inexact and natural language to be input into a control system. This is possible because fuzzy logic which is the basis of fuzzy logic controllers do not use true-false binary like Boolean logic but uses inexact representation of true and false instead. Fuzzy logic controller is therefore useful in the context where the process is too complex for quantitative analysis using conventional methods, and where available sources of information are inexact and interpreted qualitatively. The circumstance of food drying process share many of these characteristics due to the highly non-linear process (as mentioned in Mujumdar (2014)) and many process measurements are inexact and/or rely on operators' judgment. As a result, food drying control is a field which would benefit from fuzzy logic control. It is notable that fuzzy logic control is not mutually exclusive to other types of control methodology described above but can provide different flavour to these research approaches. Examples of previous works that apply fuzzy logic to control food drying processes are as followed. Bremner and Postlethwaite (1997) uses fuzzy relational model in a model-predictive control of grain drying. Ma, Zhang et al. (2015) uses fuzzy PID controller in meat drying process. Zhang and Litchfield (1993) uses fuzzy logic control in corn drying. Finally, Davidson, Matrineau et al. (1996) creates three control components in a grain-drying facility including supervisory level, feedforward controller and feedback controller. Fuzzy rules are applied to supervisory level which control qualitative criteria and to feedforward controller which determines process residence time.

Control literature mentioned above focus on controlling the output of final products such as moisture content of grains and meats etc. However, it is possible to also focus control efforts on inputs to the final process instead of the end product itself. For example, Hernández, Olejua et al. (2016) develops an automatic humidification system to supply air with specified level of humidity and temperature to a food dryer in an experimental food-drying facility. Although its primary goal is to produce air that emulate specific climate zone, it presents another approach to the control in which inputs to the process are the focus of control.

Other minor approaches found in the literature include application of H-infinity robust control to the control of fluidized tea bed drying (Moradi, Motamedi et al. 2009). In addition, integration of sensor and actuator of production facilities with PLC's and computerised system in order to provide operators with real-time report on current status and with process control is also presented in works such as Cárdenas, Moya et al. (2009). Process improvement methodology described in this section are summarised in Tables II.1 and II.2.

Table II.1: Previous works that focus on parameter optimization in food-drying process improvement classified by approaches

Approaches	Related Works
PID control	Li and Mao (2006)
	Cárdenas, Moya et al. (2009)
	Ma, Zhang et al. (2015)
Model-Predictive Control	Liu and Bakker-Arkema (2001)
	Bremner and Postlethwaite (1997)
	Zhao, Chi et al. (2007)
Fuzzy Logic Control	Bremner and Postlethwaite (1997)
	Ma, Zhang et al. (2015)
	Zhang and Litchfield (1993)
Other Approaches	Davidson, Matrineau et al. (1996)
	Hernández, Olejua et al. (2016) – Control input air
	Moradi, Motamedi et al. (2009) – H1 robus control
	Cárdenas, Moya et al. (2009) – Real-time control interface for operators

Table II.2: Previous works that focus on process control in food-drying process improvement, classified by approaches

Approaches	Related Works
Mathematical Modeling with Simulation	Imre and Környey (1990)
	Cristea, Irimita et al. (2012)
	Temple, Tambala et al. (2000)
	Petersen, Poulsen et al. (2013)
Predictive Model from Experimental Data	Gowen, Abu-Ghannam et al. (2008)
	Poonnoy, Tansakul et al. (2007)

II.2 Review of Application of Design of Experiment Method on Manufacturing Processes

In Montgomery (2009), experimental design is defined as "a test or series of tests in which purposeful changes are made to the input variables of a process so that we may observe and identify corresponding changes in the output response". The design of experiments (DoE) method can be used to improve performance of a process, making it robust to external sources of variability. There are several examples of works in the literature that uses experimental designs to analyse and optimise manufacturing processes, as listed in Table II.3.

These works follow the same methodology patterns. First, the process's control parameters and responses of interest are defined. Optimisation could involve more than one responses. Second, responses' data are systematically collected using DoE experiments. Finally, parameter values are analysed and optimised with methods such as ANOVA analysis or regression analysis.

The experimental designs vary across the literature and are selected based on the number of controllable factors and other specific circumstances that each project faces. Full factorial experiments are used in works with only a few input parameters and levels such as Vanhatalo, Vännman et al. (2007) which experiments on two factors, one with two levels and the other with three levels. For works with more factors and responses, fractional factorial designs are used to lower the total of experimental runs. For example, Amiri, Bashiri et al. (2011) uses L18 Taguchi design for its experiments on six factors. Artiles-León and Mella-Cabrera (1997) uses a two-level half fractional factorial design, i.e. having eight treatments, for its experiments over four factors and five responses. Antony (2000) uses a two-level fractional factorial (2^{5-1}) design over five most significant control parameters. A few replicates would be collected for each treatment. The number of replicates are usually determined by availability of time and resources for data collection. The designs and number of replicates used in the sample works are summarised in Table II.3.

Table II.3: Examples of works that use DoE methodology to optimise manufacturing processes

Works	**No. of Factors and Levels**	**Number of Responses**	**Number of Replicates**	**Design Used**	**Optimisation / Analysis Method**
Artiles-León and Mella-Cabrera (1997)	4 factors with 2 levels	5	18	two-level half fractional factorial (2^{4-1}) design	Model response surface with regression analysis as an exponential function
Doniavi, Mileham et al. (1999)	N/A (only CASE framework presented)				Model response surface with generic regression modeling
Antony (2000)	6 factors with 2-3 levels	3	4	L18 Taguchi design	Model response surface with generic regression analysis
Amiri, Bashiri et al. (2011)	5 factors with 2 levels	2	2	Two-level fractional factorial (2^{5-1}) design	ANOVA analysis to determine main and interaction effects and half normal probability plots
Vanhatalo, Vännman et al. (2007)	2 factors with 2 and 3 levels each	52	2	Full factorial design with 6	Find principal components and determine significant factors

				treatment s	with MANOVA analysis

Common methods used for analysis and optimisation of the experimented processes are ANOVA analysis (Antony (2000) and Vanhatalo et al. (2007)), and regression analysis (such as Amiri et al. (2011) and Artiles-León and Mella-Cabrera (1997)). ANOVA and its multivariate version, MANOVA, are used to determine levels significance of input factors to the responses. Regression analysis is a common tool used for modelling the response surface of the processes. Parameter values could then be optimised based on the solved regression functions.

II.3 Review of Lower One-tailed F-Test for Testing Equality of Two Variances

In this section, a theoretical basis of lower one-tailed F-test is reviewed. According to Snedecor and Cochran (1989), an F-test is used to determine whether variances of two population are equal. All F-test have the same null hypotheses, H_0 as followed.

$$H_0: \sigma_1^2 = \sigma_2^2 \tag{2.1}$$

F-tests can be classified into three broad types based on alternative hypotheses, H_a, including a lower one-tailed test, an upper one-tailed test, and a two-tailed test. Their alternative hypotheses are as followed.

Lower one-tailed – $H_a: \sigma_1^2 < \sigma_2^2$
Upper one-tailed – $H_a: \sigma_1^2 > \sigma_2^2$
Two-tailed – $H_a: \sigma_1^2 \neq \sigma_2^2$

As it will be discussed in Section III.2.4, the lower one-tailed test is the most relevant version of F-test for this project. Therefore, theoretical review of the test will be provided in this section. For further discussion, let the null hypothesis and alternative hypothesis of the F-test be as followed.

$$H_0: {\sigma_A}^2 \geq {\sigma_B}^2$$
$$H_a: {\sigma_A}^2 < {\sigma_B}^2 \tag{2.2}$$

II.3.1 Rejection of Null Hypothesis

To reject the null hypothesis, F-statistics for distributions A and B have to exceed a threshold. Because the goal of the F-test is to test equality between two variances, an F-statistic, F, to be used in the test can be defined as

$$F = \left(\frac{S_A^2}{\sigma_A^2}\right) \Big/ \left(\frac{S_B^2}{\sigma_B^2}\right) \tag{2.3}$$

Where S_A^2 and S_B^2 are sample variances of A and B respectively.

To properly reject the null hypothesis H_0, one must first observe unlikely effect even when H_0 is assumed to be true, meaning that $\sigma_A^2 = \sigma_B^2$ As a result, the expression of F can be simplified to

$$F = \frac{S_A^2}{S_B^2} \tag{2.4}$$

Because the alternative hypothesis, H_a, is that $\sigma_A^2 < \sigma_B^2$, the hypothesis testing is a lower one-tailed test. Therefore, if sample variances are each calculated using n_B and n_A samples drawn from their respective distributions and which is the significance level or maximum probability of making a Type-I error that can be tolerated, the null hypothesis H_0 can be rejected if

$$F < F_{1-\alpha, n_A-1, n_{B-1}-1} \tag{2.5}$$

For clarification, F_{x,d_1,d_2} is a critical value of the F-distribution with significance level at x and d_1 and d_2 degrees of freedom. The degrees of freedoms are n_B - 1 and n_A - 1 because they are degrees of freedom for calculations of sample variance in distributions B and A with sample size n_B and n_A respectively.

In an experiment, if the p-value of the F-test is lower than a specified significance level, typically at 5%, then the null hypothesis can be rejected.

II.3.2 Finding Minimum Number of Sample Size

Sample sizes for calculating sample variances in n_A and n_B to comply with both specified probability of Type-I error (α) and probability of Type-II error (β) can be calculated as followed. The definition of β is

$$\beta = P(Accept\ H_0 | H_0\ is\ false) \tag{2.6}$$

In other words, assume that $\sigma_A^2 < \sigma_B^2$ as H_a states but the F-statistic is greater than the critical value. Then, the value of β becomes

$$\beta = P(F > F_{1-\alpha,n-1,n-1} \mid \sigma_A^2 < \sigma_B^2) \tag{2.7}$$

Because σ_A^2 is assumed to no longer equal σ_B^2, the simplified form of F-statistic, F, in Equation 2.4 can no longer be used and the full definition in Equation 2.3 should be used instead. By substituting F with its equivalence according to Equation 2.3, the value of becomes

$$\beta = P(\frac{S_A^2}{S_B^2} > F_{1-\alpha,n-1,n-1} \cdot | \frac{\sigma_A^2}{\sigma_B^2} | \frac{\sigma_A^2}{\sigma_B^2} < 1) \tag{2.8}$$

Let F_β be a short-handed form of $F_{\beta,n-1,n-1}$ which is the critical value F-statistic at β with sample sizes for calculation of sample variances of A and B being *n*.

$$P(F > F_\beta) = P(\frac{S_A^2}{S_A^2} > F_{1-\alpha,n-1,n-1} \cdot | \frac{\sigma_A^2}{\sigma_B^2} | \frac{\sigma_A^2}{\sigma_B^2} < 1) \tag{2.9}$$

Based on Equation 2.9, at a threshold where $\sigma_A^2 = \sigma_B^2$ is still true,

$$F_\beta = F_{1-\alpha,n-1,n-1} \cdot \frac{\sigma_A^2}{\sigma_B^2} \tag{2.10}$$

Therefore, it can be concluded that, at the threshold,

$$R = \frac{\sigma_A^2}{\sigma_B^2} = \frac{F_{1-\alpha,n-1,n-1}}{F_{\beta,n-1,n-1}} \tag{2.11}$$

Given specific values for the ratio $R = \frac{\sigma_A^2}{\sigma_B^2} < 1$, α and β , then the minimum number of samples can be determined by iteratively solving for the rounded value of solution that satisfy Equation 2.11. The condition for $\frac{\sigma_A^2}{\sigma_B^2} < 1$ applies because it is desirable that $\sigma_A^2 < \sigma_B^2$.

For illustration, Figure II.1 shows a power curve solved using a MiniTab software for the case where $\alpha = 0.05$, $\beta = 0.2$ and each curve corresponds to the case where R = 0.5, 0.6 and 0.7. In this specific case, the formulation of R becomes

$$\frac{F_{0.95,n-1,n-1}}{F_{0.2,n-1,n-1}} = R \tag{2.12}$$

Based on the graph, the sample sizes for both moisture distribution before and after intervention with ratios R at 0.5, 0.6, 0.7 are 54, 97 and 197 samples respectively. The result agrees with manual calculation based on Equation 2.12 as followed.

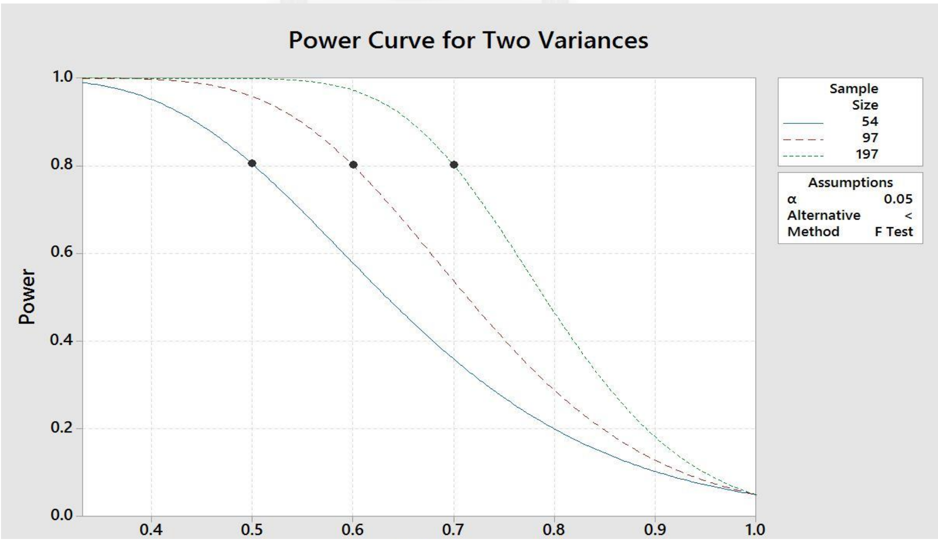


Figure II.1: Power curves for two-variance test using $\alpha = 0.05$ and $\beta = 0.2$ while variance ratio is 0.5, 0.6 and 0.7

$$\frac{F_{0.95,53,53}}{F_{0.2,53,53}} = \frac{0.633842}{1.261831} = 0.502319 \approx 0.5$$

$$\frac{F_{0.95,96,96}}{F_{0.2,96,96}} = \frac{0.713607}{1.188093} = 0.600632 \approx 0.6$$

$$\frac{F_{0.95,196,196}}{F_{0.2,196,196}} = \frac{0.790136}{1.127972} = 0.700493 \approx 0.7$$

II.4 Finding Minimum Sample Size for C_{pk} Approximation

As it will be discussed further in Section IV.2.3, the number of samples for calculation of C_{pk} values (defined in Equation 4.1 will need to be determined. Because a C_{pk} index is an aggregate value, calculated from individual moisture measurements in the experiment, many replicates of experiments were needed to ensure that values of C_{pk} index used for analysis have good precision. Approximating a minimum number of samples to acquire a specific confidence bounds are discussed in Wu and Kuo (2004). In the paper, sample size for C_{pk} are estimated using Bissell's approximation (Bissell 1990). An approximation function is given in Equation 2.13 where z is the Z score when lower confidence limit is100(1 - α)%, C_{pk} is an estimated value of C_{pk} and $C_{pk;lower}$ is the confidence lower bound of C_{pk} value.

$$n = z_a^2 \left(\frac{1}{9\hat{C}_{pk}^2} + 0.5\right)/\left(1 - C_{pk,lower}/\hat{C}_{pk}\right)^2 \qquad (2.13)$$

As an example for sample size calculation in Equation 2.13, a table with approximated minimum number of samples for various values of estimated C_{pk} ($\hat{C}_{pk}$), and the error bound ratio, $\frac{C_{pk}}{\hat{C}_{pk}}$. In this table, the default value of confidence limit of 95%, i.e. α = 0.05, C_{pk} is used. As it has been pointed out in Table 1.3, the initial value of C_{pk} for post-roasting fish sheets' moisture is as low as 0.04. Therefore, sample sizes for scenarios where values $\hat{C}_{pk}$ are value low, such as 0.10 and 0.25, are also shown in the sample size table. From the table, the narrower confidence bound or the lower the estimated C_{pk} is, the greater number of samples are required.

There are caveats for these approximations in that minimum number of samples are required for the approximated values to be accurate. Bissell's approximation of confidence interval (Bissell 1990), which forms the basis of C_{pk} approximation in Wu and Kuo (2004), suggests that the normal approximations in the paper would be accurate only when it is calculated using at least 50 samples. Lewis (1991), which explores effects of sample size in process capability index calculation, also reports that estimation of C_{pk} cannot be sufficiently reliable when sample size is under 50 because the random errors would be greater than 18%. On the contrary, Wu and Kuo (2004) suggests a less stringent minimum sample size at 30 samples. Many of the values in Table II.4 that require less than 50 samples (denoted with asterisks) are less reliable in estimating values of C_{pk}. As a result, even if the calculated number of sample size is less than 50, it is still advisable that at least 50 samples are used for C_{pk} calculation.

Table II.4: Approximated minimum number of samples to achieve lower confidence bound of C_{pk} based on Bissell's Approximation when confidence limit is 95%

$\hat{C}_{pk}$	$\frac{C_{pk}}{\hat{C}_{pk}}$	**Number of Samples**
0.10	0.70 0.75 0.8 0.9	352 506 791 3162
0.25	0.70 0.75 0.8 0.9	69 100 156 621
0.50	0.70 0.75 0.8 0.9	29 42 65 258
0.75	0.70 0.75 0.8 0.9	22 31 48 190
1.00	0.70 0.75 0.8 0.9	19 27 42 167
1.25	0.70 0.75 0.8 0.9	18 25 39 156
1.50	0.70 0.75 0.8 0.9	17 24 38 150

CHAPTER III

METHODOLOGY: MOISTURE CONTROL DURING MIXING PROCESS

III.1 Stages of Process Improvement

As described in Chapter 1, the goal of this project is to find means that can lead to automation of fish sheet production processes up to the roasting process. The focus of the project is to systematically control moisture of roasted fish sheet with minimal reliance on roasting machine operators' expertise, thus making the process less labour-intensive. More specifically, the objective of this project is to improve process capabilities of the process, using post-roast moisture of fish sheet as the key response.

To achieve the objective, four main sub-processes that lead up to the roasting process, including mixing, sheet-forming, air-drying and roasting, are evaluated. Based on preliminary analysis on these sub-processes, process improvement will be divided into two stages: improvement before or during the mixing process, and improvement after fish solution has been mixed. The reason behind the dichotomy is due to different characteristics of productions in these stages.

As discussed in Chapter 1, sheet-forming and air-drying are mass-production processes, and minimisation of human intervention in the roasting process is the goal of the project. As a result, there will be few opportunities to reactively intervene during production in theses sub-processes. It will also be difficult or impractical to apply fine-tuned intervention on specific parts of the work in process without stopping the entire production line. Furthermore, the 30-minute moisture measurement which has to be per-formed at a measurement station also prevents the possibility that real-time automated control can be applied. On the contrary, fish solution is mixed in batches, so it is possible to make preparation for intervention based on properties of input material and to apply interventions during the mixing process. Moreover, it is also possible to stop mixing part-way to make correction if necessary.

Put differently, because intervention on post-mixing sub-processes cannot be practically applied during production, any practical interventions should be applied before the start of production. Such interventions, for example, can include determining and/or solving for optimal values of production parameters that optimise the targeted process capability. However, because these production parameters are determined prior to the start of production, the success in improving process capability depends on the success in controlling moisture in this input material, namely the mixed fish solution from the mixing process.

Therefore, intervention in this project will be conducted in sequence. First, intervention to minimise moisture variation of the mixed fish solution will be applied and evaluated. Provided that the moisture of the fish solution has been sufficiently controlled, the project will conduct the second phase of intervention in determining optimal controllable production parameters for post-mixing processes. Intervention which is applied during the mixing process will be discussed in detail in this chapter while post-mixing intervention will be discussed in detail in Chapter IV.

III.2 Moisture Control Methodology during Mixing Process

To control moisture variation in the mixed fish solution, sources of moisture variability will be discussed in Section III.2.1. Procedures for controlling each controllable sources of variation will then be discussed in subsequent sections.

III.2.1 Sources of Moisture Variation in Mixing Process

One of the primary sources of variation in the mixing process already presented in Chapter I is variation of moisture in raw material especially minced fish. To be comprehensive, other potential sources of moisture variation will also be considered in this section.

To identify additional potential causes of moisture variation, more information is gathered from a brainstorming session with the manufacturing team. Potential causes from the session are summarised in Figure III.1. In addition to the high moisture variation in raw ingredients, these causes include ingredient measurement error either due to equipment malfunction or human error, leakage in mixing equipment, loss of moisture content during interprocess transfer and loss of moisture to environment during production process.

Because there are many potential causes, it is important to filter for relevant causes and focus on causes with greater priority. Prioritising these causes objectively can be difficult because of several reasons. First, because the mixing process is a large batch process, it is difficult to objectively specify single causes for each mixing batch which greatly diverge from the expected range. Second, no specification and specification limits have been set for mixing process prior to the start of the project, so no records of defects have been kept on any defects in the mixing stage.

Instead of relying on past records, in-depth interviews with six people who are involved in the production line. Selected interviewees include the factory manager, the factory's production manager and experienced machine operators who have been stationed in the production line or serve as quality control operators for more than one year. The interview involves finding out challenges that interviewees find in their daily operations and potential causes that they believe to be relevant to the problem and should be prioritised. The interviews are then summarised to find common grounds among the differing opinions.

Based on the interview, all interviewees cite moisture variation in the supplied raw ingredients among the most relevant potential causes. In addition, the production manager suggested another minor cause would be inadvertent mistakes by operators in weighing ingredients. Other than the human error, the mixing process is relatively straightforward and quality control operators routinely sample and check ingredients' weights, making it less likely that the variation of fish mixture is consistently introduced during the mixing process. Interviewees dismissed other possibilities. The mixing room is air-conditioned, so the mixing environment is controlled. Leakage in the mixing equipment should not be a problem because no visible leakage has been

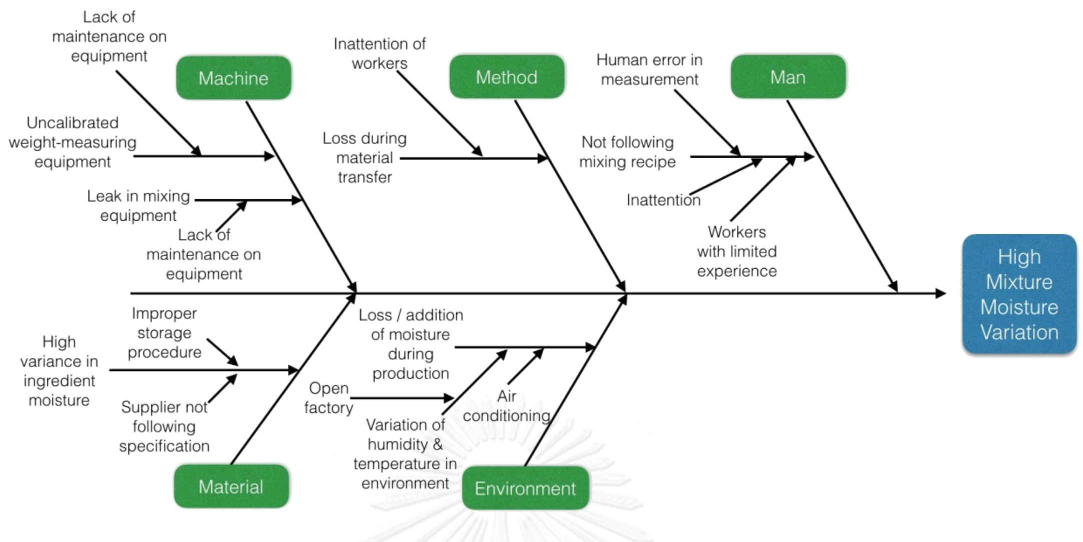


Figure III.1: Fishbone diagram of possible causes of high moisture variation in mixing process

observed. Finally, the weight-measuring equipment are also regularly calibrated. Therefore, the process improvement in the mixing phase will focus on the problem of moisture variation in the supplied raw material.

III.2.2 Control of Mixture Variation by Adaptively Adjust Recipe

In this project, frozen minced fish will be the only ingredient that the project will focus on. As argued earlier in Section I.2.4, the only key ingredients that should significantly contribute to the moisture variation is frozen minced fish which account for over 40% of the total ingredient weight. Water and ice which accounts for another 30% of the weight naturally have 100% moisture and are weighed before being added to the mixture. Other ingredients have small weights and have very low moisture. Also in Section I.2.4, it is discussed and illustrated in Table I.3 and Figure I.10 that there are significant variations in the supplied minced fish from the two suppliers. Therefore, due to the high cost of moisture measurement, the project will focus its moisture control on frozen minced fish which is the ingredient has high significant proportion in the mixture and has past statistics demonstrating significant amount of moisture variation.

While the manufacturer will also pressure minced fish suppliers to better control their moisture variation in their products, this project will pursue a procedure in controlling moisture of the mixed fish solution by systematically adjust the recipe according to moisture measured from ingredients. More details about the procedure will be discussed in Section III.2.2.

Based on discussions with the factory's production team, despite having a standardised recipe, the production team never determine standardised target moisture for the mixed fish solution. Instead, the target moisture of the mixture will be determined based on the company's recipes and past data of expected moisture for each ingredient.

In other words, the target moisture, $m_{mix;target}$, will be calculated using the following formula.

$$m_{mix,target} = \frac{\sum_i^n m_{expected,r_i}}{\sum_i^n r_i} \quad (3.1)$$

where

$m_{expected;i}$ = expected moisture content of raw material i

r_i = weight of raw material i

Given the target moisture determined with Equation 3.1, the amount of water that need to be added or removed from a given recipe can be calculated using the following formula.

$$\Delta w = \frac{m_{mix,target} \sum_i^n r_i - \sum_i^n m_i r_i}{1 - m_{mix,target}} \quad (3.2)$$

$$\frac{m_{mix,target} \sum_i^n r_i - \sum_i^n w_i}{1 - m_{mix,target}}$$

where

w = weight of water that needs to be added or reduced from the amount given in the recipe

w_i = water content by weight of raw material i

m_i = moisture (in percentage) of raw material i

r_i = weight of raw material i

$m_{mix;target}$ = target moisture (in percentage) of final mixture

For clarification, the relation of w_i, m_i and r_i for any ingredient i would be according to Equation 3.3.

$$w_i = m_i r_i \quad (3.3)$$

The proof of Equation 3.2 can be derived as followed. First, the moisture of a mixture, mmix of any n ingredients can be calculated using a weighted average.

$$m_{mix} = \frac{\sum_i^n w_i}{\sum_i^n r_i}$$

If water is added to or reduced from the mixture by w, then the adjusted moisture level, $m_{mix;adjusted}$ would be

$$m_{mix,target} = \frac{\sum_i^n w_i + \Delta w}{\sum_i^n r_i + \Delta w}$$

The above equation is valid because the water's weight is also its water content.

In order to acheive $m_{mix} = m_{mix;target}$, the amount of water to be adjusted (Δw) can be algebraically solved as followed.

$$m_{mix,target} = \frac{\sum_i^n w_i + \Delta w}{\sum_i^n r_i + \Delta w}$$

$$m_{mix,target}\left(\sum_i^n r_i + \Delta w\right) = \sum_i^n w_i + \Delta w$$

$$\left(m_{mix,target} - 1\right)\Delta w = \sum_i^n w_i - m_{mix,target}\left(\sum_i^n r_i\right)$$

$$w = \frac{\sum_i^n w_i - m_{mix,target}(\sum_i^n r_i)}{m_{mix,target} - 1}$$

$$\Delta w = \frac{m_{mix,target}(\sum_i^n r_i) - \sum_i^n w_i}{1 - m_{mix,target}}$$

Because of the relation in Equation 3.3, the proof of Equation 3.2 can be concluded that

$$\Delta w = \frac{m_{mix,target}(\sum_i^n r_i) - \sum_i^n m_i r_i}{1 - m_{mix,target}}$$

For the above water adjustment calculation in Equation 3.2 to be valid, it is assumed that weight of solid and water content of raw materials lost due to chemical reaction or evaporation during mixing process are insignificant. Moreover, for the adjustment to be practical, the formula assumes that the amount of water needs to be corrected is small compared to the overall water in the recipe. For example, it would not make sense to allow reduction of water more than the amount of water used in the recipe.

These assumptions are valid in this project's setting for several reasons. First, the loss due to environmental factors has already been ruled out with the fish bone diagram analysis in Section III.2.1. Second, based on the confidential recipe disclosed by the manufacturer, none of the ingredients have chemical reactions that would have resulted in significant loss of mass in the mixed solution. Finally, the standard deviation of the mixed solution before any intervention, according to Table 1.3, is only 3.35%. According to the recipe, water added during the mixing process constitutes around 30% of the total mixture weight, implying that the amount of water to be adjusted will be substantially smaller than total amount water in the mixture.

III.2.3 Practical Application

To facilitate calculation of water adjustment in day-to-day production, a Microsoft Excel spreadsheet is created and provided for the factory's production manager. The spreadsheet, which bases its calculation on the formula in Equation 3.2, contains two key sheets including:

1. **“Recipe” sheet** – This sheet records the recipe of each product type including weights and expected moisture of each ingredients. Expected moisture of each source of minced fish is calculated from an average value of moisture using data recorded over five months. An example of the sheet is shown in Figure III.2. To simplify operations and minimise number of expensive moisture measurement, ingredients other than water, ice and minced fish are lumped as “Other ingredients”. Justification for this lumping decision will be discussed at the end of this section.
2. **“Water adjustment” sheet** – By providing the spreadsheet with the product type and measured moisture of frozen minced fish from each source, the sheet will automatically calculate the quantity of water to be used in each mixing batch. An example of this sheet is illustrated in Figure III.3. In order to use this adjustment sheet, several key points should be noted. First, a target moisture is automatically calculated when product type is selected, using information in the recipe spread-sheet. In this case, product B is selected. Second, measured moisture of minced fish from both sources should then be filled in their respective fields (highlighted as yellow fields). Finally, after all inputs have been filled in, the total amount of water to be added are then calculated and shown in the orange highlighted field.

Using information in the recipe sheet (Figure III.2) and in the water adjustment sheet (Figure III.3), it can be inferred that minced fish from Source 1 has lower moisture than expected (74.20% as opposed to expected 75.10%) and that from Source 2 has higher moisture than expected (76.10% as opposed to expected 75.10%). The target moisture is calculated from the recipe to be 63.48% as followed:

$$
\begin{aligned}
m_{mix,target} &= \frac{m_{water}\, r_{water} + m_{source1}\, r_{source1} + m_{source2}\, r_{source2} + m_{other}\, r_{other}}{r_{water} + r_{source1} + r_{source2} + r_{other}} \\
&= \frac{1 \times 45 + 0.7510 \times 30 + 0.7510 \times 30 + 0.1157 \times 45 \times 1}{45 + 30 + 30 + 45 \times 1} \\
&= \frac{95.30807}{150.1} \\
&= 63.4764\ \% \qquad (3.4)
\end{aligned}
$$

The amount of water content to be corrected in this example would be calculated using Equation 3.2 as followed:

$$
\begin{aligned}
\Delta w &= \frac{\sum_i^n m_i r_i - m_{mix,target} \sum_i^n r_i}{m_{mix,target} - 1} \\
&= \frac{(1 \times 45 + 0.7420 \times 30 + 0.7610 \times 30 + 0.1157 \times 45 \times 1) - 0.634764(45 + 30 + 30 + 45 \times 1)}{0.634764 - 1} \\
&= \frac{95.30807 - 95.27808}{-0.3652} \\
&= -0.0821
\end{aligned}
$$

The result implies that the mixing process should reduce 0.08 kg from its recipe. In other words, the amount of water that should be used is 45 - 0.08 = 44.92 kg. These results match the suggestions provided by the "water adjustment" sheet in Figure III.3.

Due to high cost of moisture measurement, recipes in the spreadsheet are simplified to reduce the amount of measurement needed. Only three categories of ingredients are used in the spreadsheet including (1) water, (2) minced fish from both sources and (3) other minor ingredients. With eight different minor ingredients to consider, it would be impractical to measure all their moisture content before the start of each mixing batch. Therefore, these minor ingredients are lumped together as a single entry, and the mix of these ingredients are assumed to have the same moisture content for each batch of the same product type. (See Figure III.2.) This lump moisture is taken from an average of 10 different moisture measurements of the mix. For example, the product B's the mix of minor ingredients has 11.57% moisture by weight.

The decision to lump minor ingredients into a single entry in the recipe with constant moisture level can be justified because of three reasons. First, together, minor ingredients account for only 30% of the total weight in the mixed fish solution, making their moisture variation less significant than minced fish which accounts for over 40% of the total weight. Second, these minor ingredients also consist of either ingredient with low moisture (less than 3% moisture) and liquid ingredients such as soy sauce, making it difficult to make accurate measurement out of each ingredient on a regular basis.

Finally, the variance of moisture of the mixture of minor ingredients would be no more than the variance of the ingredient with the most moisture variance. In practice, the moisture variance of the mix would be substantially less than that of individual ingredients. To illustrate the point, let moisture of ingredient i be m_i and assume that the moisture of ingredients is independent of one another which means that covariance of any pair of ingredient moisture is zero. In addition, let proportion of ingredient i (in weight) in the mixture be c_i where $\sum_i c_i = 1$ and $c_i \geq 0$. Then, the variance of the mix of minor ingredients would be:

$$Var(mixture) = Var(\sum_i (c_i m_i)) = \sum_i (c_i^2 \, v_{ar(m_i)}) \tag{3.5}$$

Because it can be implied that $0 \leq c_i \leq 1$, $Var(mixture) \leq \max\big(Var(m_i)\big)$. (The upper bound happens when proportion of the ingredient i with the most variance, c_i, is 1.) The variance of the mix can also be substantially less than $\max(Var(m_i))$. For example, if all N ingredients are mixed in equal proportion and have equal variance V, then $Var(mixture) = \sum_i (\frac{1}{N^2} Var(m_i)) = \frac{1}{N^2} \sum_i (Var(m_i)) = \frac{N}{N^2} V = \frac{V}{N}$. Therefore, if it can be assumed that variance of each minor ingredient is not substantial, it should be valid to estimate the moisture of the mix as a constant.

In addition to providing the spreadsheet to guide recipe adjustment, parts of the process are also modified to facilitate the recipe adjustment practice. Because the recipe adjustment requires measurement of moisture in minced fish, schedules for measurement are set up so that samples of minced fish are sent to mixing stations at least 30 minutes prior to the start of the mixing. To save time for the first batch of each production day, the measurement of minced fish for the batch is made at the end of the previous production day.

	A	B	C
1		**Moisture (%)**	
2	**Water**	100.00%	45
3	**Minced Fish (Source 1)**	75.10%	30
4	**Minced Fish (Source 2)**	75.10%	30
5	**Other ingredients**	11.57%	45.1
6			
7			

Figure III.2: Recipe Spreadsheet for Product

	A	B
1	**Product**	
2	Target moisture (%)	**63.48%**
3	Minced fish (source 1) moisture (%)	**74.20%**
4	Minced fish (source 2) moisture (%)	**76.10%**
5		
6	Add / remove water (kg)	-0.082
7	Total amount of water in mixture (kg)	**44.918**
8		

Figure III.3: Water adjustment spreadsheet

III.2.4 Evaluation

To evaluate success of the approach, it will be determined whether the variance of the mixed fish solution is significantly less than the variance prior to the water adjustment intervention. In other words, the variance of mixture's moisture after intervention must be significantly less than that of mixture before intervention for the null hypothesis, to be rejected. F-test will be used to test the null hypothesis because moisture both before and after intervention are assumed to have normal distribution. Data of mixture's moisture both before and after the intervention will be collected from samples of the mixed fish solution after the end of each mixing batch.

The null and alternative hypotheses, H_0 and H_a, can be defined as

$$\begin{aligned} H_0 &: \sigma_A^2 \geq \sigma_B^2 \\ H_a &: \sigma_A^2 \geq \sigma_B^2 \end{aligned} \qquad (3.6)$$

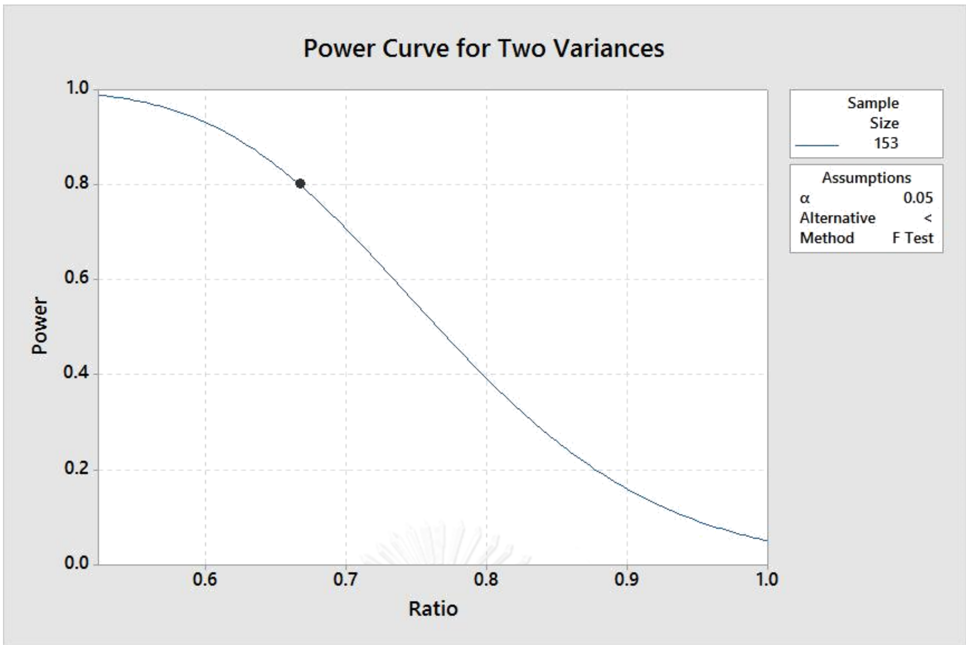


Figure III.4: Power curve with β= 0.8 at ratio = 0.6667

Where σ_B^2 and σ_A^2 are short-handed form of $\sigma^2_{\text{moisture,before}}$ and $\sigma^2_{\text{moisture,after}}$ respectively. In addition, for brevity of discussion, moisture distributions of the fish mixture before and after intervention will be henceforth referred to as distributions B and A respectively.

To reject the null hypothesis, an F-statistic for distributions A and B must exceed a threshold. It is notable that the null and alternative hypotheses listed above are in a lower one-tailed form. A theoretical review of F-test with lower one-tailed test is provided in Section II.3. The thresholds that would be used in the experiment are α = 0.05 and β = 0.2.

The minimum number of samples that should be used in the hypothesis testing such that the p-value in the F-test exceeds the threshold of α = 0.05 depends on the ratio of the variance of fish mixture's moisture after the intervention to that before the intervention. Because the real value of the ratio cannot be determined before data are collected, to determine the number of samples that would be needed, the following criteria will be used. First, an assumption will be made that, for the moisture variation in fish mixture to be satisfactorily reduced, it should be reduced to at most 0.6667 (or two-thirds) of the variance prior to intervention. Second, for simplicity of interpretation, the number of samples of moisture collected before and after the intervention should be the same.

According to Figure III.4, it is shown that when β = 0.2 and the ratio is 0.6667, the minimum number of samples should be at least 153 samples. Because the number of samples collected prior to the start of the intervention is 171, which is greater than the minimum 153 samples required, 171 samples of fish mixture moisture after the intervention has been implemented would also be collected. The data would be collected by random sampling throughout a production day at the rate of five samples per day. This implies that 38 days would be needed for data collection.

The collected data are listed in Appendix B.2. The discussion and analysis of the results will be given in Section V.1.

CHAPTER IV
METHODOLOGY: MOISTURE CONTROL IN POST-MIXING PROCESSES

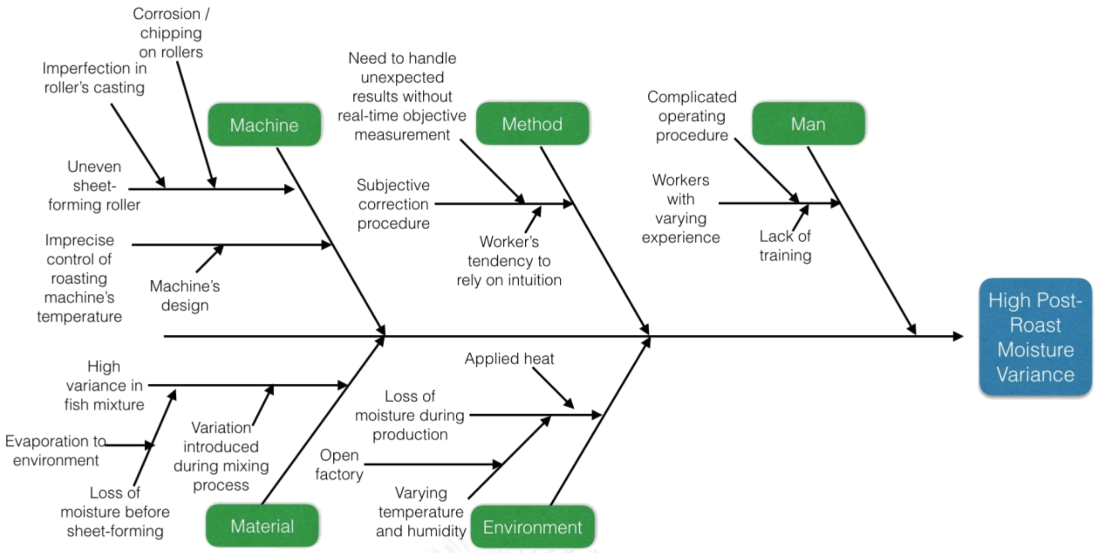
IV.1 Sources of Moisture Variation in Post-mixing Processes

This chapter will discuss methodology for identifying sources of and controlling post-roast fish sheet's moisture variation. Potential sources of moisture variation in post-mix processes (including sheet-forming, air-drying and roasting) are listed using the fish-bone diagram as shown in Figure IV.1.

Prioritisation of potential causes in post-mixing processes face challenges to the ones identified in Section III.2.1 for prioritising potential causes of moisture variation introduced in the mixing process. In addition, because fish sheets must be continuously processed under three major stages before the post-roasting moisture which is the key quality metric could be determined, it is even more difficult to determine root causes of the high moisture variation. As a result, like in Section III.2.1, in-depth interviews with experts in the production line are conducted to determine degrees of relevance of each potential cause. The interviewees are the same group as the ones interviewed for prioritising the mixing stage's causes as described in Section III.2.1. These people include the factory manager, the factory's production manager and other machine operators who have been assigned to the production line for more than one year.

Unlike the interviews in the mixing process in which the moisture variation in supplied ingredients is the only dominant potential cause, there is no consensus on what primarily cause moisture variation in fish sheets after the post-mixing process. Many potential causes for moisture variation in post-mixing processes were raised during the interviews as relevant causes. More commonly mentioned causes include high variation of the fish mixture from the mixing stage, inability to satisfactorily correct moisture in fish sheets, dependence of worker's skills in adjusting parameters, and variation of temperature and humidity in the factory. Unlike the case of mixing room, the section in the factory used for post-mixing processes is an open space which is not climate-controlled.

Among the potential causes identified above, the manufacturer has not implemented any mitigation actions for any of these potential causes, implying many potential rooms of. improvement. The most commonly cited cause, high moisture variation in the input fish mixture, has been addressed in Chapter 3. Therefore, process improvement in post-mixing processes will address other two significant potential causes: parameter adjustment with unsatisfactory results and dependence on workers' experience in parameter adjustment. Although temperature and humidity in the factory was also rated to be a significant cause of moisture variation, remodeling the



factory into a climate-controlled environment would incur significant cost to the manufacturer. As a result, an agreement with the manufacturer was reached that other less costly measures should be implemented and evaluated prior to the significant investment on production machines and the factory building.

IV.2 Optimisation of Process Parameters

As argued in Section I.2 that the current moisture correction practice cannot satisfactorily correct fish sheets' moistures. Because moisture of fish sheets need 30 minutes to measure, it is impossible for moisture measurement to happen in real time, and operators are forced to rely on subjective judgment to determent whether to adjust production process' parameters. The issue would be exacerbated if the machine operators are inexperienced.

A course of action that can address both potential causes from Section IV.1 is to stabilise the process so that production parameters can be pre-set before the start of production. As a result, workers would not be forced to make real-time adjustment and the production line would have less dependence on skills of individual workers. In addition, as it has already been recommended in Section III.1, production

Figure IV.1: Fishbone diagram of possible causes of high moisture variation in post-roasting fish sheets

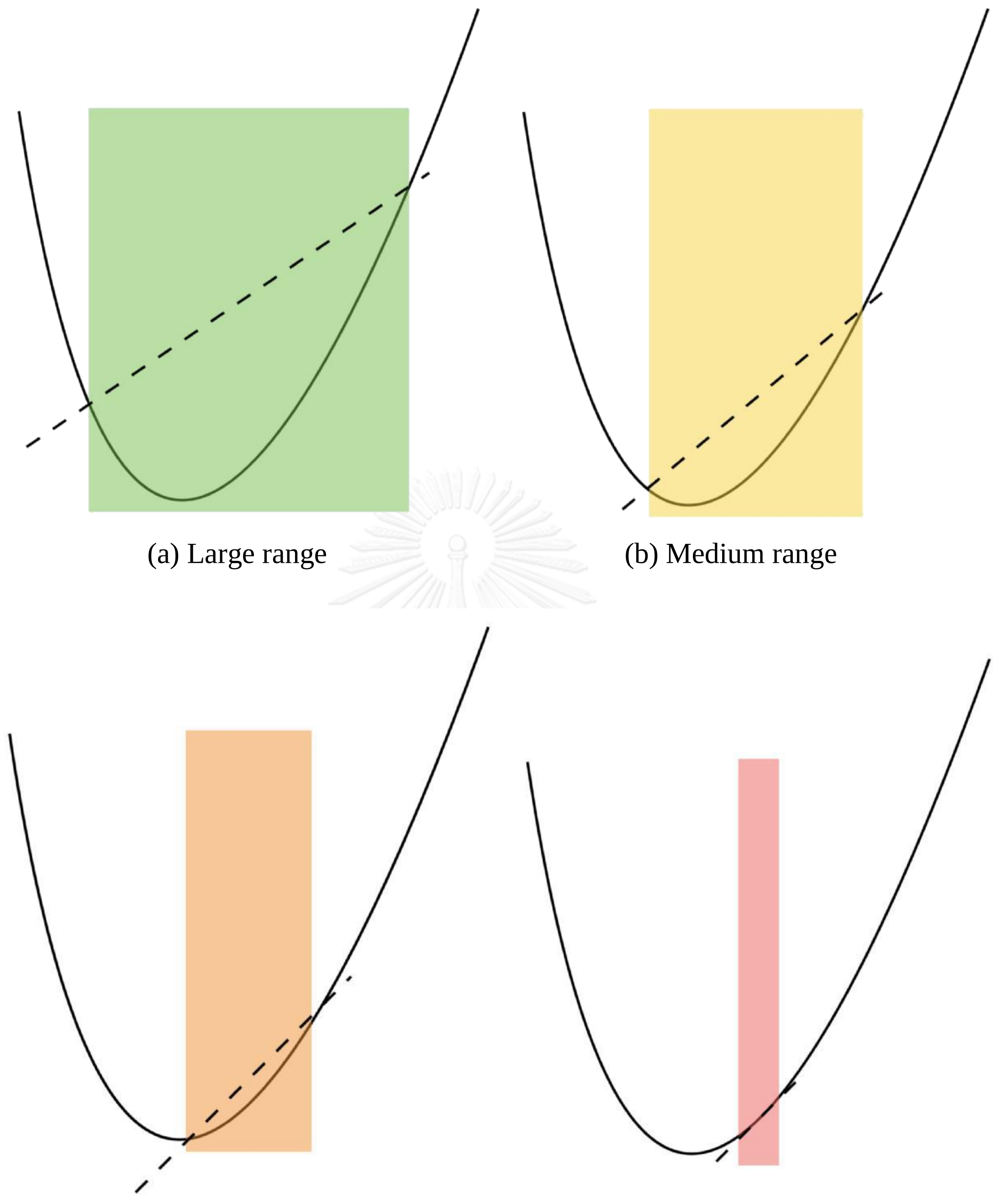
parameter values in post-mix processes should be optimised and selected before the start of the production. The objective of the optimisation would be maximisation of the process capability index, C_{pk}, of the post-roasting moisture of fish sheets. The definition of the C_{pk} value is given in Equation 4.1.

$$c_{pk} = \min\left[\frac{USL-\hat{\mu}}{3\hat{\sigma}}, \frac{\hat{\mu}-LSL}{3\hat{\sigma}}\right] \tag{4.1}$$

Creating a generic model of drying processes in this project and finding analytical solution from the solved model like other works in the literature could be challenging for several reasons. This project will approach parameter optimisation by modeling response surface within small space of input values for several reasons. First, although various works, such as Imre and Környey (1990), Cristea, Irimita et al. (2012), Temple, Tambala et al. (2000) and Petersen, Poulsen et al. (2013) as fully reviewed in Section II.1.1, seeks to formulate the drying processes as a mathematical formula, finding a generic model of drying in post-mixing processes will be complex. The drying process in this project could be even more complex than these works because it involves three consecutive stages of drying including sheet-forming heating, air-drying and roasting. Second, as argued in Li and Mao (2006), Liu and Bakker-Arkema (2001), and Cárdenas, Moya et al. (2009), drying processes are highly non-linear, which implies difficulty in creating a viable general model in any drying system. Finally, it is impractical to collect large quantity of data to generate an accurate mathematical representation of the system because of long moisture measurement time, as mentioned in Section I.1.2.

Instead of attempting to create a generic model that can represent a drying process over large range of parameter values, it is more practical to find an approximated function between inputs and the output response within a local parameter space. There are several merits in limiting the size of parameter space. First, by concentrating data collection only within a relevant parameter space, fewer data points would be required to generate a function approximation than if data points are diluted over a large parameter space. Second, it is possible to approximate a high-order function as a lower-order function within a sufficiently small local parameter space. The approximation could simplify the highly non-linear relationship between inputs and the output response in the drying process, allowing for simpler analysis and optimization of data within the local region. Consider Figure IV.2 as an example. In the figures, the underlying function is a second-order polynomial function and local linear regression over different sizes of ranges of input values are performed to approximate the underlying function. The smaller the input range is, the better approximated function becomes. However, the approximated function would not be able to represent regions of parameter outside of the range of parameter values from which data are collected. Therefore, there is a trade-off between accuracy of approximated model and the size of parameter space in which the approximated model can accurately representation.

Not finding a global optimum or an optimum over a large parameter space is not an issue for this project. Because the process is an actively running large-batch process, it is both risky and undesirable to conduct experiments involving extreme values of input parameters, especially in a large-batch process such as the air-drying stage. The goal of parameter value optimization should therefore be limited to finding a local optimum point in the parameter space.



(a) Large range (b) Medium range

(c) Small range (d) Very small range

Figure IV.2: Example of local function approximation under different sizes of ranges of inputs

This project would use design of experiment (DoE) methodology to systematically collect data points for statistical analysis such as regression and ANOVA analyses. As reviewed in Section II.2, design of experiments provides a framework for systematic series of tests such that one can observe and identify effects of changes of input values on the output response. The methodology has also been applied to optimize manufacturing processes, examples of which are also reviewed Section II.2. Output responses would then be used to find optimal parameter values of the system using regression analysis and ANOVA, which are commonly used tools for process optimisation in the literature. The results will be fully described in Section V.3. It will be assumed that the range of selected levels in the design of experiment is sufficiently small to be accurately represented using approximated low-order functions which will be solved by regression analyses.

IV.2.1 <u>Inputs in the DoE Experiment</u>

Input process variables can be classified as "controllable" and "uncontrollable". In the post-mixing processes, only three controllable process variables can be identified including the air-drying oven temperature, the roasting machine's conveyor speed, and the roasting machine's gas flow rate. The output response of the process will be the process capability index (C_{pk}) of roasted fish sheets, which is designated of the target of optimisation in this phase of experiment, as discussed earlier in Section IV.2. Other input factors such as humidity and temperature of factory and roasting temperature are uncontrollable and will be excluded from the experiments.

For clarification, while adjustment of roasting machine's gas flow rate (which is a controllable input) can theoretically control the roasting temperature, in practice, the temperature has high variation despite the machine being set up with constant gas flow rate. When the gas flow rate is set to its maximum flow rate, which is the default flow rate setup in the production line, the collected data reports temperature of 164.25 7.97, as shown in Figure IV.3 and based on data in Appendix E. As a result, roasting temperature will have a weak relationship with the gas flow rate. Because the flow

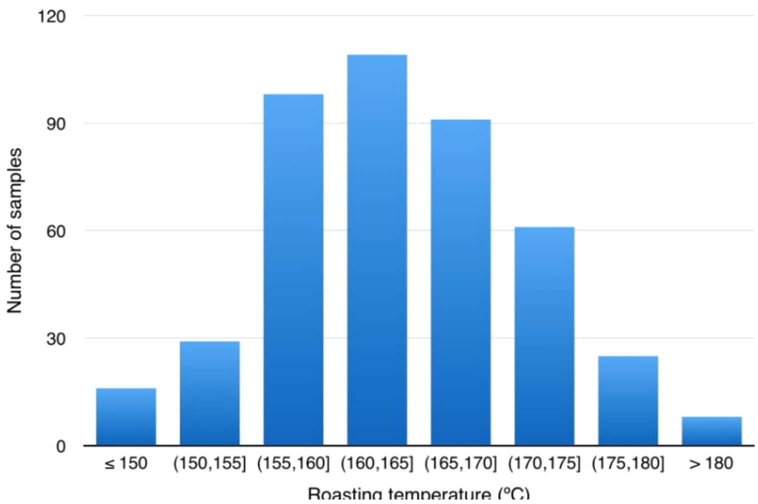


Figure IV.3: Histogram of temperature in the roasting machine with the gas flow lever in a fixed position rate of natural gas is controlled using a simple, manual gas valve, the control of the flow rate is also not precise.

Figure IV.4: The roasting gas flow rate lever with cardboard dial marked with levels used in experiments

While control of the roasting temperature is arguably an area of improvement, this project will not focus on the improvement. As stated in Section I.4, the scope of this project is limited to process improvement which does not significantly disrupt production lines and does not make technological improvement of production machines. Because any improvement would require modification of the roasting machine, the improvement is outside of the scope of this thesis. Therefore, the roasting temperature will be treated as an uncontrollable input in the DoE experiment. For the rest of the thesis, various levels of the gas flow rate used in experiments would be marked on a cardboard dial as shown in Figure IV.4.

IV.2.2 Design of Experiments

IV.2.2.1 Points of Consideration in DoE Design

There are several issues that need to be considered in the design of experiments for this project. First, some factors that could have significant relationship with the response are not controllable or cannot be precisely controlled. As noted in Section IV.2.1, the roasting temperature is not controllable, while gas flow rate in the roasting machine is controllable but cannot be precisely controlled.

Second, because the post-mixing production is a large-batch production, especially during the air-drying stage, the manufacturer is reluctant to fix production parameters to extreme low and high values for an entire production day because it can result in significant amount of scraps. Finally, the data collection process is slow. Due to the long moisture measurement time, the number of samples to be collected per day can be limited. Each day, a maximum of 5 data points that includes moisture at key stages of fish sheet production (including post-mixing, post-air-drying and post-roasting) can be collected.

IV.2.2.2 Design Decisions for DoE Design

Three factors, including the air-drying temperature, the roasting conveyor speed and the roasting machine’s gas lever position will be included in the DoE experiment. However, due to design issues indicated above, the experiments will be designed with the following characteristics. First, to handle the issue of extreme values being used in the experiments, experimented input values will be selected within “safe” ranges such that any combination of these input values do not produce significant amount of scraps. Advice from the manufacturer are used to determine these ranges.

Prior to the intervention, values of parameters for air-drying temperatures and roasting conveyor speeds are 58 to 63 degrees Celsius and 50 to 70 Hertz respectively. Based on the manufacturer’s recommendation, conservative safe ranges for the air-drying temperatures and roasting conveyor speed are set up to be 60 to 62 degrees Celsius and 60 to 70 Hertz respectively. Because the roasting gas flow rate cannot be quantified, the experiment would use “low” and “high” levels as recommended by the manufacturer. The safe ranges of quantifiable inputs are summarised in Table IV.1.

Although the selected ranges of parameter values are relatively small, it is expected that switching parameter values to each experimentation levels would result in significant differences on response values. A difference of one degree Celsius on the air-drying temperature would have sizeable impact on the post-air-drying and post-roasting moistures because of the long latency of the air-drying process. As for the roasting conveyor speed, a difference of 5 Hz in the roasting machine is expected to result in differences in the post-roasting moistures because the conveyor speed becomes noticeably faster or slower after the 5 Hz change.

Despite the relatively small range of the air-drying temperature, variation in the temperature’s level is likely to exhibit significant changes on post-air-drying and post-roasting moisture of fish sheets because of high latency on the air-drying process. As noted in Section I.1.2, fish sheets undergo approximately one hour of air-drying in an air-drying oven. It will be demonstrated in Section V.3 that the experimental results suggest that the fish sheet’s post-air-drying and post-roasting moistures significantly change because of variations in parameter values within the selected levels.

Second, it is necessary to set the low gas flow rate significantly different from the high flow rate because of the large variance of roasting temperature for any given gas flow rate, as illustrated in Figure IV.3. Otherwise, main effects and interactions involving gas flow rates could be too subtle to be observed.

Third, data for experiments with low gas flow rate will be collected in dedicated experiment sessions rather than random sampling from production line used for data collection in treatments with high gas flow rate. Setting gas flow rates to lower settings result in slower warm-up period and lower average roasting temperature which could result in portions of fish sheets not being sufficiently dried. To prevent significant amount of scraps from being produced, experiments using low gas flow rates are contained in experiment sessions instead of setting the parameter for the whole production day. These experiments are conducted during the first hour of the production day before restoring the gas flow rate to the default rate which is the high rate in the experiment. Because of accumulation of temperature in the roasting machine, the experiments could not be conducted at later time of the day. By measuring moisture of post-air-drying moisture only once per session, the number of data points that could be collected per session is increased to nine data points, compared to five data points that could be collected using random sampling.

The fourth decision is to limit the number of levels of roasting gas flow rates in the DoE experiment to two levels: high and low levels, instead of three levels like the air-drying oven's temperature and the roasting conveyor speed. This decision has a serious implication on the DoE experiment.

This decision was made to reduce the number of treatments involved in the experiment due to limited number of available experiment time slots. Because experimental treatments that use roasting gas flow rates other than "high", which is the default gas flow rate, must be tested in scheduled experimental sessions because of the manufacturer's unwillingness to run the treatment full-time in the production line. This makes data collection for treatments with non-high gas flow rates costlier than treatments with high gas flow rate. By reducing the number of the roasting gas flow rate's level, the number of treatments could be reduced from 27 treatments to 18 treatments. Another incentive to reduce the number of levels of the gas flow rate is its lack of precise control over the levels, which makes it more difficult for operators to make adjustment than the other two factors.

Despite the benefits offered by the decision, it also have implications on the experiments. According to Montgomery (2009), it is not possible to create a second-order response surface model using two-level experiments, and there are not any guarantees that the underlying surface between the two levels of the roasting gas flow rate would have linear characteristics, i.e. the model does not involve quadratic terms of the flow rate. Therefore, it is expected that the optimal gas flow rate would be either the "high" level, which is also the default level, or the "low" level used in the experiment. Due to budget and time constraints, more detailed optimisation of the gas flow rate will have to be conducted as a future work by collecting more data experiments on nine treatments which use gas flow rate at the middle level between the "high" and the "low" levels. With these additional data points, there would be three levels for the gas flow rate which would allow second-order response surface to be with respect to the flow rate to be modelled.

The fifth and final decision is that a given dedicated experiment session would include experiments on all treatments that share the same air-drying oven's temperature and the same roasting machine's gas flow rate. Because fish sheets that are used in these experiment sessions should be drawn from the same batch of air-dried fish sheets, these samples are not independent. To reduce the number of correlated samples, fish sheets in a session are processed under multiple treatments. More specifically, all samples are air-dried with the same temperature and roasted under the same gas flow rate, but the samples are split up so that many roasting conveyor speeds are used. An example of the schedule is given in Table IV.2. In the schedule, procedures alternate the roasting conveyor speed among 60, 65 and 70 Hz, allowing three data points to be collected for each speed. This procedure is feasible because among the three input factors, roasting machine's conveyor speed is the only factor whose effect of adjustment is immediate.

Table IV.1: Experiment levels of each factors

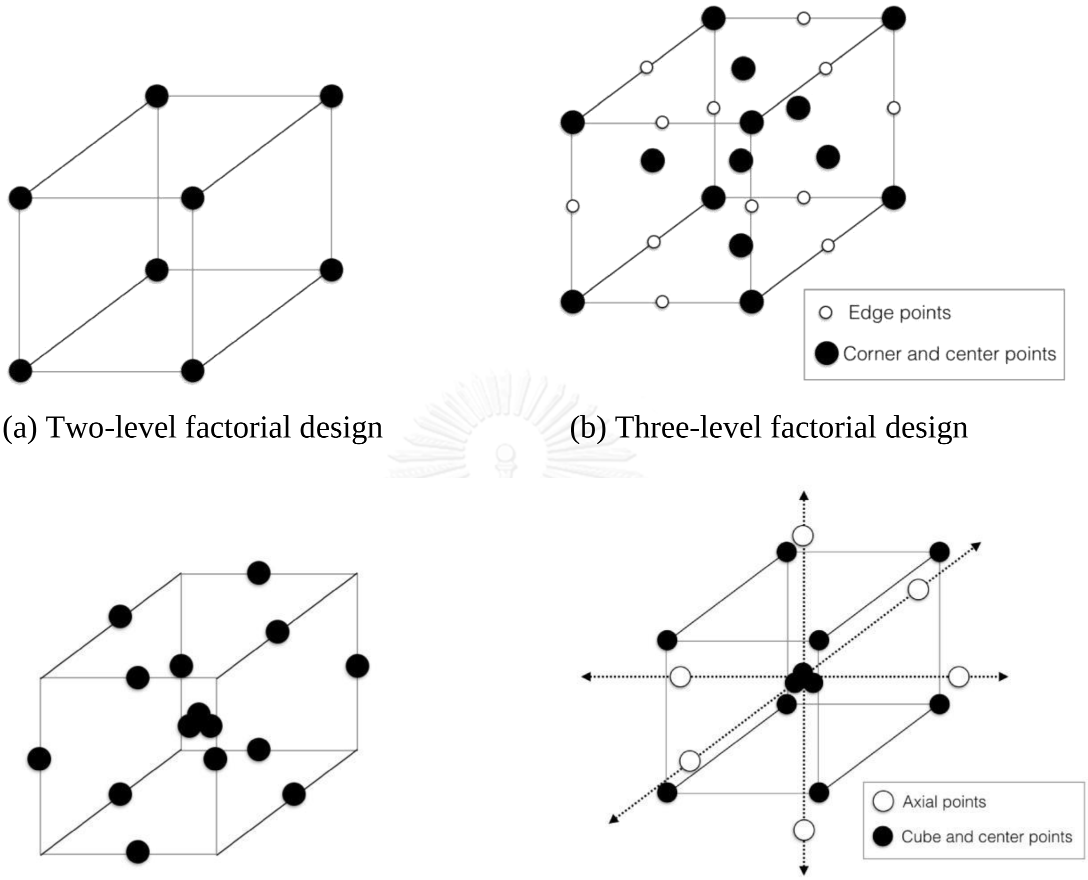
	Low	**Medium**	**High**
Air-drying temperature	60 °C	61 °C	62 °C
Roasting conveyor speed	60 Hz	65 Hz	70 Hz
Roasting gas flow rate	Low	-	High

Table IV.2: Example of experiment schedule

No	**Air-drying temperature**	**Roasting gas flow rate**	**Roasting conveyor speed**
1	62 °C	Low	60 Hz
2	62 °C	Low	65 Hz
3	62 °C	Low	70 Hz
4	62 °C	Low	60 Hz
5	62 °C	Low	65 Hz
6	62 °C	Low	70 Hz
7	62 °C	Low	60 Hz
8	62 °C	Low	65 Hz
9	62 °C	Low	70 Hz

IV.2.2.3 <u>DoE Design Selection</u>

The DoE experiment used three-level full factorial design because the design is chosen is because experimenting on three levels per factor enables detection of non-linearity in relationships between inputs and the response, i.e. the post-roasting moisture in fish sheets, which is not possible when using only two levels per factor. Other designs that have been considered include Central Composite Design (CCD), Box-Behnken Design, and two-level full factorial design. Illustration of each experimental design for three factors is provided in Figure IV.5. Advantages and disadvantages of these designs are explored in Rakić, Kasagić-Vujanović et al. (2014) under the context of development and optimization of a liquid chromatographic method for determination of fluconazole and its impurities. In this paper, Rakić, Kasagić-Vujanović et al. (2014) concludes that while two-level factorial design and Box-Behnken design require fewer experimental data points than CCD and three-level factorial design, the latter two models produce significantly better models. The authors then conclude that CCD is superior to three-level full factorial design because it requires fewer data points while still being able to produce good models. In the context of this project, CCD is, however, not a good choice because it requires experimentation in more extreme parameter spaces than in other designs which runs counter to the manufacturer's reluctance to perform experiments that risk producing significant amount of scraps. The above arguments suggest that the three-level full factorial design is the most suitable design for this project among the discussed models.



(a) Two-level factorial design (b) Three-level factorial design

(c) Box-Behnken design (d) Central composite design

Figure IV.5: Illustration of various experimental designs with 3 factors

As it was stated earlier in this section that the roasting gas flow rate would use only two factors, and there were several undesirable impacts on the experiments, including inability to model second-order response surface with respect to the gas-flow-rate factor.

Therefore, it is arguable that, instead of the compromise in the design, each factor should still have three levels per factor but fractional factorial design should be considered instead of a full factorial design. According to Montgomery (2009), under an assumption that higher-order interactions are negligible, it is possible to conduct a fractional number of experimental runs to gather information about the main effects and low-order interactions of the factors. In other words, a three-level fractional factorial design such as 3^{3-1} design could reduce the number of experimental runs to a third of the number of runs in a full factorial design. A procedure for constructing three-level fractional factorial designs could be found in the literature such as Xu (2005).

However, with only three factors, the experiment might have too coarse resolution if the fractional factorial design is used. For example, the 3^{3-1} design could be classified as a Resolution III design. According to Montgomery (2009), these designs do not have aliases between main effects but could have aliases between main effects and two-factor interactions. Because two-factor interaction could be significant to the response surface, the fractional factorial design is unsuitable for the use case of this project.

As a result, a three-level full factorial design was selected, except for the roasting gas flow rate which would have two levels. There would therefore be 18 treatments in the DoE experiment as summarised in Table IV.3.

IV.2.3 Sample Size for DoE Experiment

The sample size of data used for C_{pk} calculation vary widely depending on the cost of data collection. On one end of the spectrum are studies whose data are collected from real production line, such as Amiri, Bashiri et al. (2011), that could collect fewer data points. In the study, which explores effects of input values to process capability in a batch manufacturing process, uses only four data points for calculation of each C_{pk}. This is much lower than the minimum number of 30 data points, as discussed in Section II.4. Although no justification for the small number of data points is given in the paper, it could have been motivated by time and resource constraints because the paper requires calculation of C_{pk} in 18 treatments for three different responses. An additional data point per calculation of C_{pk} would require 54 more data points, which could incur significant extra cost to the study.

On the other end are studies whose process capability indices are calculated using data simulated by computer algorithms, which allows large data points to be produced. In studies such as Jeang (2015) and Lee, Park et al. (2010), data points are generated from Monte Carlo simulation for DoE experiments to optimise the process capability using response surface methodology (RSM). In Lee, Park et al. (2010), it is stated that as many as 10,000 data points are generated from the simulation.

Table IV.3: Input values for each treatment in the DoE experiment

No.	Air-drying temperature	Roasting conveyor speed	Roasting gas flow rate
1	60 °C	60 Hz	High
2	60 °C	65 Hz	High
3	60 °C	70 Hz	High
4	61 °C	60 Hz	High
5	61 °C	65 Hz	High
6	61 °C	70 Hz	High
7	62 °C	60 Hz	High

8	62 °C	65 Hz	High
9	62 °C	70 Hz	High
10	60 °C	60 Hz	Low
11	60 °C	65 Hz	Low
12	60 °C	70 Hz	Low
13	61 °C	60 Hz	Low
14	61 °C	65 Hz	Low
15	61 °C	70 Hz	Low
16	62 °C	60 Hz	Low
17	62 °C	65 Hz	Low
18	62 °C	70 Hz	Low

As reviewed in Section II.4, the recommended number of sample size for calculation of C_{pk} values should be 30 samples at a minimum, with 50 samples or more being the recommended number of samples. Collecting enough data points to calculate accurate C_{pk} values for all 18 treatments would require at least 540 samples. With the data collection rate at five to nine data points per production day, it would take at least 6 months to collect the recommended minimum number of samples (as summarised in Table IV.4).

Table IV.4: Expected data collection time to collect recommended amount of data

Experiment	**Total Data**	**Data per Day**	**Production Days**	**Estimated Duration**
High-flow-rate experiments	270	5	54 days	4.51 months
Low-flow-rate experiments	270	9	30 days	2.31 months

Collecting all the recommended data for over six months incur direct and opportunity cost on the manufacturer, and prevent other major improvements on processes and the machines from proceeding. A feasible solution is to trade off reliability of the C_{pk} result with the reduction of number of samples. The number of data points required for calculation of each C_{pk} was therefore reduced from 30 to 18 samples, lowering the total number of data points to 324 samples, which reduces data collection time by 35.71%. A summary of the data collection time estimation is given in Table IV.5.

Table IV.5: Expected data collection time to collect reduced amount of data

Experiment	**Total Data**	**Data per Day**	**Production Days**	**Estimated Duration**
High-flow-rate experiments	162	5	36 days	2.77 months
Low-flow-rate experiments	162	9	18 days	1.38 months

The key reason that the number of samples used in a C_{pk} calculation is selected to be eighteen is because it is a multiple of nine, which is the maximum number of data points that could be collected in an experiment session for treatments with low gas flow rate. In other words, it could use all data points that could be collect in two sessions for C_{pk} calculation. For simplicity in interpreting data, the number of samples of treatments with high gas flow rates were also eighteen to create a balanced experiment design, even though eighteen is not a multiple of five, which is the maximum number of data points that could be collected in high-flow-rate treatments.

IV.2.4 Data Collection for DoE Experiment

The eighteen treatments that would be used in the experiment have been listed in Table IV.3. As it will be argued in Section IV.2.3, the number of samples that would be collected per treatment would be eighteen. The order of data collection is randomised, and the schedule for data collection is provided in Appendix C.1. The data were collected by quality control operators who oversee moisture measurement. The format of the data collection form used in data collection is provided in Appendix C.2. The collected data used in the analysis is given in Appendix C.3. Any statistics that could be derived from the raw data would be analyzed and discussed in Section V.3.

On average, there are thirteen production days per month during which relevant products are produced. Due to slow measurement time, which limits the number of samples that could be measured per day, up to 5 data points including moistures at the end of each process could be collected per day. If some processes' moistures are ignored such as when the post-air-drying moisture is measured only once, as in the case of experiments on treatments whose roasting gas flow rate is set to the low level, up to 9 data points could be collected per day.

IV.2.5 Methodology for Parameter Optimisation

As mentioned in earlier in Section IV.2, data collected from the experiments would be used for fitting the best response surface with regression analysis. The regression function would consist of linear, quadratic and interaction terms whose p-values are above the threshold of 0.05. The solved regression function would then be used to find an optimal treatment which help maximise C_{pk} value of post-roasting fish sheet's moisture. In addition, ANOVA analysis, main-effect and interaction plots will be used to determine and confirm significance of factors to the process's response.

The above methodology would be applied in two main approaches. The first approach per-forms analysis on C_{pk} values of subgroups of data with the same input parameter values, while the second approach analyses values of individual data points. These approaches have their own stength and weaknesses. On the one hand, post-roasting moistures of fish sheets are the only response that could be used in analysis on individual data. C_{pk} values, as well as mean and variance which are key values for calculation of C_{pk} as defined in Equation 4.1, cannot be calculated for individual data points, making it unable to directly optimise the value C_{pk} index in this case. As such, the only optimisation available for the second approach of data analysis is centering the post-roasting moisture of fish sheets to targeted value of 15%. Although it is not possible to directly optimise the value of C_{pk}, centering post-roasting moisture would partially optimise its value because the value of C_{pk} index increases as the sample mean is closer to the middle point between the upper and the lower specification limits.

On the other hand, grouping data points according to input values allow calculation of C_{pk}, mean and standard deviation of subgroups and enable direct optimisation of C_{pk} with the regression function. However, as pointed out in the literature, regression anal-ysis on data generated from grouped data should be used and interpreted with caution. Observations made in Freund (1971) suggests that using means of grouped data to per-form regression analyses is inferior to analyses using all data points. Reasons given in the paper include: (1) The R-square value of the regression using means of grouped data is artificially increased, (2) Estimates of error variance can be biased and imprecise, and (3) The adequacy of the model cannot be tested. The only use case that can justify the use of means in regression analysis is when input data are subjected to errors. Similarly, Mtz-Vera de Rey, Galindo et al. (2001) finds that goodness of fit of regression models can be spuriously increased if individual scores are grouped into mean scores, and that predicative values obtained from models generated from individual scores and mean scores are different. Because of these potential pitfalls in the analysis using grouped data, it is necessary to also analyse the experiment based on both individual data points and grouped data which allows direct optimization of C_{pk} values.

Because two approaches are used, different optimisation results could be reached. As a result, the regression function and ANOVA analysis over C_{pk} would be the primary function used for optimisation. The analytical results over individual data points would be used for complementary discussion, especially to provide explanation when both sets of results are significantly different.

Results of analysis would be presented and discussed in Section V.3.

CHAPTER V
EXPERIMENTAL DATA AND ANALYSIS

V.1 Experimental Result from Intervention in Mixing Stage

This section will evaluate the result of experiments that would compare the variation of moisture in fish mixture before and after intervention in the mixing process whose methodology is described in Section III.2.2. As discussed in Section III.2.4, to evaluate the intervention's success in reducing the moisture variation in fish mixture, an F-test was used for hypothesis testing on a null hypothesis that the variances of moisture in fish mixture before and after the intervention are the same under thresholds $\alpha = 0.05$ and $\beta = 0.2$. The collected data on fish mixture's moisture before and after the intervention are listed in Appendix B.2.

Relevant statistics of the data are summarised in Table V.1. Based on the table, the ratio of variance of moisture after intervention to that of moisture before intervention, $\frac{S_{\alpha}^2}{S_{\beta}^2}$, is $\frac{0.01171^2}{0.03778^2} = 0.09607$. The calculated ratio is significantly less than the assumed ratio of 0.6667 used for determining the minimum number of samples as indicated in Section III.2.4.

According to the power curve shown in Figure V.3, the minimum number of samples that could have rejected the null hypothesis with ratio of variances being 0.09607 would be 7 samples. Because the number of collected samples far exceeds the minimum number of samples, the two-variance F-test analysis unsurprisingly rejects the null hypothesis with p-values less than 0.001, which is lower than the threshold significance level of $\alpha = 0.05$. The confidence interval plot, shown in Figure V.1 also confirms that the both groups have significantly different variances. The histogram of mixture's moisture data, shown in Figure V.2, demonstrates that despite having different variances, distributions of both groups are approximately normal, confirming that the use of F-test, which assumes normality in the data, in the hypothesis testing is appropriate.

While it could be concluded that the moisture of fish mixture has been significantly reduced, the data also show that the moisture variation and process capability of minced fish which is the raw material were also significantly reduced, presumably due to tighter control over the supplier's product quality. According to production statistics prior to any intervention as shown in Table I.3, the standard deviation of moisture in minced fish from the Source-1 supplier is 2.87% and its C_{pk} index value is 0.28. The standard deviation of moisture in minced fish from the Source-2 supplier is 3.13% and its C_{pk} index value is 0.42. After the intervention, as reported in Table V.2, the standard deviations of moisture of minced fish from Source-1 and Source-2 suppliers dropped to 2.03% and 1.99% respective. Their C_{pk} values also improved to 0.52 and 0.53 respectively. According to the F-test, it could be concluded that the decrease of moisture variation in minced fish from both sources are significant with p-values less than 0.001. The full statistical result of the two-variance test is given in Appendix D.1.

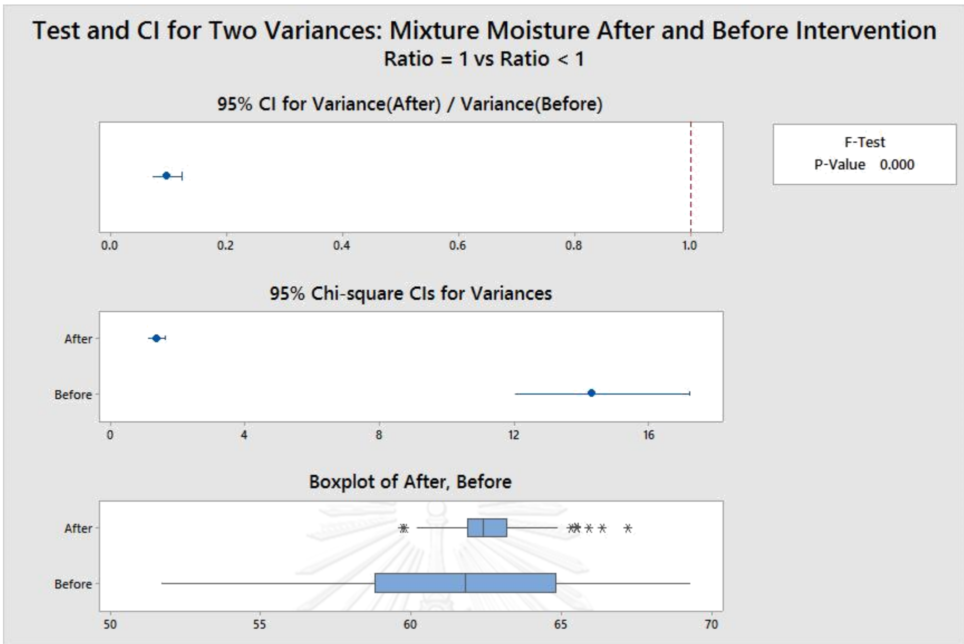


Figure V.1: Confidence interval of fish mixture moisture after and before

Table V.1: Statistics of moisture in fish mixture before and after intervention in mixing process

	Before intervention	**After intervention**
Average	61.730%	62.577%
Standard deviation	3.778%	1.171%
Minimum	51.70%	59.74%
Maximum	69.30%	67.20%
Sample Size	171	171

It is arguable that the reduction of moisture variation and the improvement of C_{pk} index value in fish mixture are due to the quality improvement in raw material and not due to the water-adjustment intervention. However, the reduction of moisture variation in minced fish alone could not fully explain the amount of reduced moisture variation observed in fish mixture after the intervention.

A model of the fish mixture's moisture that accounts for moisture variable is represented in Equation 5.1. The model is adapted from Equation 3.1 which is a deterministic formula for determining moisture of fish mixture. In this model, is a random variable that accounts for random noises not accountable by variation in ingredients' moisture and weights.

$$m_{mix} = \frac{m_{water}r_{water} + m_{source1}r_{source1} + m_{source2}r_{source2} + m_{other}r_{other}}{r_{water} + r_{source1} + r_{source2} + r_{other}} + \varepsilon \qquad (5.1)$$

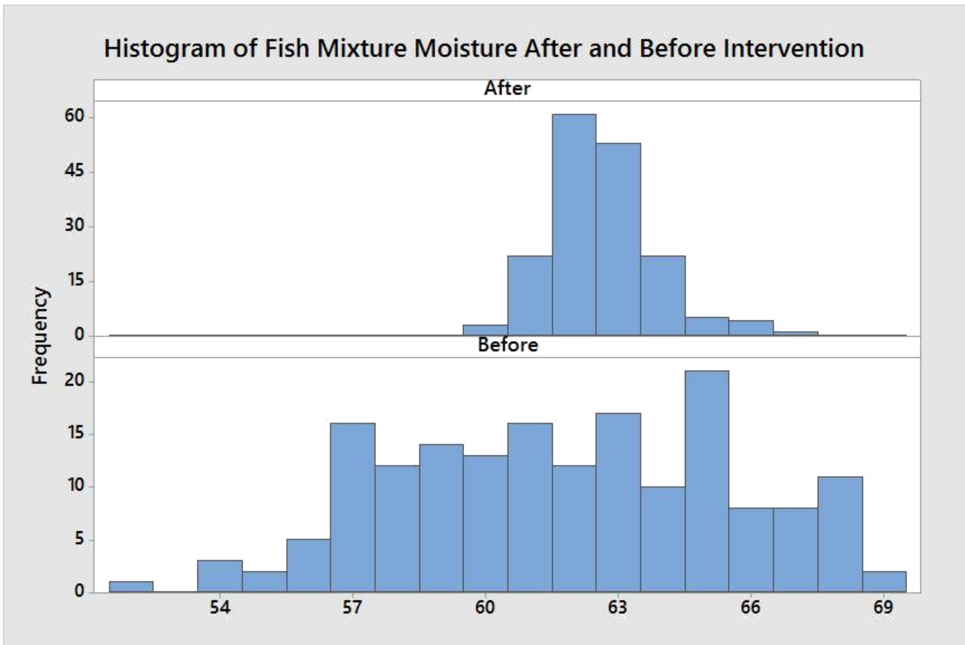


Figure V.2: Histograms of fish mixture moisture after and before intervention

From Equation 5.1, a variance of the mixture's moisture could be derived as a formula shown in Equation 5.2, where the sum of all ingredient weights is constant and represented as C, i.e. C = $r_{water} + r_{source1} + r_{source2} + r_{other}$ = 45 + 30 + 30 + 45.1 = 150.1. To derive the formula, the following two assumptions are made. First, the weights of ingredients have zero variance, and therefore are treated as constants. Second, moistures of ingredients and the random noise (ε) are independent of one another. With these two assumptions, it is possible to derive the variance of mixture's moisture as a sum of variances of ingredients' moistures because the variance of a sum of random variables is equal to a sum of variance of these random variables if the variables are i.i.d. random variables.

$$\begin{aligned} Var(m_{mix}) &= Var\left(\frac{m_{water}r_{water} + m_{source1}r_{source1} + m_{source2}r_{source2} + m_{other}r_{other}}{r_{water} + r_{source1} + r_{source2} + r_{other}} + \varepsilon\right) \\ &= \left(\frac{r_{water}}{C}\right)^2 Var(m_{water}) + \left(\frac{r_{source1}}{C}\right)^2 Var(m_{source1}) \\ &\quad + \left(\frac{r_{source2}}{C}\right)^2 Var(m_{source2}) + \left(\frac{r_{other}}{C}\right)^2 Var(m_{other}) + Var(\varepsilon) \end{aligned} \quad (5.2)$$

From Equation 5.2, no data are available to directly determine values of variances of other ingredients and the random noise. However, because the during-mixing intervention does not involve other ingredients, it would be assumed that the variance of moisture of other ingredients and the random noise remain the same after the intervention. For further discussion, let the sum of variances of other ingredients' moisture and random noise be designated as V, i.e. V = $\left(\frac{r_{other}}{C}\right)^2 Var(m_{other}) + Var(\varepsilon)$.

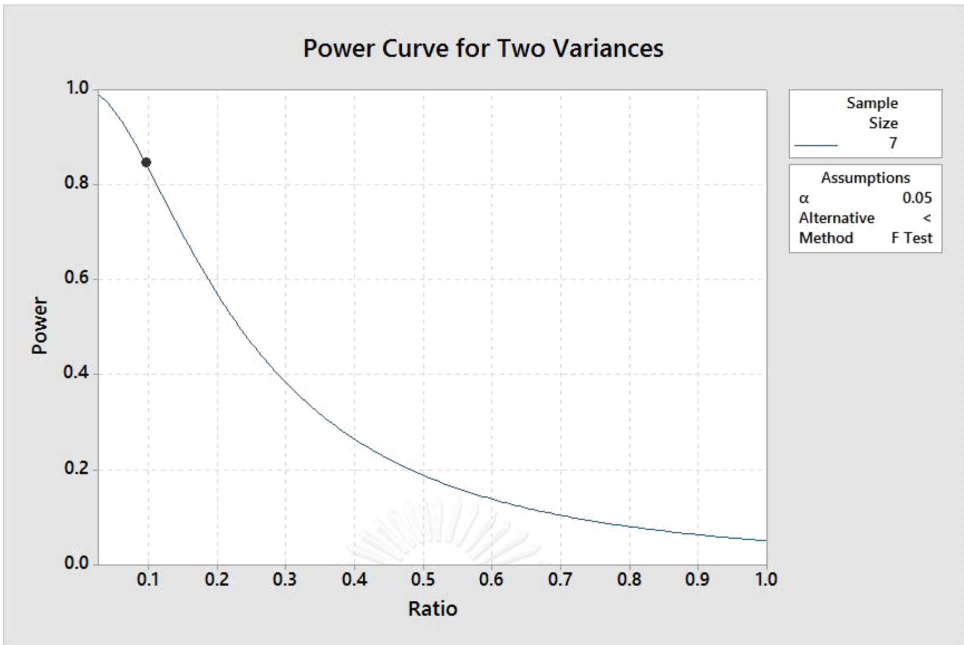


Figure V.3: Power curve with power = 0.8 at ratio = 0.09607

The value of V could be solved by substituting known variances of ingredients before intervention as shown in Equation 5.3.

$$
\begin{aligned}
Var(m_{mix,before}) &= \left(\frac{r_{water}}{C}\right)^2 Var(m_{water}) + \left(\frac{r_{source1}}{C}\right)^2 Var(m_{source1}) \\
&\quad + \left(\frac{r_{source2}}{C}\right)^2 Var(m_{source2}) + \left(\frac{r_{other}}{C}\right)^2 Var(m_{other}) + Var(\varepsilon)\cdot \\
0.03778^2 &= \left(\frac{45}{150.1}\right)^2 \cdot (0) + \left(\frac{30}{150.1}\right)^2 (0.0287)^2 + \left(\frac{30}{150.1}\right)^2 (0.0313)^2 + V \\
&= (0.039947)[(0.0287)^2 + (0.0313)^2] + V \\
0.001427 &= 0.000072 + V \\
V &= 0.001355
\end{aligned} \tag{5.3}
$$

The derivation shown in Equation 5.4 calculates an expected standard deviation of fish mixture’s moisture that has taken effects of reduction in minced fish’s variances into account. By using the solved value of V in the derivation, it is predicted that the standard deviation should have been 0.03725, 3.725%. However, the observed standard deviation of fish mixture after the intervention is only 1.171%. A one-variance Chi-square test confirms that the predicted and actual standard deviations are significantly different, with p-value less than 0.001. A full result of the one-variance Chi-square test will be given in Appendix D.2). As a result, it could be concluded that the water adjustment procedure described in Section III.2.2 succeeds in significantly reducing moisture variation in the fish mixture.

$$\begin{aligned}
Var\left(m_{mix,after,predicted}\right) &= \left(\frac{r_{water}}{C}\right)^2 Var(m_{water}) + \left(\frac{r_{source1}}{C}\right)^2 Var(m_{source1}) \\
&\quad + \left(\frac{r_{source2}}{C}\right)^2 Var(m_{source2}) + \left(\frac{r_{other}}{C}\right)^2 Var(m_{other}) + Var(\varepsilon) \\
&= \left(\frac{r_{water}}{C}\right)^2 Var(m_{water}) + \left(\frac{r_{source1}}{C}\right)^2 Var(m_{source1}) \\
&\quad + \left(\frac{r_{source2}}{C}\right)^2 Var(m_{source2}) + V \\
&= (\frac{45}{150.1})^2 \cdot 0 + (\frac{30}{150.1})^2 \cdot 0.0203^2 \\
&\quad + (\frac{30}{150.1})^2 \cdot 0.0199^2 + 0.001355 \\
&= 0 + 0.039947 \cdot [0.000412 + 0.000396] + 0.001355 \\
&= 0.001387
\end{aligned}$$

$$Stdev\left(m_{mix,after,predicted}\right) = \sqrt{0.001387} = 0.03725 \tag{5.4}$$

V.2 Performance Evaluation after Phase-1 Intervention

After the intervention, the C_{pk} value of post-roasting moisture significantly improved. Before the intervention, its value was just 0.04, as reported in Table I.3. After the intervention has been implemented, its value increased to 0.40, as shown in Table V.2, which are derived from raw data in Appendix A.2. Likewise, the C_{pk} value of the post-air-drying moisture was improved from 0.19 to 0.50.

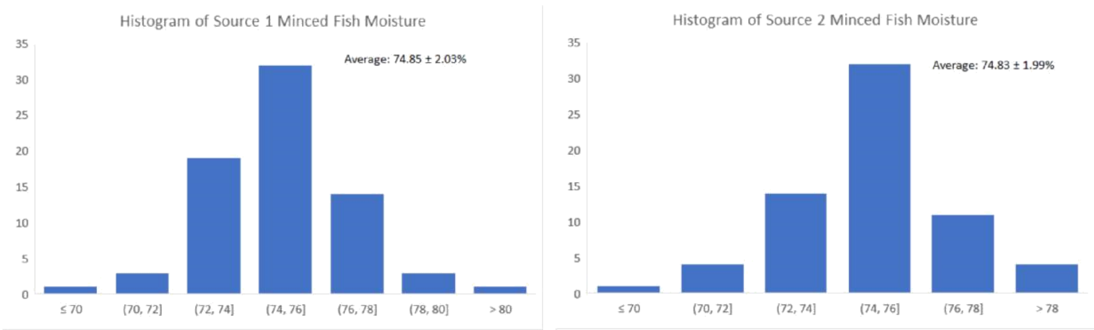
Because C_{pk} is an index calculated based on the sample mean and standard deviation, the improvement of its value could be a result of either or both factors. To better understand effects of the phase-1 intervention on the production process, comparison of production statistics before and after the intervention, as well as the significance of their difference in means and standard deviations, based on post-phase-1 data in Appendix A.2, are given in Table V.3. In Table V.3, two-variance tests are used to determine whether standard deviations of moistures before and after phase-1 intervention are different. Two-sample t-tests are used to determine whether the means of moistures before and after phase-1 intervention are statistically different. Finally, one-sample t-tests are used to determine whether the averages are not significantly close to their target levels, i.e. whether the null hypothesis that the averages are the same as the target level can be rejected. Based on the statistics, sample average of fish sheet’s moisture in all stages before and after the intervention are significantly different. The shift in means could be observed when comparing to histograms of moistures before intervention in Figures I.10 and I.11 with those of moistures after intervention in Figures V.4 and V.5. However, neither post-air-drying nor post-roasting moistures are statistically the same as their respective target levels. On the contrary, only the standard deviation of moisture of the fish mixture are statistically different after the intervention.

Table V.2: Production statistics after phase 1's intervention

	LSL	USL	Target Mean	Observed Mean (Sample Size)	Observed Stdev (Sample Size)	C_p	C_{pk}	C_{pm}
Minced fish moisture (Source 1)	70%	78%	74%	74.85% (171)	2.03% (171)	0.66	0.52	0.61
Minced fish moisture (Source 2)	70%	78%	74%	74.83% (73)	1.99% (73)	0.67	0.53	0.62
Post-mixing moisture	N/A	N/A	N/A	62.58% (73)	1.17% (73)	N/A	N/A	N/A
Post-sheet-forming moisture	N/A	N/A	N/A	50.84% (73)	1.44% (73)	N/A	N/A	N/A
Post-air-drying moisture	18%	28%	23%	23.86% (73)	2.77% (73)	0.60	0.50	0.57
Post-roasting moisture	12%	18%	15%	15.7% (73)	1.91% (73)	0.52	0.40	0.49

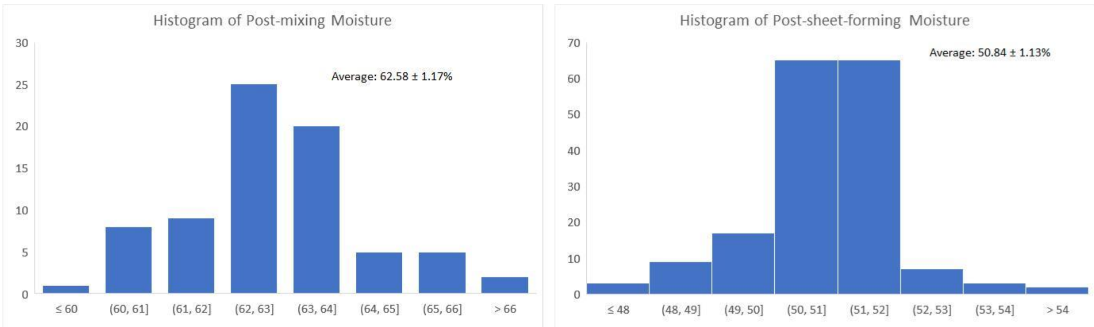
Table V.3: Comparison of production statistics before and after the phase-1 intervention and significance of their differences

Moisture at Stage	Average Before (Sample Size)	Average After (Sample Size)	Average Significantly Different? (p-value)	Average Not Significantly Not Close to Target? (p-value)	Stdev Before (Sample Size)	Stdev. After (Sample size)	Stdev. Significantly Different? (p-value)
Post-mixing	61.73 (171)	62.58 (171)	Yes (0.006)	N/A	3.778 (171)	1.171 (171)	Yes (<0.0005)
Post-sheet-forming	47.43 (171)	50.79 (73)	Yes (<0.0005)	N/A	1.338 (171)	1.435 (73)	No (0.462)
Post-air-drying	26.62 (171)	23.86 (73)	Yes (<0.0005)	Yes (0.01)	2.452 (171)	2.770 (73)	No (0.205)
Post-roasting	17.76 (171)	15.70 (73)	Yes (<0.0005)	Yes (0.003)	2.189 (171)	1.910 (73)	No (0.190)

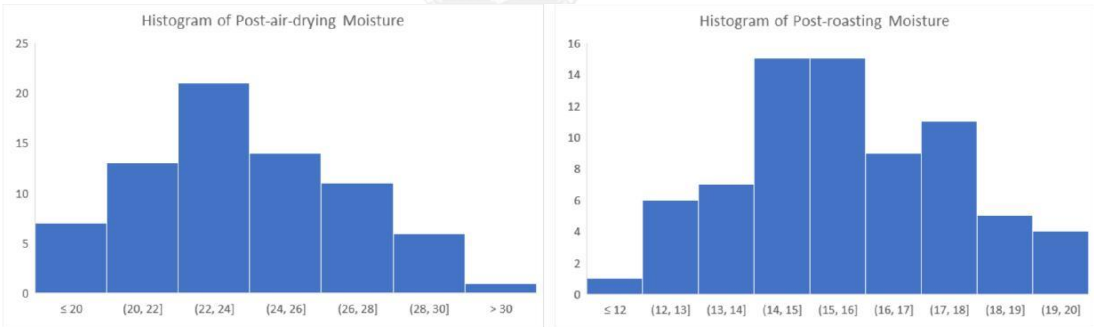


(a) Source 1 (b) Source 2

Figure V.4: Histograms of moisture of frozen minced fish from various sources after intervention in phase 1



(a) Post-mixing (b) Post-sheet-forming



(c) Post-air-drying (d) Post-roasting

Figure V.5: Histograms of moisture of fish sheets at various points in the process after intervention in phase 1

Although the primary objective of the Phase-1 intervention is the reduction of the moisture variation in fish mixture, the statistics discussed above implies that sample means of moisture in various stages are shifted closer to their specification targets, as shown in Tabl V.3. Although the averages of moistures in post-air-drying and post-roasting fish sheets are not significantly close to the target levels, the means are significantly shifted in the direction of the target level. As for the fish mixture's moisture, although no specification target is available, the expected moisture according to the recipe is 63.4764% according to Equation 3.4. According to the statistics, the sample mean of the fish mixture after intervention is statistically closer to the expected moisture than that before intervention. These shifts in sample means are most likely responsible for the improvement of C_{pk} index values of the post-air-drying and post-roasting moistures. By moving the average of mixture's moisture towards the expected level, the means of moistures in later stages are also shifted closer to the target level.

On the contrary, standard deviations of fish sheets in post-mixing stages do significantly differ from the pre-intervention level despite the reduction in fish mixture. One explanation is that significant amount of moisture variations are introduced after the mixing stage. This conclusion is unsurprising, given that production parameters in post-mixing stages can be freely adjustable according to the operators' judgment. Elimination of these subjective adjustment of parameter values is the key objective of the Phase-2 intervention which is to fix parameter values at optimised levels.

Another aspect of performance evaluation is how well the process can produce fish sheets with post-air-drying and post-roasting moistures within specification limits and, if necessary, correct samples with out-of-specification post-air-drying moistures to have post-roasting moistures within the specification limits. The base line performance for the process prior to intervention has been presented in Figure I.9, and Tables I.1 and I.2. As concluded in Section I.2, operators cannot consistently correct the samples' moisture, leaving many samples with post-roasting moisture outside of the specification limits. The baseline indicates that out of collected 171 samples, only 77 or 45.03% have both post-air-drying and post-roasting moistures within specification limits. Of the 120 samples with post-air-drying moistures within specification limits, 43 or 41.79% have post-roasting moistures outside of specification. Of the 51 samples with post-air-drying moistures out-side of specification limits, operators could correct only 21 samples or 41.18% to have post-roasting moisture within specification limits.

These statistics were greatly improved after the implementation of the Phase-1 intervention, as illustrated in Figure V.5 (whose raw data are listed in Table A.2) and summarised in Tables V.4 and V.5. Out of 73 samples collected after the experiment, 57 samples or 78.08% have both post-air-drying and post-roasting moistures within specification limits. Of the 66 samples with post-air-drying moistures within specification limits, only 9 samples or 13.64% have post-roasting moistures outside of specification limits. The correction success rate is also high, being able to correct 6 out of 7 samples, or 85.71% with out-of-specification post-air-drying moistures to have post-roasting moistures within specification.

The above statistics should be cautiously evaluated. Because the standard deviations of moistures before and after the intervention are not statistically different, the improvement does not imply that operators became more capable in correcting the sample's moisture. Instead, the improvement could be explained primarily by the shift in sample means towards the target means for both post-air-drying and post-roasting moistures after the Phase-1 intervention, as discussed in an earlier part of this section.

As shown in the scatter plot of samples' moistures before the intervention in Figure I.9, samples have both moistures far above their respective target means. On the contrary, samples in the scatter of moistures after the intervention in Figure V.6 (summarized from raw data in Appendix A.2) are more clustered within the specification limits. Because samples with out-of-specification post-air-drying and post-roasting moistures after the intervention are much closer to the specification limits than those before the intervention, it is arguable that samples' post-roasting moisture have more probability in falling back within the specification limits, resulting in better statistics. The randomness could be a result of the subjective parameter adjustment, as argued earlier, or inherent noise in the post-mixing processes.

Table V.4: Matrix of the number of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits after phase-1 intervention

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	9	1
	Inside Specification	57	6

Table V.5: Matrix of distribution of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits after phase-1 intervention

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	12.33% (9/73)	1.37% (1/73)
	Inside Specification	78.08% (57/73)	8.22% (6/73)

Anyhow, the post-intervention process is better-controlled than the process before intervention, with more samples with post-air-drying and post-roasting moistures within specification limits. This is supported by better values of process capability index, C_{pk}, as mentioned at the start of the section. The statistics presented in this section would be treated as a baseline performance for evaluation of intervention in the second phase, whose methodology has been elaborated in Chapter IV.

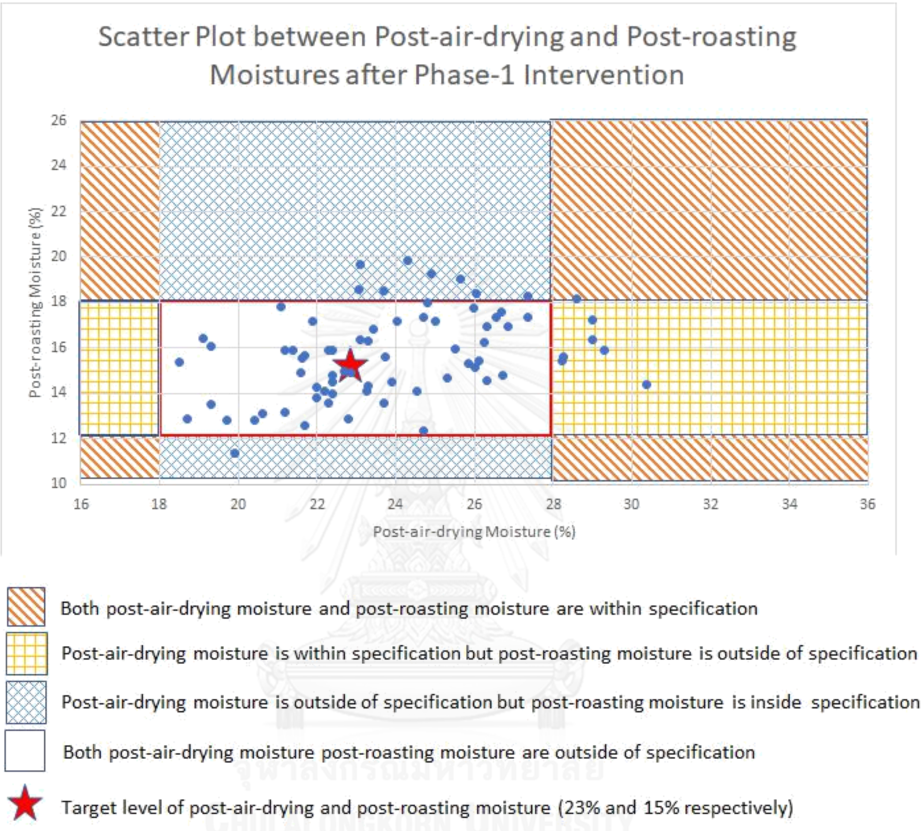


Figure V.6: Scatter plot between post-air-drying and post-roasting moistures of samples after intervention in phase 1

V.3 Experimental Result from Intervention in Post-mixing Stages

This section will analyse experimental result collected from production-parameter optimisation experiment. As described in Chapter IV, the experiment conducted a design of experiment (DoE) to systematically collect response data from production under various control parameter values. The DoE design adopted in the experiment is a full factorial design with three factors and one response. Raw data of experiments are listed in Section A.3 and C.3. Basic statistics of the experiments, grouped by treatment inputs, are summarised in the Table V.7. For brevity in further discussion and analysis, abbreviations will be used in figures, tables and equations for factor and response names. These abbreviations and their full names are listed in Table V.6.

The collected data were analysed using regression analysis to model the response surface. The regression function is then used to find optimal control parameter values. As discussed in Section IV.2.5, two responses would be considered in the analyses: individual post-roasting moisture and the C_{pk} index values of post-roasting moistures of samples produced under different treatments.

Table V.6: Abbreviations of factors and responses used in design of experiments

Abbreviation	**Full Name**
T	Air-drying temperature
S	Roasting conveyor speed
F	Roasting machine's natural gas flow rate
M	Post-roasting moisture
C_{pk}	Post-roasting process capability index C_{pk}

V.3.1 Analyses with Individual Post-roasting Moisture as a Response

As a first step, the regression analysis is first performed on all quadratic, linear and interaction terms. The result of the regression analysis is a regression function shown in Equation 5.5. According to the ANOVA statistics which tests significance of each term in the regression analysis in Tables V.8 and V.9, terms that are significant enough to be included in the regression function include the air-drying temperature (T), the roasting gas flow rate (F), the quadratic term of the air-drying temperature (T*T), and the interaction between the air-drying temperature and the roasting gas flow rate (T*F).

$$M = 2680 - 84.4T - 1.62S - 55.5F + 0.685\,T*T + 0.0141\,S*S \\ -0.0044\,T*S + 0.749\,T*F + 0.1170\,S*F \quad (5.5)$$

Table V.7: C_{pk} values and statistics of treatments in the design of experiments

Air-drying Temp. (°C)	**Roasting Conveyor Speed (Hz)**	**Roasting Gas Flow Rate**	**Average Moisture(%)**	**Std. Dev. Moisture (%)**	**C_{pk}**	**Sample Size**
60	60	High	16.13	1.88	0.333	18
60	65	High	15.28	2.05	0.440	18
60	70	High	16.80	2.29	0.174	18
61	60	High	15.27	1.43	0.639	18
61	65	High	15.62	1.66	0.479	18
61	70	High	16.12	2.00	0.313	18
62	60	High	15.22	1.89	0.491	18
62	65	High	15.04	1.81	0.544	18
62	70	High	15.63	2.39	0.331	18
60	60	Low	19.96	2.84	-0.230	18
60	65	Low	19.01	2.46	-0.137	18

60	70	Low	19.49	2.28	-0.218	18
61	60	Low	17.25	3.68	0.067	18
61	65	Low	17.23	3.88	0.065	18
61	70	Low	16.51	3.65	0.136	18
62	60	Low	17.44	3.89	0.048	18
62	65	Low	17.13	3.68	0.078	18
62	70	Low	17.07	3.21	0.097	18

To confirm the preliminary result above, another regression analysis is conducted using stepwise backward elimination with significance threshold of 0.05. The resulting regression function, shown in Equation 5.6. As expected, the function includes all terms earlier identified to be significant in the regression function. For reference, a summary of the regression analysis and significance of each term's coefficient is provided in Tables V.10 and V.11.

$$M = 2635 - 84.7\,T - 47.9\,F + 0.685\,T*T + 0.749\,T*F \quad (5.6)$$

As reported in Table V.12, its value of coefficient of determination, or R^2, and that of adjusted R^2 value are relatively low, being 19.92% and 18.92% respectively. The low values of R^2 implies that the function generated from the regression analysis do not fit well with the available data.

Table V.8: Summary of ANOVA statistics in regression analysis with individual post-roasting moisture as a response (without stepwise backward elimination)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	8	616.29	77.0361	10.38	0.000
T	1	34.25	34.2483	4.61	0.032
S	1	1.85	1.8530	0.25	0.618
F	1	42.79	42.7857	5.76	0.017
T*T	1	33.76	33.7568	4.55	0.034
S*S	1	8.96	8.9606	1.21	0.273
T*S	1	0.07	0.0711	0.01	0.922
T*F	1	30.30	30.3000	4.08	0.044
S*F	1	18.49	18.4919	2.49	0.116
Error	315	2338.49	7.4238		
Lack-of-Fit	9	50.82	5.6468	0.76	0.658
Pure Error	306	2287.67	7.476		
Total	323	2954.78			

Table V.9: Summary of significance of each term's coefficients in regression analysis with individual post-roasting moisture as a response (without stepwise backward elimination)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2680	1209	2.22	0.027	
T	-84.4	39.3	-2.15	0.032	44907.50
S	-1.62	3.23	-0.50	0.618	7611.50
F	-55.5	23.1	-2.40	0.017	5836.00
T*T	0.685	0.321	2.13	0.034	44653.00
S*S	0.0141	0.0128	1.10	0.273	2029.00
T*S	-0.0044	0.0454	-0.10	0.922	5836.00
T*F	0.749	0.371	2.02	0.044	5583.50
S*F	0.1170	0.0742	1.58	0.116	255.50

Table V.10: Summary of ANOVA statistics in regression analysis with individual post-roasting moisture as a response (with backward stepwise elimination)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	4	588.59	147.147	19.84	0.000
T	1	34.68	34.679	4.68	0.031
F	1	33.31	33.311	4.49	0.035
T*T	1	33.76	33.757	4.55	0.034
T*F	1	30.30	30.300	4.08	0.044
Error	319	2366.19	7.418		
Lack-of-Fit	13	78.52	6.040	0.81	0.652
Pure Error	306	2287.67	7.476		
Total	323	2954.78			

Table V.11: Summary of significance of each term's coefficients in regression analysis with individual post-roasting moisture as a response (with backward stepwise elimination)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2635	1194	2.21	0.028	
T	-84.7	39.2	-2.16	0.031	44654.00
F	-47.9	22.6	-2.12	0.035	5582.50
T*T	0.685	0.321	2.13	0.034	44653.00
T*F	0.749	0.371	2.02	0.044	5583.50

Table V.12: R-square values of regression analysis with post-roasting moisture as a response

S	R-sq	R-sq (adj)	R-sq (pred)
2.72351	19.92%	18.92%	17.42%

The regression function shows that the air-drying temperature (T), roasting gas flow rate (F), their interaction term (T*F), and the quadratic term of the air-drying temperature (T*T) are significant factors. A contour plot of the response surface based on values of both factors is illustrated in Figure V.7. The objective of optimisation based on the regression function is to find a set of input parameter values whose response post-roasting moisture is or approaches the target level of 15% as much as possible. By using the MiniTab software for optimisation of the response, whose details are shown in Table V.13, it is determined that an optimal set of input values is when the air-drying temperature is 61:2727 C and the roasting gas flow rate should be set to the high/maximum level. The predicted response moisture at the optimal point is 15.1675%, as shown in the optimisation plot in Figure V.9.

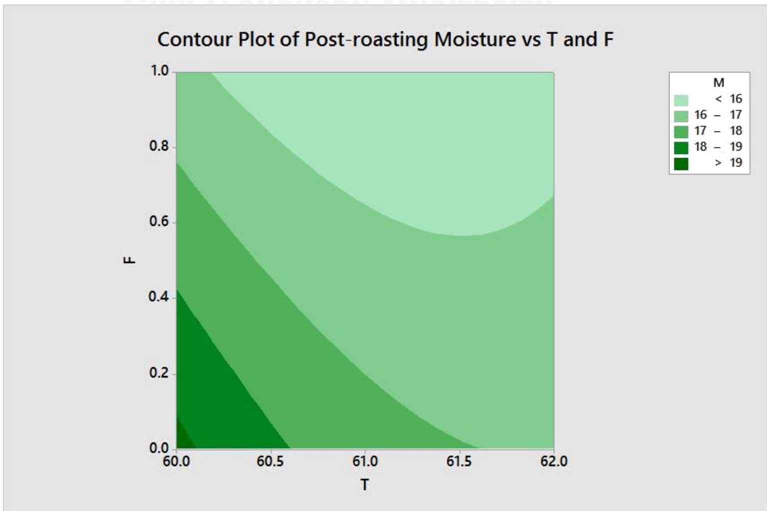
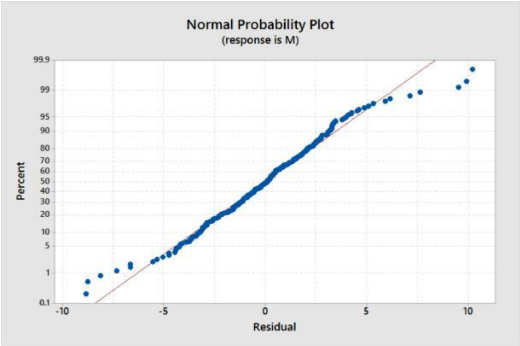
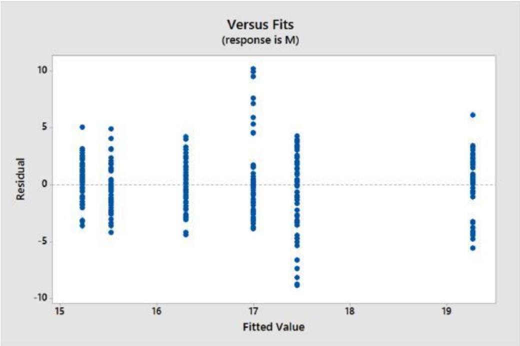


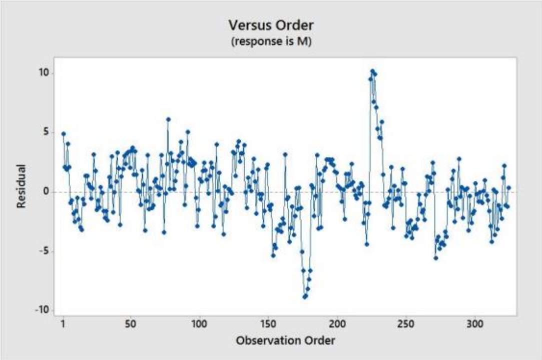
Figure V.7: Contour plot of response surface of individual post-roasting moisture generated from regression analysis



(a) Normal Probability Plot



(b) Residual VS Fits Plot



(c) Residual VS Order Plot

Figure V.8: Residual plots of regression function on individual post-roasting moistures

Table V.13: Optimisation solution for response surface model with individual post-roasting moisture as a response in the region where T = (60,62) and F = (0,1)

T	F	M Fit	Composite Desirability
61.2727	1	15.1675	0.986267

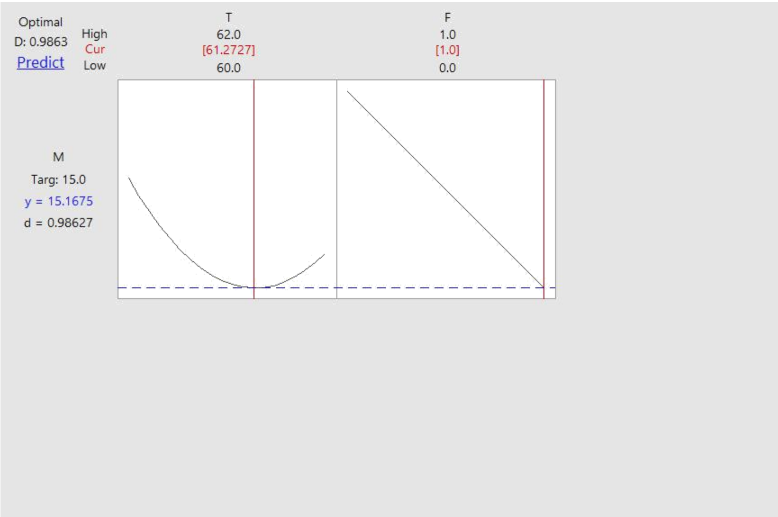


Figure V.9: Optimisation plot of post-roasting moisture (target at 15%)

However, the low R^2 value, reported in Table V.12, suggests that the regression function is a poor fit for the observed data, i.e. the function cannot model the underlying response with sufficient accuracy. As it is shown in residual histogram and normal probability plot in Figure V.8, there are some outlier data points whose residuals are either extremely high or low, suggesting that the regression function does not accurately predict post-roasting moistures for these data points. Causes of the lack of fit of the regression function could be that other factors, possibly uncontrollable ones, which have statistical significance on the response are not included in the model, or that there is significant amount of noise in the measured post-roasting moistures. Anyhow, the poor fit of the regression function in Equation 5.6 to the data suggests that the model might not be suitable for optimisation of control parameter values.

In addition, the regression function with respect to the air-drying temperature unexpectedly show a minimum point within the experimented range of temperatures. Because terms used in regression analysis are quadratic, linear and interaction terms, it is expected that the fit regression function to be a quadratic function, which should have a minimum or maximum point. Intuitively, the post-roasting moisture should be monotonically decreased as the air-drying temperature increase. Instead, the optimisation plot in Figure V.9 shows a minimum point within the experimented range. The result is counter-intuitive because it implies that fish sheet's post-roasting moisture will rise after the air-drying temperature has been increased beyond a certain threshold. One explanation could be that the regression function does not fit the observed data very well, as suggested by the low R-squared value of the regression function, as discussed earlier.

The regression function with respect to the roasting gas flow rate suggests that the post-roasting moisture monotonically decrease as the roasting gas flow rate increases. Because the roasting gas flow rate should positively correlate with the roasting temperature, the result in this respect is intuitive.

V.4 Analyses with C_{pk} Index Values for Post-roasting Moisture Under Different Treatments as a Response

It is reviewed in Section IV.2.5 that regression analysis on grouped data could artificially increase the value of R^2 value, and the literature generally favors conducting regression analysis on individual data points rather than on grouped data. Hence, the project first analyses the response surface modeling using individual post-roasting moistures as a response in Section V.3.1. However, the analysis shows that the generated regression function has low R^2 value, making it a poor representation of the response surface. To provide more well-rounded analysis, a regression analysis on C_{pk} values are used to generate an alternative, and potentially better, model for optimisation of the index value, which is the key objective of the project. A summary of C_{pk} values and relevant statistics of results for each treatment in the DoE experiment has been summarised in Table V.7, using raw data from Appendix A.3 and C.3. As shown in the table, the regression analysis would involve only 18 data points, one for each treatment used in the DoE experiment.

The regression analysis first starts with constructing a regression model from terms including linear, quadratic and interaction up to the third order. The result of the regression is shown in Equation 5.7. Based on the ANOVA result table shown in Tables V.14 and V.15, none of the terms are immediately significant.

$$\begin{aligned} Cpk = \; & -2476 + 75.4\,T + 34.8\,S + 203\,F - 0.571\,T*T - 0.083\,S*S - 0.96\,T*S \\ & -7.13\,T*F + 0.553\,S*F + 0.00648\,T*T*S + 0.0589\,T*T*F \\ & +0.00135\,T*S*S - 0.0019\,T*S*F - 0.00354\,S*S*F \end{aligned} \tag{5.7}$$

To find a regression function whose all terms have significance on the value of the response, stepwise backward-elimination was applied to the regression analysis with significance threshold of 0.05. The regression analysis generates a function shown in Equation 5.8. For reference, a summary of the regression analysis and significance of each term's coefficient is provided in Tables V.16 and V.17.

$$\begin{aligned} Cpk = \; & -458 + 14.87\,T - 0.1207\,T*T - 0.0811\,T*F + 0.1880\,S*F \\ & - 0.001614\,S*S*F \end{aligned} \tag{5.8}$$

The modelled function has a value of coefficient of determination, R^2, of 96.13% and that of adjusted R^2 being 94.52%, as reported in Table V.18. The high values of R^2 values suggest a good fit of the regression function to the data. Likewise, the normal probability plot of residuals in Figure V.11a shows that residuals in the data have approximately normal distribution, confirming that the model is a good fit to the data.

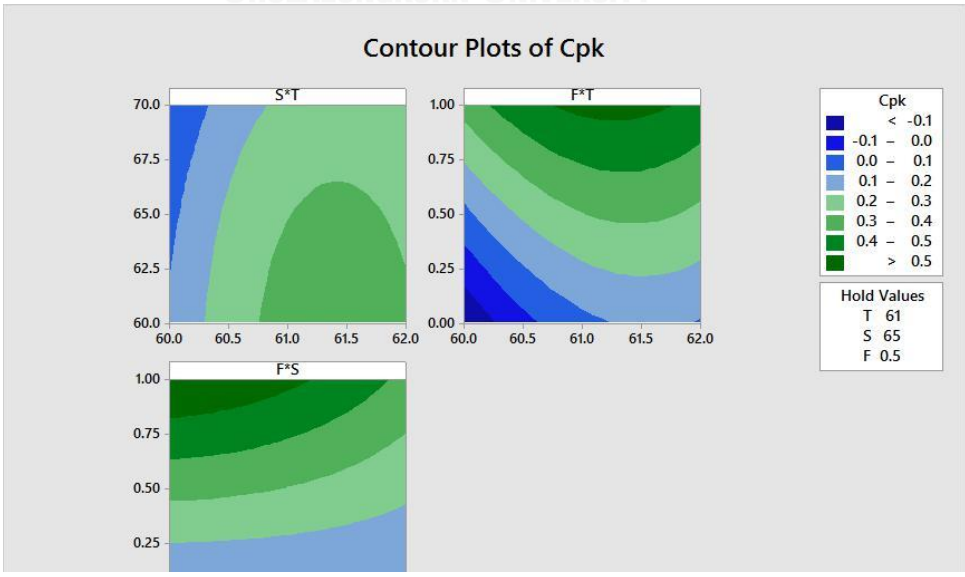


Figure V.10: Contour plot of response surface of C_{pk} index value of post-roasting moisture generated from regression analysis

The regression function's significant factors include the air-drying temperature (T), a quadratic term of air-drying temperature (T*T), the interaction term between the air-drying temperature and the roasting gas flow rate (T*F), an interaction term between the roasting conveyor speed and the roasting gas flow rate (S*F), and an interaction between a quadratic term of the conveyor speed and the roasting gas flow rate (S*S*F). Contour plots of the response surface for each pair among three factors (T, S and F) are illustrated in Figure V.10.

Because F has only two levels and the data denotes its high level as 1 and its low level as 0, the factor can be interpreted as a dummy variable whose value is 1 if the gas flow rate is set to high. As a result, Equation 5.8 can be interpreted to be consist of two cases when F = 0 and when F = 1 as shown in Equation 5.9. One notable feature in the reinterpreted equation is that the conveyor belt's speed becomes significant only if the roasting temperature is set to the high level (although its effects on the C_{pk} is off-set by the change in the air-drying temperature's coefficient). In other words, the regression analysis suggests that the significance of the roasting conveyor belt's speed is dependent on the roasting gas flow rate (which could imply the roasting temperature). Therefore, further investigation should be conducted on the effect of the roasting gas flow rate on the significance, e.g. when F has a value between 0 and 1 in future iterations of the project.

$$Cpk = \begin{cases} -458 + 14.7889\,T - 0.1207\,T * T + 0.1880\,S - 0.001614\,S * S, & F = 1 \\ -458 + 14.87\,T - 0.1207\,T * T, & F = 0 \end{cases} \quad (5.9)$$

Table V.14: Summary of ANOVA statistics in regression analysis with post-roasting C_{pk} as a response (without stepwise backward elimination)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	13	1.11965	0.086127	16.30	0.008
T	1	0.00591	0.005910	1.12	0.350
S	1	0.00493	0.004933	0.93	0.389
F	1	0.00290	0.002895	0.55	0.500
T*T	1	0.00511	0.005107	0.97	0.381
S*S	1	0.00310	0.003096	0.59	0.487
T*S	1	0.00398	0.003980	0.75	0.434
T*F	1	0.00339	0.003393	0.64	0.468
S*F	1	0.00302	0.003017	0.57	0.492
T*T*S	1	0.00280	0.002796	0.53	0.507
T*T*F	1	0.00347	0.003472	0.66	0.463
T*S*S	1	0.00304	0.003041	0.58	0.490
T*S*F	1	0.00019	0.000190	0.04	0.859
S*S*F	1	0.00783	0.007834	1.48	0.290
Error	4	0.02113	0.005283		
Total	17	1.14078			

Table V.15: Summary of significance of each term's coefficients in regression analysis with post-roasting C_{pk} as a response (without stepwise backward elimination)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-2476	2209	-1.12	0.325	
T	75.4	71.3	1.06	0.350	11536607.50
S	34.8	36.0	0.97	0.389	73618463.50
F	203	274	0.74	0.500	63832219.50
T*T	-0.571	0.581	-0.98	0.381	11408841.50
S*S	-0.083	0.109	-0.77	0.487	11328921.50
T*S	-0.96	1.11	-0.87	0.434	2.72436E+08
T*F	-7.13	8.89	-0.80	0.468	2.50735E+08
S*F	0.553	0.732	0.76	0.492	1944482.75
T*T*S	0.00648	0.00890	0.73	0.507	73692801.00
T*T*F	0.0589	0.0727	0.81	0.463	62417918.50
T*S*S	0.00135	0.00178	0.76	0.490	11456433.00
T*S*F	-0.0019	0.0103	-0.19	0.859	1426582.25
S*S*F	-0.00354	0.00291	-1.22	0.290	133598.50

Table V.16: Summary of ANOVA statistics in regression analysis with individual post-roasting C_{pk} as a response (with stepwise backward elimination)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	5	1.09669	0.219338	59.69	0.000
T	1	0.05942	0.059422	16.17	0.002
T*T	1	0.05829	0.058289	15.86	0.002
T*F	1	0.02147	0.021465	5.84	0.032
S*F	1	0.03234	0.032336	8.80	0.012
S*S*F	1	0.03963	0.039626	10.78	0.007
Error	12	0.04409	0.003675		
Total	17	1.14078			

Table V.17: Summary of significance of each term's coefficients in regression analysis with C_{pk} as a response (with stepwise backward elimination)

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	-458	113	-4.06	0.002	
T	14.87	3.70	4.02	0.002	44653.92
T*T	-0.1207	0.0303	-3.98	0.002	44653.00
T*F	-0.0811	0.0336	-2.42	0.032	5134.87
S*F	0.1880	0.0634	2.97	0.012	20949.75
S*S*F	-0.001614	0.000492	-3.28	0.007	5490.12

Table V.18: R-square values of the regression analysis with post-roasting C_{pk} as a response

S	R-sq	R-sq(adj)	R-sq(pred)
0.0606178	96.13%	94.52%	90.66%

By using the MiniTab software to maximise the C_{pk} based on Equation 5.8, it is determined that an optimal set of input values is when the air-drying temperature is 61:2525 C, the air-drying conveyor speed is 60 Hz and the roasting gas flow rate should be set to the high/maximum level. The predicted C_{pk} at the optimal point is 0.6002, as shown in the optimisation plot in Figure V.12. The detail of the optimisation result is given in Table V.19.

Table V.19: Optimisation solution for response surface model with post-roasting C_{pk} as a response in the region where T = (60,62), S = (60,70) and F = (0,1)

T	S	F	Cpk Fit	Composite Desirability
61.2525	60	1	0.600209	0.955129

Unlike the case of regression analysis which uses post-roasting moistures as a response which has been discussed in Section V.3.1, it is intuitively possible for the regression function with C_{pk} values as a response to have a minimum point within the experimented range. For example, when air-drying temperature is increased, post-roasting moisture in fish sheets would decrease. The C_{pk} value would rise until the moisture of fish sheets reach the target level of 15%. Afterwards, the C_{pk} would continue to decrease as the fish sheets' moisture become increasingly lower than the target level. Similar explanation could be given for the case of roasting conveyor speed and roasting gas flow rate.

Based on the optimisation plot in Figure V.12, the peak of the C_{pk} could be observed when air-drying temperature is between the experimented range. On the contrary, a maximum point of the regression function with respect to the conveyor speed does not exist within the experimented range and should lie in the region lower than the lower bound of 60 Hz. This observation suggests that future works on parameter optimisation should include conveyor speeds below 60 Hz in optimisation experiments. The peak of the C_{pk} index with respect to the roasting gas flow rate is observed at the high level of gas flow rate. However, because there are only two levels used in the experiment, it is possible for the maximum of the C_{pk} index to be observed in the middle region. Therefore, it is advisable that more levels of gas flow rates be included in future experiments.

The optimised control parameter values based on the C_{pk} response are similar to the parameter values which are optimised based on post-roasting moistures as discussed in Section V.3.1. Because the digital controller of the air-drying temperature and the roasting conveyor speed cannot include decimal points, the optimised parameter values would be rounded to T = 61 C, S=60Hz and F set to the high/maximum level. With the rounded-up values, it is expected that C_{pk} index would have a value of 0.5924 based on the regression function in Equation 5.8.

For convenience, a summary of optimised parameter values for each optimisation methods and their expected C_{pk} values under Equation 5.8 are given in Table V.20. Because the optimised set of parameter values for the regression function with post-roasting moisture response does not include terms involving the roasting conveyor speed (S), the conveyor speed could be set to any values between 60 and 70 Hz which is the experimented range of speeds. The comparison uses S = 60Hz to calculate the expected C_{pk} because it is the conveyor speed optimised using the regression function with C_{pk} response.

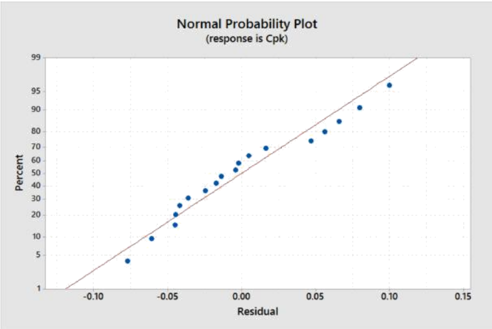
From the optimisation results discussed above, regardless of the responses used in the analysis, optimal values for two of the three factors used in the DoE experiment lie at extreme ends of the range of experimented values. The result suggests that better combination of parameter values lie in the region with greater roasting gas flow rate and the roasting conveyor speed below 60Hz. As such, it could be argued that the ranges of parameter values for these factors which are used in the DoE experiment might have been too small.

Because of the roasting machine's configuration, the roasting gas flow rate cannot be set to higher levels without modifying the roasting machine such as by changing the gas pipe's size to ones with larger radii. On the contrary, it is possible to set up the roasting conveyor speed as low as 40Hz although the fish sheets would be considered too dry or burnt if the conveyor speed is set to such slow speed. As argued in Section IV.2.2, because it is preferable to collect samples which are as independent from one another as possible, parameter values used in the DoE experiment are selected such that any combination of values would not result in sizable scraps if they are used for the entire production day.

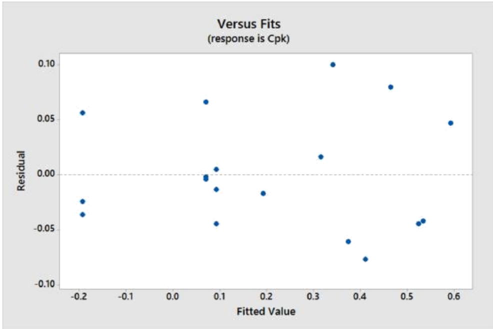
Anyhow, the analysis suggests that the experimented range for the conveyor speed might have been too conservative. Because an interaction term between the conveyor speed and the roasting gas flow level is statistically significant in the regression with C_{pk} as a response, statistical significance of the conveyor speed could be more pronounced if larger ranges of the speed were experimented. The collected data and analytical result could be used to defend the use of slower speed for roasting conveyor in future iterations of the experiment.

Table V.20: Comparison of optimised parameter values based on types of responses

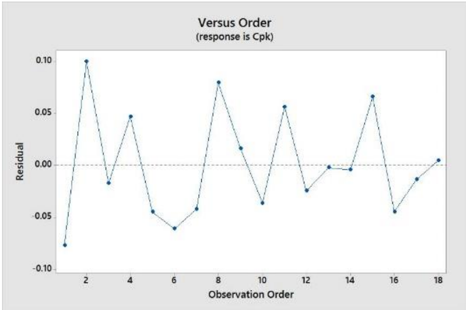
Factors	**Response**		**Rounded-up Values**
	Post-roasting Moisture	**Cpk**	
Air-drying Temperature (T)	61.2727	61.2525	61
Roasting Conveyor Speed (S)	N/A	60	60
Roasting Gas Flow Level (F)	High / Maximum	High / Maximum	High / Maximum
Estimated C_{pk} using Equation 5.8	0.6001 (with S=60)	0.6002	0.5924



(a) Normal Probability Plot



(b) Residual Versus Fits Plot



(c) Residual Versus Order Plot

Figure V.11: Residual plots of regression function on C_{pk} index value of post-roasting moisture

V.5 Performance Evaluation after Phase-2 Intervention

According to the optimisation result in Section V.4, it is expected that the C_{pk} value after the Phase-2 intervention could be as high as 0.5924. It is a considerable improvement compared to 0.40 which is the C_{pk} value after the Phase-1 intervention, as summarised in Section V.2.

To evaluate the performance of the process after the optimisation based on the Phase-2 intervention, data points of fish sheets produced under the optimised parameter values are collected. The parameter values solved in Section V.4 include the air-drying temperature (T) being set to 61 C, the roasting conveyor speed (S) being set to 60Hz and the roasting gas flow rate (F) being set to the high level. The data are collected using the data collection form shown in Section C.2 and the collected data are listed in Section C.4.

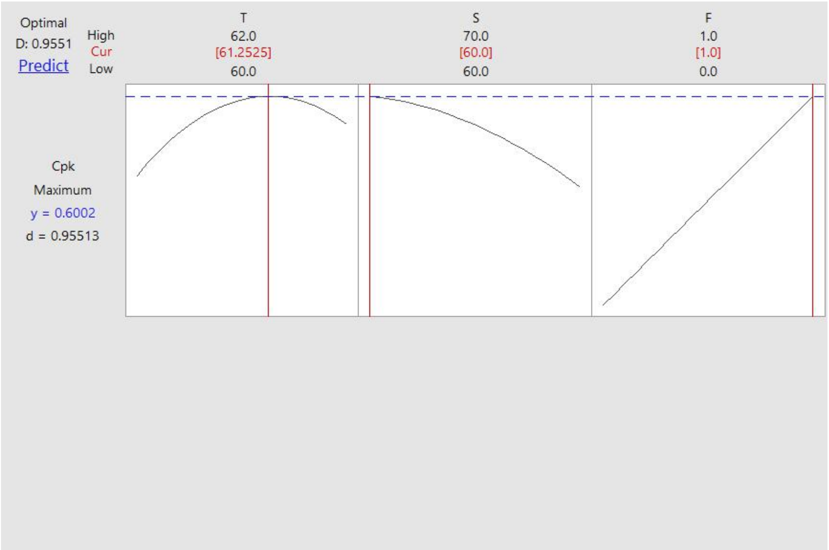


Figure V.12: Optimisation plot of post-roasting moisture's C_{pk} values (maximising)

The production statistics of the evaluation experiments can be summarised in Table V.21, based on raw data from Appendix A.4. Compared to the post-phase-1 statistics in Table V.2, the C_{pk} for post-air-drying moisture increased from 0.50 at the end of the phase-1 intervention to 0.75 after the implement of the phase-2 intervention, while the C_{pk} for post-roasting moisture increased from 0.40 to only 0.46 after the end of phase-2 intervention. The measured C_{pk} value of post-roasting moisture is significantly less than 0.5942 which is the value predicted in Section V.4.

To determine whether the increase in C_{pk} values are statistically significant, two-sample t-tests and two-variance tests are used to determine whether means and variances of moisture distribution before and after the intervention are different. In addition, the post-phase-2 intervention means are also tested with a one-sample t-test to determine whether the averages are not significantly close to their target levels, i.e. whether the null hypothesis that the averages are the same as the target level can be rejected. Because C_{pk} indices are calculated with sample means and variances, significant changes in sample means and variances could provide suggestions on whether the change in the value of C_{pk} indices are significant.

From the test result summarised in Table V.22, it is found that sample means and standard deviations which are significantly different from their respective levels after the first phase of intervention are as followed.

- The post-mixing moisture's sample means was increased from 62.58% to 63.39%.
- The post-mixing moisture's sample standard deviations was increased from 1.171% to 1.642%.
- The post-sheet-forming moisture's sample means was decreased from 50.79% to 49.89%.
- The post-air-drying moisture's standard deviation was decreased from 2.770% to 2.031%.

- The post-roasting moisture's sample means was decreased from 15.70% to 14.57%.

It is hypothesised in Section IV.1 that constant and subjective adjustment of control parameter values by machine operators is one of the major sources of moisture variation in post-roasting moisture of fish sheets. If the hypothesis were true, when values of all significant control parameters are held constant, variation of the post-air-drying and post-roasting moisture distribution should be significantly less than the pre-phase-2 levels. Unlike changes in the production statistics after the first phase of intervention, changes after the second phase of intervention are not as uniform and require more interpretation. The interpretation of changes in post-air-drying and post-roasting moistures that are likely results of the implementation will be discussed first. Changes in post-mixing and post-sheet-forming moisture distribution which should be unaffected by the parameter optimising intervention will then be discussed.

The change in post-air-drying moisture's standard deviation is expected. Before the intervention, there are frequent adjustments to air-drying oven's temperature. It was hypothesised that, due to the long latency of the air-drying process which lasts approximately one hour, the parameter adjustment during production line would lead to large batches of fish sheets receiving varying levels of treatment. Therefore, by holding the air-drying temperature constant, it was expected that the standard deviation of the post-air-drying moisture should drop from the respective level in the post-phase-1 process.

Despite the decrease in moisture variation in post-air-drying fish sheets, there are not any significant reduction in the post-roasting moisture's variation. One possible explanation is that there are other sources of variation in the roasting process that are not controlled by the experiment's procedure that holds control parameter values constant. An example of other possible source of variation is variation in roasting temperature which should be one of the significant factors to the post-roasting moisture but cannot be directly controlled. Although roasting gas flow rate was used as its proxy, it has weak correlation and the roasting temperature can have large variance, as shown in Figure IV.3. The shift in the post-roasting moisture's sample means is significant but not surprising because the post-phase-1 process is a sample means calculated from samples which are produced under various combinations of air-drying temperature and roasting conveyor speed.

As the comparison in Table V.22 shows that the t-test cannot reject the null hypothesis that the real post-roasting average is the same as the target 15% However, the failure to reject the null hypothesis could only be due to the small sample size for the post-phase-2 data (which has only 35 samples). In fact, the distance between post-phase-1 average and the target level is less than the distance between post-phase-2 average to the target value. The average of post-roasting moisture after phase-1 intervention is 15.70% while the average after phase-2 intervention is 14.57%. The distance from the new means to the target moisture of 15% is relatively similar to the distance from the old means to the target moisture (0.70% vs 0.43%). This is a possible explanation on why the improvement of post-roasting C_{pk} value is relatively modest.

Meanwhile, significant changes in the post-air-drying moisture's standard deviation confirms that the improvement of post-air-drying C_{pk} value is significant, suggesting that holding the air-drying temperature constant helped reduce variation in post-air-drying moisture, as predicted by the hypothesis.

Significant changes in post-mixing and post-sheet-forming moistures' sample means and standard deviations are unexpected because parameters involved in the experiment are parameters in air-drying and roasting processes. Intuitively, changes of values of these parameters should not have impacts on fish sheets' moisture in earlier stages. Moreover, it is reported that the standard deviation of the fix mixture significantly increased even though the standard deviation of minced fish from both sources decreased from the post-phase-1 level. Although the reported moisture of fish mixture is significantly less than the respective level before any interventions and does not detract the validity of the conclusion stated in Section V.2, the result is unexpected.

If measurement of minced fish moisture is reasonably accurate, a possible explanation for the incident is coarse measurement of water used in the mixture. As explained in Section III.2.2, the amount of water used in the mixture is the weight, using the adjustment calculation presented in the section, rounded to the nearest number. However, further investigation will be required to confirm and determine root causes of the problem.

Due to significant improvement in C_{pk} in the post-air-drying moisture and less significant improvement in C_{pk} in the post-roasting moisture, more proportion of samples lie within specification limits. Compared to the baseline sample distribution after the Phase-1 intervention in terms of samples having moistures within or outside of specification limits, samples collected after Phase-2 intervention have fewer samples that deviate from the specification-limit ranges, as illustrated in Figure V.15. The number of samples collected after Phase-1 intervention with post-air-drying and post-roasting moistures within specification limits is 57 out of 73 samples, or 78.08% of all samples. On the contrary, the number of samples collected after Phase-2 intervention within such moisture ranges is 31 out of 35 samples, or 88.57% of all samples, which is approximately 10.49% greater than the ratio of samples among post-phase-1 samples whose moistures are within specification limits. The improvement could be explained by the increase in values of C_{pk} indices for both post-air-drying and post-roasting moistures as reported in Table V.21.

There are several possible reasons that could explain why some samples still have out-of-specification post-roasting moistures after the intervention. First, these samples might be scattered due to fluctuations of roasting temperature. Although the temperature has been found to have significant relationship with the post-roasting moisture (as shown in Equation 5.9), it cannot be controlled, and only roasting gas flow rate can be directly adjusted. Second, the outlying data points could simply be a result of high variation in post-roasting moisture.

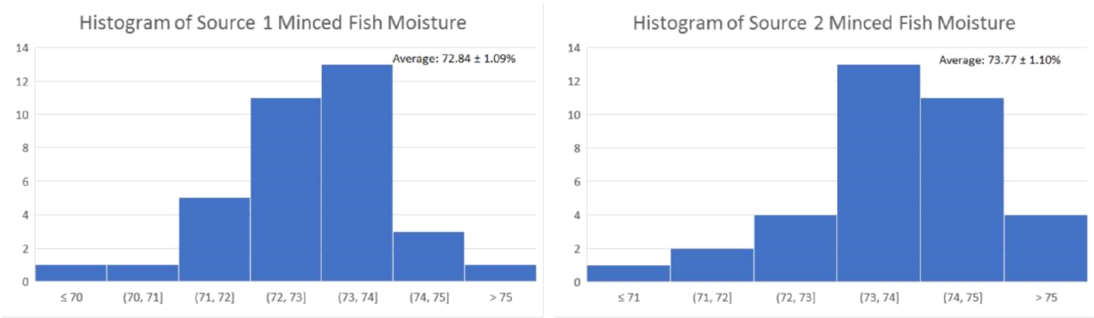
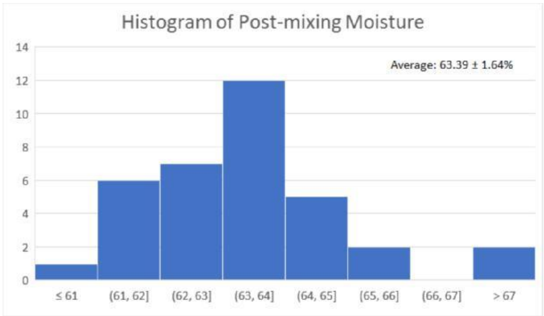
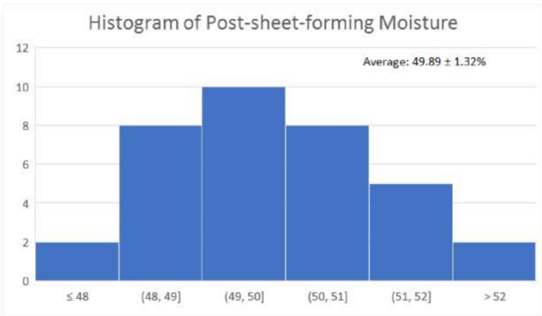


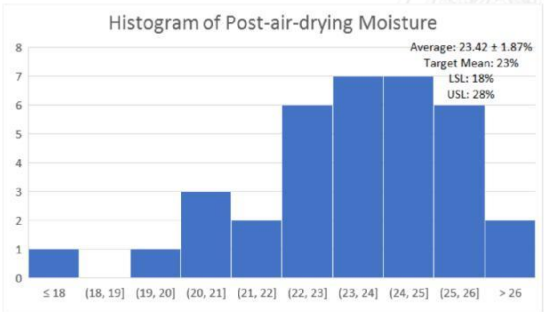
Figure V.13: Histograms of moisture of frozen minced fish from various sources after intervention in phase 2



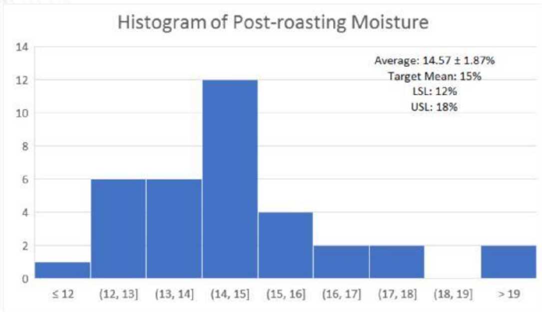
(a) Post-mixing



(b) Post-sheet-forming



(c) Post-airdrying



(d) Post-roasting

Figure V.14: Histograms of moisture of fish sheets at various points in the process after intervention in phase 2

Table V.21: Production statistics after phase 2's intervention

	LSL	USL	Target Mean	Observed Mean (Sample Size)	Observed Stdev. (Sample Size)	C_p	C_{pk}	C_{pm}
Minced fish moisture (Source 1)	70%	78%	74%	72.84% (35)	1.09% (35)	1.22	0.87	0.84
Minced fish moisture (Source 2)	70%	78%	74%	73.77% (35)	1.09% (35)	1.21	1.14	1.19
Post-mixing moisture	N/A	N/A	N/A	63.39% (35)	1.64% (35)	N/A	N/A	N/A
Post-sheet-forming moisture	N/A	N/A	N/A	49.89% (35)	1.32% (35)	N/A	N/A	N/A
Post-air-drying moisture	18%	28%	23%	23.42% (35)	2.03% (35)	0.82	0.75	0.80
Post-roasting moisture	12%	18%	15%	14.57% (35)	1.87% (35)	0.53	0.46	0.52

Table V.22: Comparison of production statistics before and after the phase-2 intervention and significance of their differences

Moisture at Stage	Average Before (Sample size)	Average After (Sample size)	Average Significant Different? (p-value)	Average Significantly Not Close to Target? (p-value)	Stdev. Before (Sample size)	Stdev. After (Sample size)	Stdev. Significantly Different? (p-value)
Post-mixing	62.58 (171)	63.39 (35)	Yes (0.008)	N/A	1.171 (171)	1.642 (35)	Yes (0.005)
Post-sheet-forming	50.79 (73)	49.89 (35)	Yes (0.002)	N/A	1.435 (73)	1.318 (35)	No (0.593)
Post-air-drying	23.86 (73)	23.42 (35)	No (0.350)	Yes (<0.0005)	2.770 (73)	2.031 (35)	Yes (0.048)
Post-roasting	15.70 (73)	14.57 (35)	Yes (0.005)	No (0.108)	1.910 (73)	1.875 (35)	No (0.927)

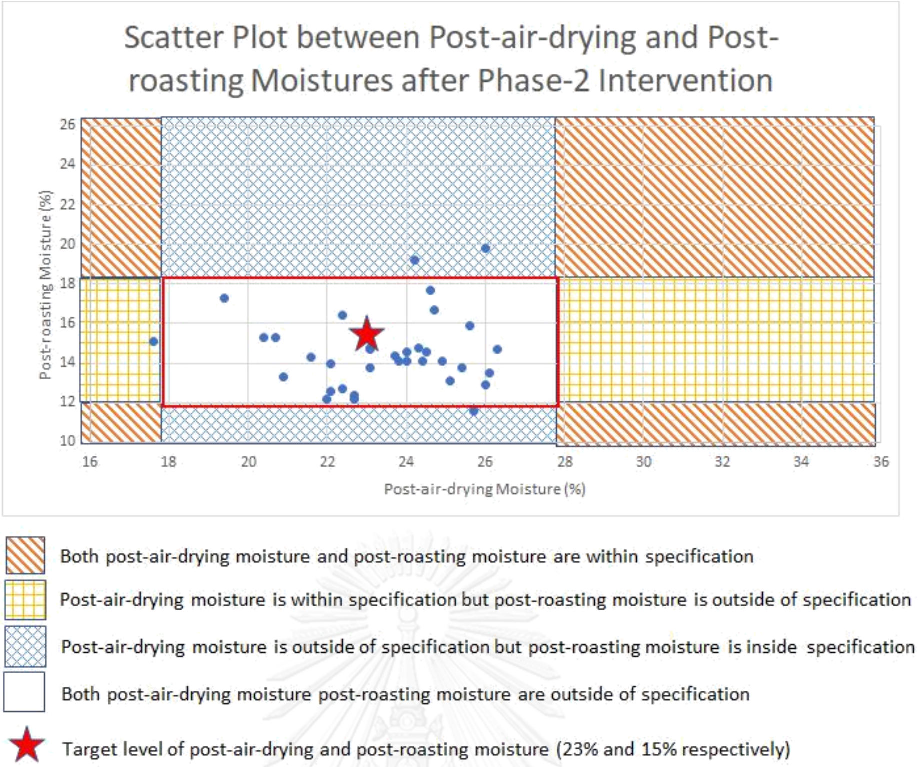


Figure V.15: Scatter plot between post-air-drying and post-roasting moistures of samples after intervention in phase 2

Table V.23: Matrix of the number of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits after phase-2 intervention

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	3	0
	Inside specification	31	1

Table V.24: Matrix of distribution of samples whose post-air-drying and post-roasting moistures lie within or outside of specification limits after Phase-2 intervention

		Post-air-drying Moisture	
		Inside specification	Out-of-specification
Post-roasting Moisture	Out-of-specification	8.57% (3/35)	0.00% (0/35)
	Inside specification	88.57% (31/35)	2.86% (1/35)

CHAPTER VI
CONCLUSION AND FURTHER RESEARCH

VI.1 Discussion and Conclusion

As stated in Section I.3, this project's objective primarily concerns with the improvement of process capability index in post-air-drying and post-roasting fish sheets' moistures. The two process improvement interventions used in this project are designed based on a hypothesis that the moisture variations in fish sheets' moisture originate from the high moisture variation in the raw material, i.e. the fish mixture, and the arbitrarily subjective control parameter adjustment in post-mixing stages. The first intervention, whose methodology was described in Chapter III, intends to reduce moisture variation in the fish mixture. The intervention implements an adaptive water adjustment procedure in the mixing stage based on measured moisture of minced fish, which is the primary non-water ingredients. The second intervention, elaborated in Chapter IV, would like to standardise and remove subjectivity in control parameter adjustment from the production line. An optimal set of control parameter values are selected using optimisation on the response surface model, created using data collected in a DoE experiment. After the selection, the production line would use the optimised control values for all production. As a summary of the improvement because of both interventions, values of process capability indices (C_{pk}) of post-air-drying and post-roasting moistures of fish sheets after each stage of intervention is given in Table VI.1.

Table VI.1: Summary of C_{pk} index values after intervention

	Post-air-drying C_{pk}	**Post-roasting C_{pk}**
Before intervention	0.19	0.04
After phase-1 intervention	0.50	0.40
After phase-2 intervention	0.75	0.46

The indices are considerably improved after the implementation of the first intervention. The fish mixture's moisture variation is reduced and the sample means of the moisture is shifted towards the level expected by the recipe. However, the reduction of moisture variation in the fish mixture does not lead to similar reduction in fish sheets at later stages. As discussed in Section V.2, moisture variation in fish sheets remain statistically the same as those of fish sheets produced under the process before any interventions. Instead, it is observed that the sample means of fish sheets in all stages shift towards the target values according to the specification, which is the middle value between specification limits. Because the value of C_{pk} index is proportional to the distance of the sample means to the middle points between specification limits, the shifts in sample means result in significant improvement of C_{pk} index observed after the implementation of the first phase of intervention. The shift in averages are evident when scatter plots between the post-air-drying and post-roasting moistures before and after the intervention (illustrated in Figures V.6 and V.15 respectively) are compared.

As stated earlier, the intervention in the second phase of the experiment rests on the hypothesis that observed variation in post-air-drying and post-roasting moistures are caused by constant and subjective adjustment of production parameters by the machine operators. After holding control parameter values in post-roasting processes constant, it is observed that there is improvement in C_{pk} values, especially for the post-air-drying C_{pk} value. As summarised in Table V.22, the post-air-drying C_{pk} is significantly improved, rising from 0.50 to 0.75, primarily due to significantly smaller sample variance. On the contrary, improvement of the post-roasting C_{pk} is more modest, rising from 0.40 to only 0.46, falling significantly short of the expected level solved in Section V.4. It was concluded in Section V.5 that the less evident improvement in roasting C_{pk} is likely a result of inability to control all significant factors especially the roasting temperature which is not directly controllable based on the current configuration in the production line. Therefore, modification of the production line to allow better control of these factors could be possible future direction of the project.

VI.2 Contribution

This work analysed the problem presented in the fish sheet production process and made the following tangible contributions to the manufacturing process. First, it introduced a systematic and routine moisture measurement of raw material, particularly the frozen fish, and fish sheets in each process to allow quality improvement based on past data. Prior to the start of the project, fish sheets' moisture used to be objectively measured only once per day and were rarely used for quality improvement purposes. The data would allow for more data-driven process improvement in the future. Second, the water adjustment procedure significantly reduced moisture variation in fish mixture, resulting in significant improvement of values of C_{pk} indices for post-air-drying and post-roasting moistures of fish sheets. Third, production parameters for post-mixing processes were optimised and resulted in a significant improvement of post-air-drying moisture's C_{pk}, suggesting that fixing the air-drying temperature to a single optimised value leads to better process capability index than when the temperature is subjectively and reactively altered. Fourth, the experimentation result suggests that fixing parameter values in the roasting process results in the C_{pk} value that is not significantly different from when parameter values are reactively adjusted. The C_{pk} index for post-roasting moisture is slightly improved from 0.40 to only 0.46. Therefore, the fifth and final contribution is that the work shows that reactive parameter adjustment is unnecessary, and that that the post-mixing process would be able to operate with less supervision, and potentially with fewer and/or less experienced workers, once the production parameter values have been optimised. In addition, rework in the form of reroasting is eliminated with the new procedure, and help reduce production time and energy used in the production.

In addition to the practical contributions described above, there are some academic merits to the works. First, the work describes and analyses an example of processes involving large-batch food production. Second, the work shows that it is possible to cope with high variations in parameters of input materials by using a pre-process treatment that depends on the input's parameter values that are objectively measured. In this case, while there are moisture variations in input frozen fish ingredient, moisture variation in resulting fish mixtures could be successfully reduced by adapting the amount of water used in the mixing process based on moisture of frozen fish measured prior to the mixing sessions. Finally, this work provides an example of application of response surface method in optimisation of production parameters in a large-batch food drying process.

VI.3 Future Directions

The intervention presented in this project significantly improved the C_{pk} index for the post-air-drying and the post-roasting moistures. However, with post-air-drying moisture C_{pk} and post-roasting moisture C_{pk} being improved to 0.76 and 0.42 respectively, the improved indices still fall short of the C_{pk} of 1.33, which is the recommended minimum process capability for two-sided specifications in an existing process suggested by Montgomery (2009). The gap between the improved indices and the target level indicates that the process still need further process improvements.

There are five future directions for improvement. First, to allow better model of the response surface, more factors, whether they are control parameters or uncontrollable environmental variables, should be included in the regression analysis. Acquiring a robust and accurate regression model of a highly non-linear process, such as the drying process, with only a few dimensions of parameters could be challenging. The result from the regression analysis with fish sheets' post-roasting moistures as a response, discussed in Section V.3.1, achieved a model with low R^2 value, suggesting that the model cannot accurately predict post-roasting moistures of each data point. Although the regression analysis with fish sheets' C_{pk} index value as a response, discussed in Section V.4, generated a model with high R^2 value, it has been demonstrated in Section V.5 that the observed C_{pk} in the optimised treatment is much lower than predicted. The discrepancy between the observed and the predicted value suggests that the model is still not an accurate representation of the response surface. Adding more dimensions to the model is one possible way to improve it.

Second, measurements of the production line's control parameters, responses and environmental variables should be digitalised with digital controllers and sensors. The digitalisation allows factors to be better and more precisely quantified which can allow more factors to be included in the model as stated earlier. Some key variables, such as the roasting temperatures, were not directly controlled and other control variables, including the roasting gas flow rate, were used as proxies. Therefore, implementation of digital controllers for these variables could provide more direct and precise control over moisture variation of the fish sheets. Third, other production responses should be investigated to serve as proxies of the fish sheet’s moisture which has slow measurement time. If these alternative responses have sufficiently high correlation to the fish sheet’s moisture but takes much less time to measure their values, then more data could be collected and better models can be generated.

Fourth, additional DoE experiments should be conducted on treatments with “medium” gas flow rate. As discussed in Section IV.2.2, only two levels of the roasting gas flow rate are used in the DoE experiment. By using three levels of roasting gas flow rates, it is possible to generate a second-order response surface model with respect to the flow-rate factor. Finally, to find treatments with better C_{pk} with respect to the roasting conveyor speed, additional DoE experiments should be conducted on treatments with the conveyor speed below 60 Hz. Because the optimised level of the roasting conveyor belt speed, as solved in Section V.4 is 60 Hz, which is the low level of the experimented range. Therefore, it can be inferred that an optimal value of the conveyor speed is below 60 Hz.

REFERENCES

APPENDIX

APPENDIX A
RAW DATA OF MEASURED MOISTURE IN FISH SHEETS

A.1 Moisture Data before Intervention

Table A.1: Moisture data in the pre-intervention system

Date	Source 1 Fish Moisture (%)	Source 2 Fish Moisture (%)	Water Used (kg)	Post-mix Moisture (%)	Post-sheet-forming Moisture (%)	Post-air-drying Moisture (%)	Post-roasting Moisture (%)
4 Apr 16	70.7	N/A	24	65.1	48.4	28.8	17.5
5 Apr 16	72.2	N/A	24	62.7	43.2	29.7	15.5
5 Apr 16	76.5	N/A	24	63.1	46.5	26.7	17.1
5 Apr 16	75.4	N/A	24	60.2	48.1	24.9	16.1
6 Apr 16	73.2	N/A	24	57.2	46.4	26.3	15.5
6 Apr 16	70.1	N/A	24	57.3	46.9	25.2	15.4
6 Apr 16	72.8	N/A	24	55.9	45	22.8	14.3
7 Apr 16	71	N/A	24	57	46.8	29.4	20.2
7 Apr 16	72.6	N/A	24	65.3	46.7	24.2	15.2
7 Apr 16	72.5	N/A	24	57.1	47.2	29.4	17.4
9 Apr 16	73.2	N/A	24	64	50	29.6	18.5
9 Apr 16	72.9	N/A	24	65.3	45.7	26.2	17.4
9 Apr 16	74	N/A	24	64.2	47.4	23.5	15.3
11 Apr 16	70.2	N/A	24	59.8	48.5	24.5	16.1
11 Apr 16	73.4	N/A	24	67.4	47.7	24.2	14.3
11 Apr 16	73.6	N/A	24	64.5	47.2	24.6	14.9
12 Apr 16	72.6	N/A	24	68.1	49	25.2	16.8
12 Apr 16	70.6	N/A	24	68.1	48.4	26.5	21.6
12 Apr 16	74.5	N/A	24	67.9	47	25.7	15.8
20 Apr 16	72.7	71.1	24	56.5	47.7	21.6	18.6
20 Apr 16	75.1	65.5	24	56.5	47.4	24.3	14.8
20 Apr 16	77.7	75.6	24	53.9	44.9	23	15.3
21 Apr 16	74.2	76.5	24	58.8	46.8	24.5	17.8
21 Apr 16	74.7	76.6	24	54.8	46.9	21.1	15.8
21 Apr 16	76	75.9	24	58.2	48.6	22.4	14.3
22 Apr 16	71.9	74.7	24	56.7	47	24.1	17.4
22 Apr 16	76.6	73.3	24	56.5	48.1	24.5	16.9
22 Apr 16	73.3	70.3	24	54.3	47.3	25	16.8
23 Apr 16	70.4	76.6	24	60.7	45.9	25.6	15.4
23 Apr 16	74.1	68.5	24	59.8	48.5	25	17.4
23 Apr 16	72.1	71.1	24	61.6	48.4	25.7	17.6
25 Apr 16	78	72.6	24	60.5	46.6	27.2	16.4
25 Apr 16	76.2	71.5	24	59.9	45.9	28.7	19.1
25 Apr 16	77.2	75.4	24	65.3	47	22.9	16.8
27 Apr 16	80.2	74.6	24	58.1	45.9	25	15.7
27 Apr 16	75.1	72.6	24	56.5	45.9	26.5	14.8
27 Apr 16	74.5	70.8	24	60.6	48.2	25.2	15.4
28 Apr 16	76.8	73.6	24	64.7	48.9	28.7	21.8
28 Apr 16	70.4	73.9	24	57.7	46.6	25.9	19.3
28 Apr 16	76	75.4	24	63.5	47.7	28.1	17.5
29 Apr 16	76.5	79.2	24	63.3	48.1	28.1	20.5
29 Apr 16	77.7	76.1	24	59.4	46.4	33.4	16.1

29 Apr 16	78	72.9	24	57.6	48.4	27.5	17.9
30 Apr 16	70.4	75.6	24	55.9	48.6	28.1	19.3
30 Apr 16	76.3	73	24	59.4	47.1	25.5	19.6
3 May 16	77	64.1	24	57.2	47.3	24.9	16
3 May 16	76.4	72.7	24	60.7	46.8	20.3	15.3
3 May 16	77.1	75.2	24	60.9	47	22.5	14.6
4 May 16	73.2	77.4	24	63.3	46	25.7	20.2
4 May 16	76.5	75.8	24	62.3	46.8	25.5	17.1
4 May 16	75.1	68.8	24	59.4	46.2	24.2	16
5 May 16	73.5	73.7	24	57.8	48	24.9	15.3
5 May 16	77.2	73.2	24	56.4	45	23.1	14.9
5 May 16	76.9	75.2	24	57.1	47.9	29	17.5
6 May 16	68.4	71.7	24	62.4	46.5	28.2	17.9
6 May 16	76.8	72.3	24	54.1	47.5	24	18.1
6 May 16	77.3	73.9	24	55.4	46.2	25.2	15.7
7 May 16	75.2	73.2	24	58.8	48.3	28.2	16.3
7 May 16	77.9	62.7	24	61.3	46	25.4	15.2
7 May 16	77.4	71.4	24	56.9	45.5	27.3	22.6
10 May 16	77.5	73.6	24	56.4	47.1	26.8	20.1
10 May 16	74.6	74.3	24	57.3	45.3	24.1	15.6
10 May 16	77	73.7	24	60.2	47.6	23.5	14.9
13 May 16	76.6	73.1	24	59.4	46.8	27.9	15.8
13 May 16	75.8	75.4	24	59.5	47	26.1	15.3
13 May 16	71.6	74.1	24	57.2	45.7	24.8	15.6
14 May 16	76.7	77.5	24	68.2	48.9	30.1	23
14 May 16	75.7	74.8	24	66.5	46.9	27.1	18.7
14 May 16	75.2	75.5	24	65.3	46.2	26.6	17.6
19 May 16	74.1	72.3	24	58	46.5	28.2	17.1
19 May 16	67.3	75.1	24	62	46.2	25.1	16.2
19 May 16	76.7	74.3	24	59.6	47.4	26.5	16.9
20 May 16	76.7	71.9	24	60.6	46.4	27	14
20 May 16	76.2	73.2	24	51.7	44.2	27	18.3
20 May 16	73	75.9	24	56.9	46.2	26.9	15.4
23 May 16	75.3	72.6	24	64.8	48	30.8	19
23 May 16	75.6	76.4	24	65.3	47.8	28.5	18.6
23 May 16	73.4	77.4	24	59.1	47.1	25.1	16.2
24 May 16	76	75.9	24	64.9	47.8	26.2	19.4
24 May 16	78	76	24	60.5	49.3	26	18.8
24 May 16	77.8	75.5	24	68.2	47	25.2	17.9
25 May 16	77.8	74.3	24	63	48	26.6	17.7
25 May 16	75.4	76.2	24	64.1	49.8	26.9	16
25 May 16	78.2	74.5	24	62	47.8	29.3	23.5
26 May 16	74.9	75.5	24	66.8	47.6	26.2	19.9
26 May 16	78.1	71.6	24	63.2	46.3	26.8	18.4
26 May 16	78.3	73.1	24	62.7	46	28.8	18
27 May 16	76.5	74.5	24	61.5	46.7	28.5	18.6
27 May 16	76.6	75.9	24	57.7	46	25.6	17.2
27 May 16	77.6	75	24	58.6	46.3	24.1	17.4
31 May 16	73.4	76.1	24	64.8	49.1	27.3	19.1
31 May 16	73.2	79.1	24	58.1	45.4	29.9	20.1
1 Jun 16	80.3	75.2	24	60	49	29.3	21.4
1 Jun 16	80.9	76.1	24	65	47.5	27.1	18.2
1 Jun 16	78.9	76.2	24	65.6	47	30.3	19.2
3 Jun 16	75	70.1	24	60.6	49	25.3	19.1
3 Jun 16	76.9	74.9	24	65.9	48	27.7	17.7
3 Jun 16	77.6	74.6	24	59.8	40.8	24.8	17.1

10 Jun 16	76.5	79	24	57.6	47.8	28.1	19.4
10 Jun 16	72.5	77.8	24	57.6	45.7	26.9	18.1
10 Jun 16	74.3	77.4	24	56.9	45.2	24.5	15.8
14 Jun 16	75.1	73.1	24	66.9	48.6	28	22.1
14 Jun 16	62.1	71.9	24	59.1	47.5	27.7	18.1
14 Jun 16	78	76.9	24	57.7	47.5	26.4	18.6
17 Jun 16	79.2	75.3	24	58.8	47.2	31.4	22.5
17 Jun 16	71.5	76.5	24	60.9	45.6	30.6	19.3
21 Jun 16	74.3	74.4	24	61.5	50.4	31.3	19.4
21 Jun 16	75.7	79.1	24	61.4	47.1	30.6	17.2
21 Jun 16	77.6	71.7	24	59.8	47	29.8	17.6
22 Jun 16	75.9	77.6	24	61.4	47.7	28.5	22.9
22 Jun 16	77.5	76.2	24	65.3	48.2	31.6	18.2
23 Jun 16	77.5	69.4	24	64.9	47.1	29.4	15.6
23 Jun 16	77.5	73.7	24	64.3	47.5	19.7	19.7
23 Jun 16	77.9	75.5	24	67.6	50.1	21.6	21.6
29 Jun 16	78.2	76	24	60.9	48.6	27.1	17.7
29 Jun 16	73.9	75.1	24	61.2	48.3	23.2	16.2
29 Jun 16	83.6	75.9	24	66.2	48.3	28.3	17.6
30 Jun 16	77.3	76.7	24	65.3	48.7	27.4	18.6
30 Jun 16	74.6	70.5	24	67.6	48.4	31	16.8
30 Jun 16	76.2	75.6	24	66	48.2	29	17.4
1 Jul 16	77.6	70.7	24	62	50.1	30.7	22.7
1 Jul 16	76.6	73.7	24	66.6	45.3	25.2	18.4
4 Jul 16	76.6	77	24	61.8	47.9	30.2	20.3
4 Jul 16	76.9	75	24	64.6	48.3	25.4	18.6
6 Jul 16	77.5	76.6	24	68.1	46.7	27.4	15.2
6 Jul 16	78.4	73.7	24	68.5	46.1	26.6	19.2
6 Jul 16	77.2	75.5	24	67.9	46.3	26.4	19.6
9 Jul 16	75.9	77.1	24	63.3	49.4	27.4	20.8
9 Jul 16	74.4	77.6	24	63.3	47.5	28.6	20.5
9 Jul 16	77.6	74.1	24	64.9	48.2	25	17.9
11 Jul 16	77.7	68	24	66.1	48.6	28.1	17
11 Jul 16	73.9	67.2	24	68.4	47.6	25.7	16.4
11 Jul 16	81.2	78	24	63.9	48.2	26.8	18.5
12 Jul 16	78.7	64.3	24	66.9	48.7	29	20.3
12 Jul 16	72.7	75.5	24	64.4	47	25.2	15.2
12 Jul 16	78.1	72.9	24	62.4	47	23.1	14.9
14 Jul 16	79.1	75.1	24	64.8	48.4	26.6	21.5
14 Jul 16	79.3	76	24	64.8	49.2	25.8	16.6
14 Jul 16	77.1	76.9	24	59.7	47.6	26.5	18.8
15 Jul 16	77.6	69.5	24	65.9	49.4	29.3	20.3
15 Jul 16	79.5	76.4	24	60.4	49	26.4	18.5
15 Jul 16	76.1	77	24	58.9	47.1	26	19.8
18 Jul 16	77	73.8	24	63.8	48.8	26.5	14.8
18 Jul 16	74.4	66.9	24	60.2	47.9	29.7	19
18 Jul 16	77.3	76.5	24	60.7	47.1	26.8	18.5
22 Jul 16	77.1	72.1	24	63.1	46.9	26.2	22
22 Jul 16	74.1	73.3	24	59.1	49.8	32.4	22.7
22 Jul 16	79.2	74.6	24	58.5	46.4	23.9	18.4
23 Jul 16	77.5	76.7	24	62.3	48.4	28	19.9
23 Jul 16	79.9	74.1	24	63	48.4	27.3	20.1
23 Jul 16	73.1	77.5	24	62.6	47.8	26.9	18.4
29 Jul 16	70.3	70	24	66.7	47.8	23.2	15
29 Jul 16	80	75.4	24	63.9	48.8	25	16.2
29 Jul 16	76.6	73.3	24	59.1	49.1	29.5	16.6

30 Jul 16	78.6	76.2	24	62.7	48.6	24.3	13.5
30 Jul 16	67.6	75.6	24	65.5	47.7	23.4	14.7
30 Jul 16	74.4	74.3	24	63.2	46.6	23.9	18.2
4 Aug 16	74.4	66.8	24	64.7	48.7	29.9	17.5
4 Aug 16	77.3	68.6	24	63.7	47.9	28.2	20.8
4 Aug 16	75.4	73.3	24	62.6	46.8	22.7	15
5 Aug 16	75.5	77.1	24	65.5	48.7	30	19
5 Aug 16	77.3	69.2	24	55.8	47.6	26.5	16.9
5 Aug 16	75.7	73.8	24	62.1	47.2	30	16.9
6 Aug 16	77.1	73.8	24	68.4	50.2	31.7	21.5
6 Aug 16	77.4	75	24	65.3	48.2	27.4	19.9
6 Aug 16	70	75.1	24	63	49.4	25.1	15.8
10 Aug 16	75.1	73.4	24	66.6	49.8	26.2	18
10 Aug 16	77.2	75	24	60.9	47.3	26.9	19.4
10 Aug 16	77.2	75.8	24	58.3	47.3	24.8	16
11 Aug 16	77.1	62.6	24	62.9	47.6	27.1	18
11 Aug 16	76.5	74.3	24	69.3	47.4	28.1	14.2

A.2 Moisture Data after Phase-1 Intervention

Table A.2: Moisture data in the post-phase-1-intervention system

Date	Source 1 Fish Moisture (%)	Source 2 Fish Moisture (%)	Water Used (kg)	Post-mix Moisture (%)	Post-sheet-forming Moisture (%)	Post-air-drying Moisture (%)	Post-roasting Moisture (%)
27 Sep 16	75.15	75.15	24	63.54	53.79	25.99	17.74
27 Sep 16	77.52	72.97	24	65.3	50.53	26.55	17.37
27 Sep 16	77.64	77.18	19	60.18	50.93	25.65	19.03
27 Sep 16	78.63	76.2	20	62.06	49.52	21.62	15.57
28 Sep 16	75.56	75.95	23	60.86	48.22	26.71	14.8
28 Sep 16	75.7	78.01	21	63.25	48.31	22.86	14.92
28 Sep 16	77.37	76.59	21	62.18	54.44	28.58	18.18
28 Sep 16	73.82	77.51	23	63.83	53.13	28.99	17.22
30 Sep 16	74.3	74.90	25	66.37	49.17	25.84	15.32
30 Sep 16	74.7	75.85	24	61.3	48.94	26	15.16
30 Sep 16	77.28	73.05	24	61.25	50.21	23.73	15.6
30 Sep 16	74.8	76.67	23	62.5	53.01	26.11	15.46
8 Oct 16	73.64	71.77	28	63.78	55.36	24.3	19.87
8 Oct 16	77.10	79.61	19	63	47.4	24.03	17.16
8 Oct 16	78.42	71.44	24	62.59	48.56	24.69	17.36
8 Oct 16	76.33	71.04	26	63	50.45	23.09	16.37
12 Oct 16	76.33	74.95	23	61.51	52.27	28.22	15.42
12 Oct 16	82.6	72.74	20	62.7	50.75	26.32	16.96
12 Oct 16	74.33	73.8	26	60.74	51.37	23.9	14.49
12 Oct 16	76.33	75.18	23	62.04	52.9	24.7	12.36
13 Oct 16	76.33	72.17	25	65.32	51.05	26.06	18.43
13 Oct 16	76.15	77.22	21	62.27	51.43	24.79	17.98
13 Oct 16	77.89	76.52	21	60.97	49.38	26.86	16.97

13 Oct 16	77.78	72.08	24	63.37	50.65	25.52	15.99
18 Oct 16	74.29	75.95	24	62.05	50.62	28.27	15.61
18 Oct 16	74.2	76.69	24	64.87	52.2	24.54	14.12
18 Oct 16	74.52	70.92	28	63.95	51.72	27.36	17.38
18 Oct 16	74.36	72.36	27	63.91	49.1	23.3	14.33
19 Oct 16	69.73	75.32	29	65.91	51.97	23.44	16.83
19 Oct 16	74.01	74.46	26	64.14	50.22	23.28	14.08
19 Oct 16	75.61	74.68	25	60.94	48	24.91	19.3
19 Oct 16	74.51	74.31	26	61.15	51.64	23.05	18.57
21 Oct 16	74.51	78.69	23	63.42	51.64	27.35	18.27
21 Oct 16	77.37	78.55	20	61.53	49.79	30.38	14.4
21 Oct 16	75.45	75.22	24	59.74	50.79	26.31	14.58
21 Oct 16	74.64	69.49	29	64.37	49.44	29.29	15.91
22 Oct 16	74.64	75.2	25	63.58	50.24	29.01	16.38
22 Oct 16	78.76	77.66	20	62.58	51.93	26.24	16.28
10 Jan 17	72.5	75.7	23	62.2	51.7	26.7	17.6
10 Jan 17	75.4	74.9	21	61	49.9	22.3	13.6
10 Jan 17	73.4	74.7	25	61.3	48.7	25.3	14.7
10 Jan 17	71.8	74.7	24	62.3	50.2	18.5	15.4
10 Jan 17	72	75.6	24	62.5	50.8	19.1	16.4
13 Jan 17	73.2	74	24	63.6	51.2	19.7	12.8
13 Jan 17	75.3	74.7	22	61.5	49.9	22.2	14.1
13 Jan 17	73.2	73.7	25	67.2	51.2	19.3	13.5
13 Jan 17	73.9	73	25	64.8	50.8	18.7	12.9
13 Jan 17	73.9	75	24	65.5	51.5	20.6	13.1
16 Jan 17	71.2	73	26	63.7	50.9	22.4	15.9
16 Jan 17	72.5	73.1	26	61	51.5	20.4	12.8

16 Jan 17	73	73.4	26	62.1	49.4	22	13.8
16 Jan 17	73.2	74.8	25	60.7	50.7	22.8	12.9
16 Jan 17	72.8	72.1	27	62.6	51.1	22.4	14.5
17 Jan 17	74.3	77.4	21	63.5	50.1	25	17.2
17 Jan 17	74.7	74.3	24	61.9	51.5	23.3	16.3
17 Jan 17	72.6	75.1	24	62.3	51.4	19.3	16.1
17 Jan 17	73	74.6	25	63.9	50.9	21.2	13.2
17 Jan 17	74.3	77.7	22	62.1	49.8	22.7	15
20 Jan 17	72.5	74.6	25	64.9	51.6	23.7	18.5
20 Jan 17	76.4	74.4	22	61.3	51.3	22.3	15.9
20 Jan 17	73.2	75	24	62.3	51.3	21.1	17.8
20 Jan 17	74	75.3	25	63.5	51.6	21.7	12.6
20 Jan 17	74.2	74.3	25	63.2	51.4	23.1	19.7
21 Jan 17	74.4	75.3	23	63.9	50.8	22	14.3
21 Jan 17	74.9	75.2	23	62.3	50.4	21.9	17.2
21 Jan 17	74.3	N/A	22	62.8	51.8	21.2	15.9
21 Jan 17	75.7	N/A	22	62.3	50.9	21.4	15.9
21 Jan 17	74.5	N/A	24	62.2	51	21.7	15.7
24 Jan 17	73.9	75.2	24	63.2	48.2	23.7	13.6
24 Jan 17	72.3	N/A	27	63.9	51.7	22.4	14
24 Jan 17	75.5	N/A	23	63.7	51.5	22.4	14.8
24 Jan 17	75.4	N/A	21	62.5	50.2	19.9	11.4
24 Jan 17	74.2	N/A	24	62.3	49.4	21.6	14.9

A.3 Moisture Data in Phase-2 Experiments

Table A.3: Moisture data in the phase-2 experiments

Date	Source 1 Fish Moisture (%)	Source 2 Fish Moisture (%)	Water Used (kg)	Post-mix Moist. (%)	Post-sheet-forming Moist. (%)	Post-air-drying Moist. (%)	Post-roasting Moist. (%)	Air-drying Temp (C)	Roasting Conveyor Speed (Hz)	Roast Gas Flow Rate Level
9 Nov 16	N/A	76.4	21	65.5	50.7	29.9	20.4	62	70	High
9 Nov 16	76.1	75.6	21	63.7	50.7	24.8	17.6	62	70	High
9 Nov 16	75.1	75.1	22	62.2	50.3	24.8	17.4	62	70	High
9 Nov 16	75.6	76.2	22	63.5	50.5	28.1	19.6	62	70	High
9 Nov 16	75.6	75.3	22	63.3	50.4	24.6	17.6	62	70	High
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	16.1	62	60	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	16.3	62	65	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	15.2	62	70	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	14.5	62	60	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	15.4	62	65	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	16.5	62	70	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	14.7	62	60	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	14	62	65	Low
11 Nov 16	74.4	75.7	25	N/A	N/A	21.5	13.8	62	70	Low
12 Nov 16	76.8	73.4	24	63.2	52.8	27.3	14.6	61	60	High
12 Nov 16	74.7	76.2	22	61.3	50.7	24	14.2	61	60	High
12 Nov 16	74.2	75.3	24	62.9	51.7	25.7	16.6	61	60	High
12 Nov 16	75.1	76.1	22	62.8	51.4	26.9	16.6	61	60	High
12 Nov 16	75.7	74.6	23	61.9	51	25.5	15.9	61	60	High
14 Nov 16	74	76.1	23	63.3	51.8	24.4	15.7	61	65	High
14 Nov 16	75.3	74.3	23	61.8	51.2	23.5	14.7	61	65	High
14 Nov 16	74.8	75.7	22	63.2	49.3	22.5	15.5	61	65	High
14 Nov 16	76.3	74.5	22	62.1	49	22.7	18.4	61	65	High
14 Nov 16	75	74.5	24	62.2	51.1	23.3	17	61	65	High
15 Nov 16	70.6	76.1	25	N/A	N/A	23	15.5	62	60	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	16.3	62	65	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	15.7	62	70	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	17.4	62	60	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	16.9	62	65	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	15.4	62	70	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	14.8	62	60	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	15.4	62	65	Low
15 Nov 16	70.6	76.1	25	N/A	N/A	23	14.6	62	70	Low
17 Nov 16	77.1	N/A	20	62.8	52.4	24.9	16.5	61	60	High
17 Nov 16	75.3	N/A	23	63.4	51.8	27.7	15.7	61	60	High
17 Nov 16	78	N/A	22	62.4	49	26.9	18.2	61	60	High
17 Nov 16	78	N/A	22	60.7	47.4	22.7	13.5	61	60	High
17 Nov 16	75.8	N/A	23	62.1	49.7	24.1	15.2	61	60	High
19 Nov 16	75.2	75.6	22	63.8	51.2	27.6	17.2	60	65	High
19 Nov 16	73.6	74	24	61.6	51.4	27.7	19.6	60	65	High
19 Nov 16	75.2	76.6	21	61.2	51.3	26.8	18.3	60	65	High
19 Nov 16	74.7	75.1	22	62	50.7	27.9	13.5	60	65	High
19 Nov 16	74.6	75.7	23	61.8	51.2	27.7	17.6	60	65	High
24 Nov 16	74.2	74.4	24	N/A	N/A	24	19.4	61	60	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	20.5	61	65	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	19.8	61	70	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	20.7	61	60	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	20.8	61	65	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	19.5	61	70	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	20.9	61	60	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	21.2	61	65	Low
24 Nov 16	74.2	74.4	24	N/A	N/A	24	18.9	61	70	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	22.7	60	60	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	20.7	60	65	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	19.4	60	70	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	19.3	60	60	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	18.2	60	65	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	21.1	60	70	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	19.9	60	60	Low

25 Nov 16	72.5	74	24	N/A	N/A	24.3	16	60	65	Low
25 Nov 16	72.5	74	24	N/A	N/A	24.3	18.5	60	70	Low
26 Nov 16	76.1	75.1	22	62.8	52.4	28.3	18.6	62	60	High
26 Nov 16	74.6	75.3	23	60.9	50.2	26.9	14.1	62	60	High
26 Nov 16	73.8	75.2	23	62.4	51.4	25.1	15.8	62	60	High
26 Nov 16	76	74.4	23	61.3	50.8	21.6	14.2	62	60	High
26 Nov 16	75.1	75.2	23	62.1	51.3	25.9	14.4	62	60	High
2 Dec 16	74.1	75.2	24	63.4	51.7	25.1	16.1	61	65	High
2 Dec 16	73.9	75.1	23	61.8	50	16.9	16.3	61	65	High
2 Dec 16	73.5	75.1	24	62.4	51.8	25.8	15.7	61	65	High
2 Dec 16	74.2	74.9	23	62.3	50.9	24.4	15	61	65	High
2 Dec 16	74	75	24	62.6	50.7	22.6	15.5	61	65	High
3 Dec 16	75.3	75.7	22	62.5	51.5	26.6	18.6	62	60	High
3 Dec 16	77.2	75.3	21	62.4	51.6	25.4	16.9	62	60	High
3 Dec 16	76.3	75.4	22	62.5	50.9	26.9	12.1	62	60	High
3 Dec 16	75.1	75.6	23	61.5	51	25.5	15.4	62	60	High
3 Dec 16	76.7	75.5	22	61.9	51.5	26.5	17.9	62	60	High
7 Dec 16	77	74.6	22	N/A	N/A	27.2	25.4	60	60	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	19.5	60	65	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	22.5	60	70	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	21.9	60	60	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	19.5	60	65	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	20.2	60	70	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	21	60	60	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	21.9	60	65	Low
7 Dec 16	77	74.6	22	N/A	N/A	27.2	22.3	60	70	Low
9 Dec 16	75.3	75.6	23	64	51.2	26.7	20.5	60	70	High
9 Dec 16	77.8	75.3	21	62.8	51.5	27.1	19.6	60	70	High
9 Dec 16	74.2	76	22	61.7	51.8	26.7	18.8	60	70	High
9 Dec 16	76.1	74.9	23	62.4	50.5	24.2	15.2	60	70	High
9 Dec 16	76.9	75.4	22	62.2	51.7	26.4	16.8	60	70	High
10 Dec 16	75.2	74.9	23	64.1	51.1	29.5	20.3	61	70	High
10 Dec 16	78.6	76	19	61.4	51	25.7	17.6	61	70	High
10 Dec 16	78.2	73.4	23	60.6	50.3	26.5	18	61	70	High
10 Dec 16	73.2	76.3	21	59.8	51.8	26.2	17.4	61	70	High
10 Dec 16	76.8	75.5	22	60.9	51.3	25.6	17.8	61	70	High
13 Dec 16	74	76.3	23	63.4	51	26.8	18.7	60	60	High
13 Dec 16	75.3	76.4	21	63.2	51.5	25.4	15.8	60	60	High
13 Dec 16	73.3	75.1	24	61.4	50.1	23.7	13.4	60	60	High
13 Dec 16	73.1	76.4	23	62	51.9	22.9	14.8	60	60	High
13 Dec 16	73.7	76	23	62.4	50.9	24.6	17.4	60	60	High
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	18.3	61	60	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	19.2	61	65	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	19.9	61	70	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	19.3	61	60	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	18.5	61	65	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	17.3	61	70	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	18.8	61	60	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	19.9	61	65	Low
14 Dec 16	71.5	74.4	26	N/A	N/A	25.7	19.5	61	70	Low
15 Dec 16	72.7	76.4	22	61.5	49.7	22	13.4	60	60	High
15 Dec 16	74.3	74.8	23	62.5	50.1	25.9	14.2	60	60	High
15 Dec 16	73.3	74.4	24	63	51.4	25.4	20.3	60	60	High
15 Dec 16	72.1	75.9	23	62.4	50.7	26.7	16.4	60	60	High
15 Dec 16	73.2	76.1	23	62.5	50.2	26.5	17.9	60	60	High
16 Dec 16	73.8	74.3	23	N/A	N/A	26	16.3	61	60	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	16.5	61	65	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	13.9	61	70	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	17.9	61	60	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	15.8	61	65	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	16.8	61	70	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	17.7	61	60	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	17.5	61	65	Low
16 Dec 16	73.8	74.3	23	N/A	N/A	26	17.3	61	70	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	20.8	61	60	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	20.7	61	65	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	18.8	61	70	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	21.3	61	60	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	21.7	61	65	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	20	61	70	Low

21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	20.7	61	60	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	20.7	61	65	Low
21 Dec 16	72.8	75.1	24	N/A	N/A	25.2	21.4	61	70	Low
22 Dec 16	80	75.9	19	61.9	51.1	26.9	15.5	62	65	High
22 Dec 16	74	74.3	23	61.6	52	25.2	14.2	62	65	High
22 Dec 16	74.3	76.1	23	62.3	51	26.4	16.7	62	65	High
22 Dec 16	74.2	76.6	22	62.5	48.4	25.4	16	62	65	High
22 Dec 16	74.6	75.2	23	61.9	51.4	25.4	15.6	62	65	High
24 Dec 16	74.4	76.6	22	62.3	51.2	25.7	16.9	61	70	High
24 Dec 16	73.2	75	23	63.4	51.5	23.9	18	61	70	High
24 Dec 16	72.6	74.9	24	62.6	51.5	26.8	16.1	61	70	High
24 Dec 16	72.1	77.9	23	63.9	50.9	20.5	13.4	61	70	High
24 Dec 16	73.5	76.9	22	62.9	51.5	24.1	17.1	61	70	High
27 Dec 16	71.2	77.9	22	62.5	51	25.1	16.1	60	65	High
27 Dec 16	75.7	75.3	22	61.9	49.5	23.7	15.7	60	65	High
27 Dec 16	73.1	73.1	25	62.6	51.5	26.6	16.1	60	65	High
27 Dec 16	76.1	74	23	62.3	50.1	22.1	13.4	60	65	High
27 Dec 16	74	76.3	23	62.1	50	25.4	14.7	60	65	High
4 Jan 17	73.4	74.9	24	62.9	50.7	28.2	18.3	60	70	High
4 Jan 17	74.4	75.3	23	61.4	51.2	25.9	18.6	60	70	High
4 Jan 17	73.9	74.5	23	63.2	50.3	24.5	15.1	60	70	High
4 Jan 17	74.4	74.5	23	63.2	50.2	23.7	14.8	60	70	High
4 Jan 17	73.8	74.7	24	62.7	50.6	24.4	15.2	60	70	High
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	12.1	61	60	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	13	61	65	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	12.7	61	70	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	14.3	61	60	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	14.2	61	65	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	14.7	61	70	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	14.1	61	60	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	15.2	61	65	Low
5 Jan 17	74.4	70.1	26	N/A	N/A	20.6	14.8	61	70	Low
6 Jan 17	73.2	74.5	24	62.9	50.9	25.7	18.7	62	65	High
6 Jan 17	75.3	75.1	22	61.9	50.7	25.6	14.9	62	65	High
6 Jan 17	71.9	75.3	25	62.9	50.8	21.2	15.1	62	65	High
6 Jan 17	70.9	78.8	22	61.9	50.3	23.1	11.3	62	65	High
6 Jan 17	73	75.7	24	62	50.7	23.8	12.5	62	65	High
7 Jan 17	72.1	78.8	22	62.1	50.2	23.9	14.3	62	70	High
7 Jan 17	74.7	75.2	22	61.5	50.3	21.2	11.9	62	70	High
7 Jan 17	71.4	74.4	25	62.5	50.1	24	13.5	62	70	High
7 Jan 17	72.3	75.3	23	62.8	50.2	22	15.8	62	70	High
7 Jan 17	72.1	75.3	24	62.2	50.2	22.6	14.1	62	70	High
10 Feb 17	73.1	75	24	N/A	N/A	24.4	17.8	61	60	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	16.1	61	65	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	12.4	61	70	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	10.8	61	60	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	8.6	61	65	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	8.7	61	70	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	9.3	61	60	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	10.1	61	65	Low
10 Feb 17	73.1	75	24	N/A	N/A	24.4	10.8	61	70	Low
11 Feb 17	72.4	75.3	24	63.2	51.1	26.7	15.8	61	60	High
11 Feb 17	75.7	75.9	22	62.5	51	25	15.6	61	60	High
11 Feb 17	73.3	77.3	22	61.9	51.1	23.6	13.2	61	60	High
11 Feb 17	70.6	76.8	25	62	52.2	24.2	14.9	61	60	High
13 Feb 17	74	76.8	21	62.9	51.9	25.5	19.4	60	70	High
13 Feb 17	76.9	74.4	22	62.4	50.9	23.9	13.2	60	70	High
13 Feb 17	77	73	24	62.5	51.4	26.5	17.8	60	70	High
13 Feb 17	75.6	75.7	22	62.9	50.6	27	13.3	60	70	High
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	20.2	60	60	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	21.1	60	65	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	21.3	60	70	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	22	60	60	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	22	60	65	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	22	60	70	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	21.7	60	60	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	22	60	65	Low
14 Feb 17	70.9	74.9	26	N/A	N/A	23.8	21.5	60	70	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	18.7	62	60	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	18.6	62	65	Low

16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	17.5	62	70	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	17.4	62	60	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	17.3	62	65	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	16.2	62	70	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	17.2	62	60	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	14.7	62	65	Low
16 Feb 17	69.7	75.1	26	N/A	N/A	24.3	18.5	62	70	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	19.7	60	60	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	20.8	60	65	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	19.9	60	70	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	21.6	60	60	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	20.1	60	65	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	19.4	60	70	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	19	60	60	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	18.7	60	65	Low
17 Feb 17	73.2	78.2	25	N/A	N/A	23.2	19.6	60	70	Low
18 Feb 17	75.3	74.8	24	62.9	50.5	24.3	16.1	60	60	High
18 Feb 17	76.5	76	22	62.3	49.5	26.1	17	60	60	High
18 Feb 17	76.6	75.5	22	60.9	50.5	25.3	16.8	60	60	High
18 Feb 17	76.6	75	23	62.1	51.6	24.2	13.7	60	60	High
21 Feb 17	75.5	76.7	22	62.7	51.6	26.3	15.4	60	65	High
21 Feb 17	73.3	74.8	24	61.9	51	24.1	11.9	60	65	High
21 Feb 17	73.9	75.6	23	62.4	52	26.1	14.4	60	65	High
21 Feb 17	76.2	74.4	23	61.8	50.6	25.4	15.4	60	65	High
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	26.5	62	60	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	27.2	62	65	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	24.6	62	70	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	26.9	62	60	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	24.1	62	65	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	22.3	62	70	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	21.6	62	60	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	21.5	62	65	Low
22 Feb 17	72.3	75.1	23	N/A	N/A	29.3	22.9	62	70	Low
7 Mar 17	72.4	75.3	24	60.7	51	26.7	17	62	60	High
7 Mar 17	73.8	74.4	24	63.5	52.3	25.4	14.4	62	60	High
7 Mar 17	72.4	75.3	24	62.8	48.2	24.8	14.3	62	60	High
7 Mar 17	78.6	75.8	21	63.6	50.8	24.9	14.6	62	60	High
8 Mar 17	77.1	75.8	21	61.5	51	23.9	15	62	70	High
8 Mar 17	75.7	76.1	22	62.7	50.8	23.4	15.6	62	70	High
8 Mar 17	80.2	73.7	22	63.5	51.4	24.8	17.6	62	70	High
8 Mar 17	73.4	75.9	23	62.7	51	21.5	12.5	62	70	High
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	19.8	60	60	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	18.6	60	65	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	18.7	60	70	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	19.4	60	60	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	18.7	60	65	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	18.2	60	70	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	21.2	60	60	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	20	60	65	Low
9 Mar 17	72.2	74.1	25	N/A	N/A	28.7	20	60	70	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	13.3	62	60	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	14.4	62	65	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	13.6	62	70	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	14.6	62	60	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	13.1	62	65	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	13.9	62	70	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	14.1	62	60	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	13.9	62	65	Low
10 Mar 17	76	74.9	22	N/A	N/A	22.6	14.7	62	70	Low
15 Mar 17	76.4	74.7	21	63.3	50.6	21.8	15	61	70	High
15 Mar 17	75.1	76.8	21	61.9	50.2	19.6	14.2	61	70	High
15 Mar 17	74.1	75.1	23	63.1	51.3	18.6	13.5	61	70	High
15 Mar 17	74.5	73.9	24	61.3	50.5	20.1	13.7	61	70	High
16 Mar 17	75.2	74.6	24	62.9	50.2	23.3	13.2	62	65	High
16 Mar 17	77.3	75.3	22	62.4	51.4	25.7	15.3	62	65	High
16 Mar 17	72.1	76.1	24	61.7	50.9	26.5	16.8	62	65	High
16 Mar 17	76.4	74.1	24	63.1	51.5	25.5	15.6	62	65	High
17 Mar 17	73.6	75.8	23	63.1	51.7	22.7	16.4	61	65	High
17 Mar 17	73.3	76.6	23	62.7	50.8	23.4	16	61	65	High
17 Mar 17	74.5	75.6	23	62.3	50.9	21.7	17.7	61	65	High

17 Mar 17	72.9	77.3	22	60.6	51.9	21.9	16.8	61	65	High
18 Mar 17	75.7	75.5	22	N/A	N/A	23	13.7	60	60	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	14.5	60	65	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	14.8	60	70	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	15.2	60	60	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	14.9	60	65	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	15.9	60	70	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	15.5	60	60	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	15	60	65	Low
18 Mar 17	75.7	75.5	22	N/A	N/A	23	15.5	60	70	Low
20 Mar 17	74.3	75	23	63.9	51	26.5	16.5	60	60	High
20 Mar 17	74.2	N/A	26	63.2	51.5	24.5	15.4	60	60	High
20 Mar 17	75.7	N/A	25	63.6	50	23.2	15.1	60	60	High
20 Mar 17	72.3	N/A	26	63.2	50.4	24.6	17.4	60	60	High
21 Mar 17	75.1	75	23	61.3	50.5	24.6	17.3	62	65	High
21 Mar 17	74.7	74.5	23	63.3	48.8	22.6	13	62	65	High
21 Mar 17	75.9	74.3	23	62.1	50.1	22.8	15	62	65	High
21 Mar 17	71.8	74.5	24	64.3	48.6	20.7	14.1	62	65	High
23 Mar 17	73.9	75.5	23	62.9	50.1	26.8	19.1	60	70	High
23 Mar 17	69	73.8	27	63.8	50.5	23.1	15.9	60	70	High
23 Mar 17	73.8	74.3	24	65.8	49.9	20.7	16.7	60	70	High
23 Mar 17	73.5	74.2	25	63.1	49.6	21.1	14.1	60	70	High
24 Mar 17	73.5	75.5	23	63.6	50.4	20.2	15.4	61	60	High
24 Mar 17	74.8	75.5	23	62.8	49	22	15.4	61	60	High
24 Mar 17	73.1	75.5	23	60.1	48.7	22.1	15.5	61	60	High
24 Mar 17	71.1	74.5	26	62.9	50	19.4	12	61	60	High
27 Mar 17	75.4	74.8	24	62.9	50.4	26.7	15.2	62	60	High
27 Mar 17	74.4	75.4	23	63.6	50.8	19.4	12.9	62	60	High
27 Mar 17	72.7	75.2	24	62.5	48.8	22.5	13.7	62	60	High
27 Mar 17	73.5	74.8	24	63.9	50.1	21.5	13.9	62	60	High
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	17.7	62	60	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	17	62	65	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	17.1	62	70	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	16.8	62	60	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	16.2	62	65	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	18	62	70	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	16.2	62	60	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	16.1	62	65	Low
28 Mar 17	76.4	77.5	24	N/A	N/A	25.4	16.7	62	70	Low
29 Mar 17	73.2	74.5	24	63.7	49.7	24.5	15.6	60	65	High
29 Mar 17	74.4	73.4	25	63.1	50.2	23	14.7	60	65	High
29 Mar 17	75.8	74.7	23	62.2	48.6	23.1	13.4	60	65	High
29 Mar 17	74.1	73.4	24	62.3	49	22.1	12.1	60	65	High
10 Apr 17	71.5	75.1	25	64.4	51.1	24.3	15.4	61	65	High
10 Apr 17	74.5	75.8	23	62.3	49.5	22.2	11.6	61	65	High
10 Apr 17	73.7	73.3	25	61.4	48.1	20.1	15.2	61	65	High
10 Apr 17	73.1	75.3	24	63.1	49.6	21.6	12.1	61	65	High
11 Apr 17	72.8	75.3	24	63.6	50	23.4	14.4	62	70	High
11 Apr 17	75.5	73.2	24	63.6	49	21.8	14	62	70	High
11 Apr 17	68.6	73.4	28	63.6	47.4	19.5	13.3	62	70	High
11 Apr 17	77.1	74.6	23	62.9	47.9	23.9	16.7	62	70	High
12 Apr 17	75.4	74.2	24	63	51.5	23.7	17.4	61	70	High
12 Apr 17	75.9	73.6	25	63.2	49.4	22.6	14.1	61	70	High
12 Apr 17	74.9	73.1	23	63.5	49.5	22	14	61	70	High
12 Apr 17	72.4	73.1	26	61.4	49.3	22.3	15.6	61	70	High

A.4 Moisture Data after Phase-2 Intervention

Table A.4: Moisture data in the post-phase-2-intervention system

Date	Source 1 Fish Moisture (%)	Source 2 Fish Moisture (%)	Water Used (kg)	Post-mix Moist. (%)	Post- sheet-forming Moist. (%)	Post-air-drying Moist. (%)	Post-roasting Moist. (%)
18 Apr 17	73.2	74.9	24	59.4	47.9	23.6	16.4
18 Apr 17	73.8	74.4	24	60.1	43.5	19.4	13.4
18 Apr 17	74.1	72.1	26	60.6	45.4	19.5	15.7
18 Apr 17	73.6	74.1	25	58.8	46.6	18.8	12.3
18 Apr 17	74	73.7	25	58.4	46.3	20.8	15.1
19 Apr 17	73.4	70.8	27	65.9	50.1	24.4	14.1
19 Apr 17	75.1	72.3	25	61.9	51.5	25.7	11.6
19 Apr 17	74.4	75.2	23	62.1	49.4	20.7	15.3
19 Apr 17	69.5	75.3	27	61.4	52.6	17.6	15.1
19 Apr 17	73.1	74.9	25	60.5	49.4	20.4	15.3
21 Apr 17	73.6	74.2	24	61.5	48.6	24.3	14.8
21 Apr 17	70.2	74.3	27	63.3	51	24.7	16.7
21 Apr 17	72.5	74.4	25	64.2	49	21.6	14.3
21 Apr 17	73.2	72	27	62.5	48.9	22.7	12.4
21 Apr 17	72.6	73.2	25	63.5	48.5	22.4	12.7
22 Apr 17	71.8	73.2	27	61.5	51.5	24.6	17.7
22 Apr 17	71.9	73.8	26	63.2	51.1	19.4	17.3
22 Apr 17	72.2	75.6	25	63.6	49.4	25.1	13.1
22 Apr 17	73.5	71.9	27	61.9	47.4	22.1	12.6
22 Apr 17	72.5	75.6	24	63.4	52.4	24	14.1
24 Apr 17	74.2	73.1	25	65.8	51.5	25.6	15.9
24 Apr 17	71.6	73.8	27	62.5	50.8	26	19.8
24 Apr 17	73.4	74.9	24	67.9	51.5	25.4	13.8
24 Apr 17	72.5	74.3	25	61.3	49.3	23.1	13.8
24 Apr 17	73.6	74	25	63.2	50	24	14.6
25 Apr 17	72.9	73.6	26	63.9	49.9	22.7	12.2
25 Apr 17	71.7	73.7	27	63.2	50.8	24.5	14.6
25 Apr 17	72.7	73	26	64.9	49.7	20.9	13.3
25 Apr 17	74.1	72.2	26	67.7	49.5	22	12.2
25 Apr 17	74	72.7	26	63.5	50.5	23.8	14.1
27 Apr 17	73.4	74.4	24	62.9	48.2	23.1	14.8
27 Apr 17	73.4	73.6	25	63.2	50.4	23.1	14.7
27 Apr 17	72.5	74.2	26	62.9	48.4	22.4	16.4
27 Apr 17	73	74.2	25	62.2	47.3	23.7	14.4
27 Apr 17	72.7	74.4	26	63	48.3	22.1	14
28 Apr 17	72.5	73.2	26	64.4	49	24.9	14.1
28 Apr 17	73.2	73.7	25	63.7	51	26.3	14.7
28 Apr 17	73.2	75	24	63.2	49.1	24.2	19.2
28 Apr 17	72	73.3	27	64.5	49.7	26	12.9
28 Apr 17	73.3	73.8	25	64.5	50.3	26.1	13.5
3 May 17	73.3	73.2	26	62.9	49.9	22.2	12.1
3 May 17	72.7	73	26	63	50.5	26.2	17.9
3 May 17	73.4	71.4	27	63.4	50.8	22.7	15.3
3 May 17	75.2	73.2	24	61.1	48.6	22.2	15.2

3 May 17	75.2	72.9	25	63.6	49.7	23	15.7
5 May 17	73.7	74.8	24	63.4	50.1	23.2	15.7
5 May 17	74.4	74.2	24	62	49.4	19.8	10.3
5 May 17	73.4	74.4	24	62.1	50.3	21.7	14.8

APPENDIX B

DATA OF DURING-MIXING EXPERIMENT

B.1 Form for Collecting Data of Mixture Moisture before and after During-mixing Intervention

Table B.1: Form for collecting data of mixture moisture before and after during-mixing (phase-1) intervention

Date	Sample Number	Mixture Moisture (%)
Day 1	1	...
	2	...
	3	...
	4	...
	5	...
Day 2	1	...
	2	...
	3	...
	4	...
	5	...
...	...	...

B.2 Data of Post-mixing Moisture Before and After Intervention on During-mixing Intervention

Table B.2: Data of post-mixing moisture before and after intervention on during-mixing (phase-1) intervention

Sample ID	Before Intervention (%)	After Intervention (%)
1	65.1	63.54
2	62.7	65.3
3	63.1	60.18
4	60.2	62.06
5	57.2	60.86
6	57.3	63.25
7	55.9	62.18
8	57	63.83
9	65.3	66.37
10	57.1	61.3
11	64	61.25
12	65.3	62.5
13	64.2	63.78
14	59.8	63
15	67.4	62.59
16	64.5	63
17	68.1	61.51
18	68.1	62.7
19	67.9	60.74
20	56.5	62.04
21	56.5	65.32
22	53.9	62.27
23	58.8	60.97
24	54.8	63.37
25	58.2	62.05
26	56.7	64.87

27	56.5	63.95
28	54.3	63.91
29	60.7	65.91
30	59.8	64.14
31	61.6	60.94
32	60.5	61.15
33	59.9	63.42
34	65.3	61.53
35	58.1	59.74
36	56.5	64.37
37	60.6	63.58
38	64.7	62.58
39	57.7	62.2
40	63.5	61
41	63.3	61.3
42	59.4	62.3
43	57.6	62.5
44	55.9	63.6
45	59.4	61.5
46	57.2	67.2
47	60.7	64.8
48	60.9	65.5
49	63.3	63.7
50	62.3	61
51	59.4	62.1
52	57.8	60.7
53	56.4	62.6
54	57.1	63.5
55	62.4	61.9
56	54.1	62.3

57	55.4	63.9
58	58.8	62.1
59	61.3	64.9
60	56.9	61.3
61	56.4	62.3
62	57.3	63.5
63	60.2	63.2
64	59.4	63.9
65	59.5	62.3
66	57.2	62.8
67	68.2	62.3
68	66.5	62.2
69	65.3	63.2
70	58	63.9
71	62	63.7
72	59.6	62.5
73	60.6	62.3
74	51.7	65.5
75	56.9	63.7
76	64.8	62.2
77	65.3	63.5
78	59.1	63.3
79	64.9	63.2
80	60.5	61.3
81	68.2	62.9
82	63	62.8
83	64.1	61.9
84	62	63.3
85	66.8	61.8
86	63.2	63.2

87	62.7	62.1
88	61.5	62.2
89	57.7	62.8
90	58.6	63.4
91	64.8	62.4
92	58.1	60.7
93	60	62.1
94	65	63.8
95	65.6	61.6
96	60.6	61.2
97	65.9	62
98	59.8	61.8
99	57.6	62.8
100	57.6	60.9
101	56.9	62.4
102	66.9	61.3
103	59.1	62.1
104	57.7	63.4
105	58.8	61.8
106	60.9	62.4
107	61.5	62.3
108	61.4	62.6
109	59.8	62.5
110	61.4	62.4
111	65.3	62.5
112	64.9	61.5
113	64.3	61.9
114	67.6	64
115	60.9	62.8
116	61.2	61.7

117	66.2	62.4
118	65.3	62.2
119	67.6	64.1
120	66	61.4
121	62	60.6
122	66.6	59.8
123	61.8	60.9
124	64.6	63.4
125	68.1	63.2
126	68.5	61.4
127	67.9	62
128	63.3	62.4
129	63.3	61.5
130	64.9	62.5
131	66.1	63
132	68.4	62.4
133	63.9	62.5
134	66.9	61.9
135	64.4	61.6
136	62.4	62.3
137	64.8	62.5
138	64.8	61.9
139	59.7	62.3
140	65.9	63.4
141	60.4	62.6
142	58.9	63.9
143	63.8	62.9
144	60.2	62.5
145	60.7	61.9
146	63.1	62.6

147	59.1	62.3
148	58.5	62.1
149	62.3	62.9
150	63	61.4
151	62.6	63.2
152	66.7	63.2
153	63.9	62.7
154	59.1	62.9
155	62.7	61.9
156	65.5	62.9
157	63.2	61.9
158	64.7	62
159	63.7	62.1
160	62.6	61.5
161	65.5	62.5
162	55.8	62.8
163	62.1	62.2
164	68.4	63.2
165	65.3	62.5
166	63	61.9
167	66.6	62
168	60.9	62.8
169	58.3	62.9
170	62.9	62.4
171	69.3	62.5

APPENDIX C

DATA OF POST-MIXING EXPERIMENT

C.1 Data Collection Schedule for Post-mixing Design of Experiments

Table C.1: Data collection schedule for post-mixing design of experiments

Day	**Air-drying Temp (C)**	**Roasting conveyor speed (Hz)**	**Roasting gas flow rate**	**Collection Procedure**
1	62	70	High	Random sampling (5 samples)
2	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
3	61	60	High	Random sampling (5 samples)
4	61	65	High	Random sampling (5 samples)
5	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
6	61	60	High	Random sampling (5 samples)
7	60	65	High	Random sampling (5 samples)
8	61	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
9	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
10	62	60	High	Random sampling (5 samples)
11	61	65	High	Random sampling (5 samples)
12	62	60	High	Random sampling (5 samples)
13	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
14	60	70	High	Random sampling (5 samples)
15	61	70	High	Random sampling (5 samples)
16	60	60	High	Random sampling (5 samples)
17	61	60, 65, 70	Low	Experiment session (3 samples for each

				conveyor roasting speed)
18	60	60	High	Random sampling (5 samples)
19	61	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
20	61	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
21	62	65	High	Random sampling (5 samples)
22	61	70	High	Random sampling (5 samples)
23	60	65	High	Random sampling (5 samples)
24	60	70	High	Random sampling (5 samples)
25	61	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
26	62	65	High	Random sampling (5 samples)
27	62	70	High	Random sampling (5 samples)
28	61	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
29	61	60	High	Random sampling (5 samples)
30	60	70	High	Random sampling (5 samples)
31	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
32	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
33	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
34	60	60	High	Random sampling (5 samples)
35	60	65	High	Random sampling (5 samples)
36	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
37	62	60	High	Random sampling (5 samples)
38	62	70	High	Random sampling (5 samples)

39	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
40	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
41	61	70	High	Random sampling (5 samples)
42	62	65	High	Random sampling (5 samples)
43	61	65	High	Random sampling (5 samples)
44	60	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
45	60	60	High	Random sampling (5 samples)
46	62	65	High	Random sampling (5 samples)
47	60	70	High	Random sampling (5 samples)
48	61	60	High	Random sampling (5 samples)
49	62	60	High	Random sampling (5 samples)
50	62	60, 65, 70	Low	Experiment session (3 samples for each conveyor roasting speed)
51	60	65	High	Random sampling (5 samples)
52	61	65	High	Random sampling (5 samples)
53	62	70	High	Random sampling (5 samples)
54	61	70	High	Random sampling (5 samples)

C.2 Format of Data Collection Form for DoE Experiments

Table C.2: Format of data collection form for high-gas-flow-rate treatments in post-mixing design of experiments

Date	Sample Number	Air-drying Temperature (C)	Roasting Conveyor Speed (Hz)	Roasting Gas Flow Rate	Post-roasting Moisture
Day 1	1	...	...	...	...
	2	...	...	...	...
	3	...	...	...	...
	4	...	...	...	...
	5	...	...	...	...
Day 2	1	...	...	...	...
	2	...	...	...	...
	3	...	...	...	...
	4	...	...	...	...
	5	...	...	...	...
...	...	...	...	...	...

Table C.3: Format of data collection form for low-gas-flow-rate treatments in post-mixing design of experiments

Date	Sample Number	Air-drying Temperature (C)	Roasting Conveyor Speed (Hz)	Roasting Gas Flow Rate	Post-roasting Moisture
Day 1	1	...	60	...	...
	2	...	65	...	...
	3	...	70	...	...
	4	...	60	...	...
	5	...	65	...	...
	6	...	70	...	...
	7	...	60	...	...
	8	...	65	...	...
	9	...	70	...	...
Day 2	1	...	60	...	...
	2	...	65	...	...
	3	...	70	...	...
	4	...	60	...	...
	5	...	65	...	...
	6	...	70	...	...
	7	...	60	...	...
	8	...	65	...	...
	9	...	70	...	...
...	...	...	...	...	...

C.3 Data of DoE Experiment sorted by Order of Collection

Table C.4: Data of design of experiment sorted by order of collection

Day	Air-drying Temp (C)	Roasting Conveyor Speed (Hz)	Roasting Gas Flow Rate	Post-roast Moisture (%)
1	62	70	High	20.4
	62	70	High	17.6
	62	70	High	17.4
	62	70	High	19.6
	62	70	High	17.6
2	62	60	Low	16.1
	62	65	Low	16.3
	62	70	Low	15.2
	62	60	Low	14.5
	62	65	Low	15.4
	62	70	Low	16.5
	62	60	Low	14.7
	62	65	Low	14
	62	70	Low	13.8
3	61	60	High	14.6
	61	60	High	14.2
	61	60	High	16.6
	61	60	High	16.6
	61	60	High	15.9
4	61	65	High	15.7
	61	65	High	14.7
	61	65	High	15.5
	61	65	High	18.4
	61	65	High	17
5	62	60	Low	15.5
	62	65	Low	16.3
	62	70	Low	15.7
	62	60	Low	17.4
	62	65	Low	16.9
	62	70	Low	15.4
	62	60	Low	14.8
	62	65	Low	15.4
	62	70	Low	14.6
6	61	60	High	16.5
	61	60	High	15.7
	61	60	High	18.2
	61	60	High	13.5
	61	60	High	15.2
7	60	65	High	17.2
	60	65	High	19.6
	60	65	High	18.3
	60	65	High	13.5

	60	65	High	17.6
	61	60	Low	19.4
	61	65	Low	20.5
	61	70	Low	19.8
	61	60	Low	20.7
8	61	65	Low	20.8
	61	70	Low	19.5
	61	60	Low	20.9
	61	65	Low	21.2
	61	70	Low	18.9
	60	60	Low	22.7
	60	65	Low	20.7
	60	70	Low	19.4
	60	60	Low	19.3
	60	65	Low	18.2
	60	70	Low	21.1
	60	60	Low	19.9
	60	65	Low	16
9	60	70	Low	18.5
	62	60	High	18.6
	62	60	High	14.1
	62	60	High	15.8
	62	60	High	14.2
10	62	60	High	14.4
	61	65	High	16.1
	61	65	High	16.3
	61	65	High	15.7
	61	65	High	15
11	61	65	High	15.5
	62	60	High	18.6
	62	60	High	16.9
12	62	60	High	12.1
	62	60	High	15.4
	62	60	High	17.9
	60	60	Low	25.4
	60	65	Low	19.5
	60	70	Low	22.5
	60	60	Low	21.9
13	60	65	Low	19.5
	60	70	Low	20.2
	60	60	Low	21
	60	65	Low	21.9
	60	70	Low	22.3
	60	70	High	20.5
	60	70	High	19.6
14	60	70	High	18.8
	60	70	High	15.2
	60	70	High	16.8

	61	70	High	20.3
	61	70	High	17.6
15	61	70	High	18
	61	70	High	17.4
	61	70	High	17.8
	60	60	High	18.7
	60	60	High	15.8
16	60	60	High	13.4
	60	60	High	14.8
	60	60	High	17.4
	61	60	Low	18.3
	61	65	Low	19.2
	61	70	Low	19.9
	61	60	Low	19.3
17	61	65	Low	18.5
	61	70	Low	17.3
	61	60	Low	18.8
	61	65	Low	19.9
	61	70	Low	19.5
	60	60	High	13.4
	60	60	High	14.2
18	60	60	High	20.3
	60	60	High	16.4
	60	60	High	17.9
	61	60	Low	16.3
	61	65	Low	16.5
	61	70	Low	13.9
	61	60	Low	17.9
19	61	65	Low	15.8
	61	70	Low	16.8
	61	60	Low	17.7
	61	65	Low	17.5
	61	70	Low	17.3
	61	60	Low	20.8
	61	65	Low	20.7
	61	70	Low	18.8
	61	60	Low	21.3
20	61	65	Low	21.7
	61	70	Low	20
	61	60	Low	20.7
	61	65	Low	20.7
	61	70	Low	21.4
	62	65	High	15.5
	62	65	High	14.2
21	62	65	High	16.7
	62	65	High	16
	62	65	High	15.6

22	61	70	High	16.9
	61	70	High	18
	61	70	High	16.1
	61	70	High	13.4
	61	70	High	17.1
23	60	65	High	16.1
	60	65	High	15.7
	60	65	High	16.1
	60	65	High	13.4
	60	65	High	14.7
24	60	70	High	18.3
	60	70	High	18.6
	60	70	High	15.1
	60	70	High	14.8
	60	70	High	15.2
25	61	60	Low	12.1
	61	65	Low	13
	61	70	Low	12.7
	61	60	Low	14.3
	61	65	Low	14.2
	61	70	Low	14.7
	61	60	Low	14.1
	61	65	Low	15.2
	61	70	Low	14.8
26	62	65	High	18.7
	62	65	High	14.9
	62	65	High	15.1
	62	65	High	11.3
	62	65	High	12.5
27	62	70	High	14.3
	62	70	High	11.9
	62	70	High	13.5
	62	70	High	15.8
	62	70	High	14.1
28	61	60	Low	17.8
	61	65	Low	16.1
	61	70	Low	12.4
	61	60	Low	10.8
	61	65	Low	8.6
	61	70	Low	8.7
	61	60	Low	9.3
	61	65	Low	10.1
	61	70	Low	10.8
29	61	60	High	15.8
	61	60	High	15.6
	61	60	High	13.2

	61	60	High	14.9
30	60	70	High	19.4
	60	70	High	13.2
	60	70	High	17.8
	60	70	High	13.3
31	60	60	Low	20.2
	60	65	Low	21.1
	60	70	Low	21.3
	60	60	Low	22
	60	65	Low	22
	60	70	Low	22
	60	60	Low	21.7
	60	65	Low	22
	60	70	Low	21.5
32	62	60	Low	18.7
	62	65	Low	18.6
	62	70	Low	17.5
	62	60	Low	17.4
	62	65	Low	17.3
	62	70	Low	16.2
	62	60	Low	17.2
	62	65	Low	14.7
	62	70	Low	18.5
33	60	60	Low	19.7
	60	65	Low	20.8
	60	70	Low	19.9
	60	60	Low	21.6
	60	65	Low	20.1
	60	70	Low	19.4
	60	60	Low	19
	60	65	Low	18.7
	60	70	Low	19.6
34	60	60	High	16.1
	60	60	High	17
	60	60	High	16.8
	60	60	High	13.7
35	60	65	High	15.4
	60	65	High	11.9
	60	65	High	14.4
	60	65	High	15.4
36	62	60	Low	26.5
	62	65	Low	27.2
	62	70	Low	24.6
	62	60	Low	26.9
	62	65	Low	24.1
	62	70	Low	22.3

	62	60	Low	21.6
	62	65	Low	21.5
	62	70	Low	22.9
37	62	60	High	17
	62	60	High	14.4
	62	60	High	14.3
	62	60	High	14.6
38	62	70	High	15
	62	70	High	15.6
	62	70	High	17.6
	62	70	High	12.5
39	60	60	Low	19.8
	60	65	Low	18.6
	60	70	Low	18.7
	60	60	Low	19.4
	60	65	Low	18.7
	60	70	Low	18.2
	60	60	Low	21.2
	60	65	Low	20
	60	70	Low	20
40	62	60	Low	13.3
	62	65	Low	14.4
	62	70	Low	13.6
	62	60	Low	14.6
	62	65	Low	13.1
	62	70	Low	13.9
	62	60	Low	14.1
	62	65	Low	13.9
	62	70	Low	14.7
41	61	70	High	15
	61	70	High	14.2
	61	70	High	13.5
	61	70	High	13.7
42	62	65	High	13.2
	62	65	High	15.3
	62	65	High	16.8
	62	65	High	15.6
43	61	65	High	16.4
	61	65	High	16
	61	65	High	17.7
	61	65	High	16.8
44	60	60	Low	13.7
	60	60	Low	15.2
	60	60	Low	15.5
	60	65	Low	14.5
	60	65	Low	14.9

	60	65	Low	15
	60	70	Low	14.8
	60	70	Low	15.9
	60	70	Low	15.5
45	60	60	High	16.5
	60	60	High	15.4
	60	60	High	15.1
	60	60	High	17.4
46	62	65	High	17.3
	62	65	High	13
	62	65	High	15
	62	65	High	14.1
47	60	70	High	19.1
	60	70	High	15.9
	60	70	High	16.7
	60	70	High	14.1
48	61	60	High	15.4
	61	60	High	15.4
	61	60	High	15.5
	61	60	High	12
49	62	60	High	15.2
	62	60	High	12.9
	62	60	High	13.7
	62	60	High	13.9
50	62	60	Low	17.7
	62	60	Low	16.8
	62	60	Low	16.2
	62	65	Low	17
	62	65	Low	16.2
	62	65	Low	16.1
	62	70	Low	17.1
	62	70	Low	18
	62	70	Low	16.7
51	60	65	High	15.6
	60	65	High	14.7
	60	65	High	13.4
	60	65	High	12.1
52	61	65	High	15.4
	61	65	High	11.6
	61	65	High	15.2
	61	65	High	12.1
53	62	70	High	14.4
	62	70	High	14
	62	70	High	13.3
	62	70	High	16.7
54	61	70	High	17.3
	61	70	High	14.1
	61	70	High	14

	61	70	High	15.6

C.4 Data of Evaluation Experiment Under Air-drying Temperature of 61 C, the Roasting Conveyor Speed of 60Hz, and High Roasting Gas Flow Rate Sorted by Order of Collection

Table C.5: Data of evaluation experiments under air-drying temperature of 61 C, the roasting conveyor speed of 60Hz and high roasting gas flow rate sorted by the order of collection

Day	Post-air-drying Moisture (%)	Post-roast Moisture (%)
1	24.4	14.1
	25.7	11.6
	20.7	15.3
	17.6	15.1
	20.4	15.3
2	24.3	14.8
	24.7	16.7
	21.6	14.3
	22.7	12.4
	22.4	12.7
3	24.6	17.7
	19.4	17.3
	25.1	13.1
	22.1	12.6
	24	14.1
4	25.6	15.9
	26	19.8
	25.4	13.8
	23.1	13.8
	24	14.6
5	22.7	12.2
	24.5	14.6
	20.9	13.3
	22	12.2
	23.8	14.1
6	23.1	14.8
	23.1	14.7
	22.4	16.4
	23.7	14.4
	22.1	14
7	24.9	14.1
	26.3	14.7
	24.2	19.2
	26	12.9
	26.1	13.5

APPENDIX D
STATISTICAL OUTPUT OF DURING-MIXING EXPERIMENT'S ANALYSIS

D.1 Result of Two-variance Test Comparing Observed Moistures of Fish Mixture Before and After During-mixing Intervention

Method

Null hypothesis	Variance(After) / Variance(Before) = 1
Alternative hypothesis	Variance(After) / Variance(Before) < 1
Significance level	a = 0.05

F method was used. This method is accurate for normal data only.

Statistics

Variable	N	StDev	Variance	95% Upper Bound for Variances
After	171	1.171	1.372	1.656
Before	171	3.778	14.271	17.224

Ratio of standard deviations = 0.310
Ratio of variances = 0.096

95% One-Sided Confidence Intervals

Method	Upper Bound for StDev Ratio	Upper Bound for Variance Ratio
F	0.352	0.124

Tests

Method	DF1	DF2	Test Statistic	P-Value
F	170	170	0.10	0.000

D.2 Result of One-variance Test Comparing Observed Moistures of Fish Mixture to Predicted Moisture (Calculated in Equation 5.4)

Method

Null hypothesis	s =3.725
Alternative hypothesis	s <3.725

The chi-square method is only for the normal distribution.
The Bonett method is for any continuous distribution.

Statistics

Variable	N	StDev	Variance
After	171	1.17	1.37

95% One-Sided Confidence Intervals

Variable	Method	Upper Bound for StDev	Upper Bound for Variance
After	Chi-Square	1.29	1.66
	Bonett	1.33	1.78

Tests

Variable	Method	Test Statistic	DF	P-Value
After	Chi-Square	16.81	170	0.000
	Bonett	-	-	0.000

APPENDIX E
ROASTING TEMPERATURE DATA AT FIXED GAS FLOW RATE

Sample No.	Temp. (C)	Samples No.	Temp. (C)	Sample No.	Temp. (C)
1	159	**2**	161	**3**	163
4	169	**5**	167	**6**	169
7	178	**8**	177	**9**	151
10	159	**11**	172	**12**	177
13	176	**14**	173	**15**	175
16	180	**17**	188	**18**	165
19	169	**20**	173	**21**	155
22	149	**23**	165	**24**	167
25	176	**26**	171	**27**	160
28	165	**29**	168	**30**	148
31	172	**32**	168	**33**	148
34	148	**35**	166	**36**	155
37	163	**38**	164	**39**	145
40	142	**41**	160	**42**	162
43	164	**44**	168	**45**	168
46	164	**47**	159	**48**	162
49	169	**50**	168	**51**	158
52	169	**53**	168	**54**	166
55	162	**56**	162	**57**	158
58	166	**59**	172	**60**	173
61	166	**62**	159	**63**	166
64	160	**65**	159	**66**	159
67	163	**68**	168	**69**	170
70	160	**71**	157	**72**	159
73	164	**74**	165	**75**	167
76	158	**77**	156	**78**	165
79	166	**80**	152	**81**	144
82	159	**83**	153	**84**	166
85	162	**86**	158	**87**	166
88	161	**89**	157	**90**	172
91	168	**92**	166	**93**	165
94	163	**95**	163	**96**	167
97	153	**98**	153	**99**	161
100	159	**101**	159	**102**	161
103	156	**104**	156	**105**	161
106	170	**107**	168	**108**	162
109	166	**110**	163	**111**	178
112	170	**113**	165	**114**	168
115	166	**116**	146	**117**	158

118	159	**119**	159	**120**	160
121	161	**122**	154	**123**	158
124	159	**125**	157	**126**	164
127	180	**128**	166	**129**	159
130	158	**131**	166	**132**	160
133	175	**134**	171	**135**	161
136	175	**137**	178	**138**	176
139	178	**140**	168	**141**	172
142	171	**143**	166	**144**	154
145	160	**146**	161	**147**	160
148	157	**149**	159	**150**	166
151	153	**152**	159	**153**	161
154	165	**155**	166	**156**	160
157	166	**158**	165	**159**	154
160	161	**161**	163	**162**	165
163	177	**164**	161	**165**	151
166	165	**167**	160	**168**	171
169	165	**170**	160	**171**	171
172	151	**173**	160	**174**	163
175	164	**176**	151	**177**	158
178	163	**179**	160	**180**	163
181	159	**182**	165	**183**	159
184	160	**185**	162	**186**	163
187	160	**188**	159	**189**	162
190	161	**191**	160	**192**	167
193	162	**194**	162	**195**	163
196	156	**197**	163	**198**	158
199	156	**200**	167	**201**	159
202	172	**203**	165	**204**	136
205	166	**206**	159	**207**	144
208	160	**209**	167	**210**	161
211	157	**212**	153	**213**	173
214	165	**215**	157	**216**	165
217	158	**218**	167	**219**	160
220	157	**221**	163	**222**	158
223	170	**224**	170	**225**	158
226	150	**227**	162	**228**	155
229	160	**230**	161	**231**	158
232	161	**233**	166	**234**	156
235	156	**236**	161	**237**	165
238	159	**239**	162	**240**	162
241	161	**242**	158	**243**	157
244	161	**245**	156	**246**	166
247	161	**248**	166	**249**	167
250	161	**251**	162	**252**	160
253	163	**254**	151	**255**	151
256	158	**257**	156	**258**	165

259	165	**260**	165	**261**	168
262	165	**263**	176	**264**	178
265	164	**266**	174	**267**	177
268	159	**269**	157	**270**	147
271	166	**272**	168	**273**	170
274	171	**275**	162	**276**	160
277	159	**278**	161	**279**	160
280	162	**281**	163	**282**	165
283	141	**284**	171	**285**	166
286	163	**287**	169	**288**	160
289	161	**290**	168	**291**	165
292	161	**293**	164	**294**	165
295	170	**296**	174	**297**	171
298	170	**299**	166	**300**	176
301	164	**302**	166	**303**	165
304	166	**305**	174	**306**	156
307	161	**308**	159	**309**	154
310	171	**311**	173	**312**	180
313	172	**314**	173	**315**	166
316	165	**317**	169	**318**	155
319	180	**320**	173	**321**	174
322	156	**323**	163	**324**	160
325	161	**326**	152	**327**	155
328	146	**329**	160	**330**	155
331	162	**332**	157	**333**	157
334	158	**335**	158	**336**	148
337	153	**338**	154	**339**	155
340	154	**341**	156	**342**	161
343	160	**344**	189	**345**	170
346	174	**347**	172	**348**	183
349	184	**350**	175	**351**	172
352	173	**353**	173	**354**	183
355	168	**356**	173	**357**	176
358	174	**359**	175	**360**	157
361	169	**362**	184	**363**	184
364	161	**365**	173	**366**	179
367	179	**368**	175	**369**	167
370	164	**371**	167	**372**	157
373	167	**374**	168	**375**	162
376	159	**377**	169	**378**	180
379	179	**380**	159	**381**	173
382	173	**383**	163	**384**	158
385	169	**386**	174	**387**	173
388	167	**389**	171	**390**	174
391	174	**392**	168	**393**	167
394	171	**395**	174	**396**	161
397	166	**398**	169	**399**	167

400	162	**401**	165	**402**	163
403	164	**404**	165	**405**	170
406	159	**407**	165	**408**	165
409	176	**410**	174	**411**	188
412	168	**413**	172	**414**	175
415	169	**416**	167	**417**	172
418	173	**419**	174	**420**	166
421	163	**422**	160	**423**	171
424	167	**425**	171	**426**	169
427	166				

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REFERENCES

APPENDIX

VITA

Thananat Jitapunkul was born on July 27th, 1987 at San Francisco, CA, USA. He has received a Bachelor of Science and Master of Engineering Degree in Electrical Engineering and Computer Science from Massachusetts Institute of Technology in 2010. Thananat Jitapunkul has studied for the degree of Master of Engineering at the Regional Centre for Manufacturing Systems Engineering since 2014.