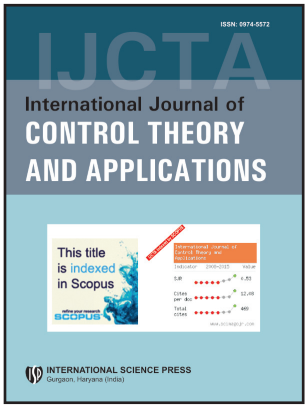

International Journal of Control Theory and Applications

ISSN : 0974-5572

Volume 9 • Number 44 • 2016

Using Statistical Experimental Design and RSM to Improve the Canning Process: A Case Study in the Fish Industry

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Abstract: Product weight is a crucial aspect in the Fish Industry. In this regard, the cans whose net weight is below LSL (Lower Specification Level) may increase customer complaints and financial sanctions. On the other hand, net weights above USL (Upper Specification Limit) represent significant economic burdens for the companies associated with this sector. Therefore, this paper focuses on the application of statistical experimental design and response surface methodologies to reduce the variability in net weight of canned tuna. First, the effects of two factors: Tomato Sauce Temperature (65°C-70°C, 70°C-75°C and 75°C-80°C), Conveyor Belt Speed (135 rpm, 140 rpm, and 145 rpm) and their interactions, were assessed via applying the 3^k factorial design. Then, a response surface analysis was performed to define the optimal conditions for the canning process. Finally, a bivariate regression analysis was carried out to develop a predictive model for average standard deviation of net weight per unit. In this case, the results demonstrated that both interaction and factors were found to be statistically significant (P-value < 0.05). Additionally, it is shown that the regression model is capable of predicting the response variable with high accuracy (Q^2 = 89.89%).

Keywords: Statistical Experimental Design, Response Surface Methodology (RSM), Optimization, Fish Industry.

1. INTRODUCTION

Product net weight is very critical in the Fish Industry. In this respect, the manufacturers have to deal with weight variation in order to reduce it. This is due to increases in variation correspond to decreases in quality which must be detected [1]. Therefore, the fish companies (e.g. Tuna manufacturers) must design effective tools to ensure that end customers will get the quantity of product they purchased, i.e. with net weight equal or above the declared LSL. Additionally, this characteristic is frequently monitored by the regulatory agencies (e.g. Food and Drug Administration – FDA) to check whether it is acceptable based on customers' expectations. On the other hand, if net weight is over the maximum allowed value (USL), the operational costs will be negatively affected and profits per unit will automatically drop [2]-[3]. This should not be erroneously ignored by quality managers who have to implement a set of process improvements to address this problem.

To overcome these difficulties, it is necessary to find methodologies identifying the sources of weight variation. That is to reduce or eliminate the aforementioned effects in both customers and companies from the Fish Industry. In this regard, some authors have worked on using different applications to address the variation problem in the Food Industry. In [4], the authors described the implementation of control charts in different companies from this sector. The empirical findings demonstrated that control chart application can be beneficial to minimize the variability of product weight and provides significant outcomes for effective monitoring and improvement. Another meaningful contribution in this field is found in [5], where the researchers presented a systematic review (41 articles) on the reported implementation of Statistical Process Control (SPC) in the Food Industry. As a key output, it was concluded that SPC has highly contributed to reducing process variation in this sector. Other examples of SPC implementations can be found in [6]-[8].

Considering the reported literature, only one study was found to be related to reducing variation in net weight of canned fish. The search string used in the literature survey was "*Variability*" AND "*Product weight*" AND *"Fish Industry"* The string was defined considering the standards of Scopus database. The aforementioned study [9] developed a predictive model incorporating the variability of fish, as a natural raw material, to improve process control of key parameters (e.g. weight). In this work, Hoki, the largest fishing resource of New Zealand, was considered to provide better forecasting, processing operations and the consistency of product quality. However, this model did not include variations derived from canning process parameters. In light of this, the conducted literature review evidenced that the studies concentrating on reducing variation in net weight of canned fish are largely limited. Thus, we proposed a combination of Statistical Experimental Design and Response Surface methodologies to address this problem and contribute to the development of this research area.

The remainder of this paper is organized as follows: In Section II, the 3^k factorial design and Response Surface Methodology (RSM) are presented. In Section III, a case study focused on the canning process of a company from the Tuna Industry is described. Finally, Section IV presents conclusions.

2. THE 3^K FACTORIAL DESIGN AND RESPONSE SURFACE METHODOLOGY (RSM)

Statistical Experimental Design or Design of Experiments (DOE) is a powerful tool evaluating the effects and interactions of different parameters on a set of response variables via using Multiple Linear Regression (MLR) [10]-[11]. Additionally, DOE provides a strict mathematical framework to simultaneously and independently change experimental factors in order to evaluate statistical significance with the smallest sample size [11]. One of the main strengths of DOE is the ability to identify the factor's effects on the response variables with high accuracy. Being aware of these benefits, since its origins, DOE has been widely applied in different sectors and processes of the Food Industry. In Sugar industry [12],[21], crayfish production [13], extruded products [14], lactic acid production [15], clarification of sapodilla juice [16], pectin extraction [17], extrusion cooking for rice flour [18], processing conditions on acrylamide levels in fried potato crisps [19], citric acid production [20]; and other applications. Particularly, the three-level design (3^k factorial design) was proposed to model possible curvature in the response function (non-linearity assumption) and to include nominal variables at three levels [22]-[23]. Furthermore, in this special case, each main effect has two degrees of freedom used to calculate the first-order and second-order components of the statistical model [24].

On the other hand, Response Surface Methodology (RSM) is a stepwise collection of statistical and numerical tools improving and optimizing processes and product designs [25]. RSM is useful to describe the influence of several independent variables on a set of responses [26] and to consequently increase the process or product yield without increasing costs [27]. The result is a mathematical model describing the response variable values obtained from some particular combination of the input variables [28]. As a consequence, extensive applications of RSM can be found in Food Industry. In fluid extraction of omega-3 [29], leavened bread [30], probiotic soy milk [31], storage conditions of malta [32], chicken shred and noodles [33]-[34], fermentation process of removal of cadmium in rice powder [35], preparation of cowpea protein concentrate [36], thermal processing of winter melon puree [37]; and other implementations.

To effectively perform 3^k factorial design and RSM, it is necessary to follow these steps:

Step 1: Define the independent factors, levels, and response variables

Establish k independent factors whose significance will be assessed through hypothesis tests on a set of response variables. Each factor (A, B, …) must be defined by three levels: 0 (low), 1 (intermediate) and 2 (high) to model possible curvature of response variable y. Each 3^k treatment combination is denoted with k digits where the first digit indicates the A level, the second digit refers to the B level,…, and the *k-esim* digit is the K level.

Step 2: Generate the null and alternative hypothesis for each factor and interaction

The hypotheses are based on available information and the researcher's belief regarding the population parameters [38]. In this, the means of factor treatments are compared (refer to Eq. 1-2) to validate if statistical equivalent (P-value < 0.05). Additionally, it is necessary to evaluate whether the interaction is significant (refer to Eq. 3).

$$\begin{aligned} &H_0: \tau_1 = \tau_2 = \cdots = \tau_a = 0 \\ &H_1: \text{At least one } \tau_i \neq 0 \end{aligned} \tag{1}$$

$$\begin{aligned} &H_0: \beta_1 = \beta_2 = \cdots = \beta_b = 0 \\ &H_1: \text{At least one } \beta_j \neq 0 \end{aligned} \tag{2}$$

$$\begin{aligned} &H_0: (\tau\beta)_{ij} = 0 \text{ for all the } i, j \\ &H_1: \text{At least one } (\tau\beta)_{ij} \neq 0 \end{aligned} \tag{3}$$

Step 3: Calculate the number of runs required in the experimental design

Determine the number of samples needed to determine, with high accuracy, if different levels perform statistically equal or different. This is subject to the probability (95% is recommended) of detecting a significant difference (D) when one truly exists (*Power*). To illustrate this, a power curve should be graphed with basis on the process standard deviation (σ), the number of factors (k), the number of factor levels (3) and α (usually 0.05).

Step 4: Data collection and random running order

After checking whether the metering system is suitable [39], the samples can be collected. Then, the measurements are performed randomly to eliminate the influence of extraneous factors in the experiment.

Step 5: Calculate the residuals and verify the DOE assumptions

First, compute the residuals by using Eq. 4. Then, use the residuals versus fits plot to examine the assumption that the residuals have a constant variance (*Homoscedasticity assumption*). In addition, analyse the residuals versus order plot to verify the assumption that the residual are uncorrelated with each other (*Independence assumption*). Finally, evaluate the normal plot of residuals to verify the assumption that the residuals are normally distributed with a mean of 0 and σ^2 (*Normality assumption* – N [0, σ^2]).

Step 6: Perform ANOVA (Analysis of Variance) to assess the significance of factors and interactions

To verify the significance of main factors and interactions, P-values and observed F-statistics must be calculated. If P-value is below 5%, the factor/interaction is concluded to be statistically significant. This can be also determined if the observed F statistics is greater than the critical value [40].

Step 7: Determine the optimal operating conditions by using RSM

Via applying the 3D surface and contour plots, the relationship between three variables can be explored. Both graphs display the predictor variables on the *x*- and *y*-scales, and the response (*z*) variable is represented by contours (contour plot) and a smooth surface (3D surface plot). With these plots, optimal operating conditions can be identified for any process or product.

Step 8: Set a regression model to predict the response variable

Finally, a regression analysis is carried out to generate an equation to describe the relationship between one or more predictors and the response variable. The mathematical expression considers the quadratic terms that let us model the curvature of the response variable. Particularly, for 3^2 factorial designs, the response can be modelled as stated in Eq. 4:

$$y = \mu + \gamma_i + \delta_j + (\gamma\delta)_{ij} + \varepsilon \tag{4}$$

3. CASE STUDY

To validate the proposed approach, a case study focused on the canning process of a company from the Tuna Industry is presented. The company's products derive from two main product lines: *pre-cooked tuna loins with vacuum packaging bag* and *canned tuna*. These products are frequently exported to different countries from South America and the European Union.

In order to significantly expand the product portfolio, the company has been working on developing a new tomato sauce based tuna. Nonetheless, some difficulties appeared due to uncontrolled variations of net weights as a result of the canning process. Theoretically, the canning machine places the pieces of tuna steaks and adds the tomato sauce according to the predefined specifications. However, some sources of variation negatively affect the process performance and thus, it was necessary to identify them for reduction or elimination. To do this, the stepwise procedure explained in Section II was effectively applied. Initially, the independent factors, treatments and response variables were defined. In this regard, the potential predictors and levels were: *Tomato Sauce Temperature "A" (65°C-70°C, 70°C-75°C and 75°C-80°C)* and *Conveyor Belt Speed "B" (135 rpm, 140 rpm, and 145 rpm)*. On the other hand, the response variable was established as the *average standard deviation of net weight in canned tuna.* Then, the null and alternative hypotheses were set via applying Eq. 2-4:

$$H_0: \tau_{65°C-70°C} = \tau_{70°C-75°C} = \tau_{75°C-80°C} = 0$$

$$H_a: At\ least\ one\ \tau_i \neq 0$$

$$H_0: \beta_{135} = \beta_{140} = \beta_{145} = 0$$

$$H_a: At\ least\ one\ \beta_j \neq 0$$

$$\begin{aligned} H_0: (\tau\beta)_{65°C-70°C,135} &= (\tau\beta)_{65°C-70°C,140} = (\tau\beta)_{65°C-70°C,145} = (\tau\beta)_{70°C-75°C,135} \\ &= (\tau\beta)_{70°C-75°C,140} = (\tau\beta)_{70°C-75°C,145} = (\tau\beta)_{75°C-80°C,135} = (\tau\beta)_{75°C-80°C,140} \\ &= (\tau\beta)_{75°C-80°C,145} = 0 \end{aligned}$$

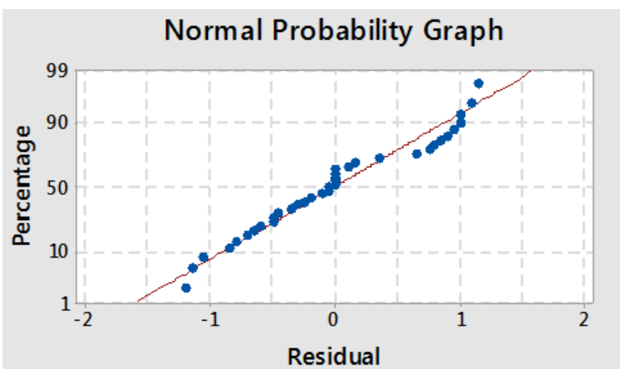
$$H_a: At\ least\ one\ (\tau\beta)_{ij} \neq 0$$

The next step involved calculating the sample size of the experiment. Via using the power curve supported by Minitab® software, four replications ($D = 5g$; $1 - \beta = 95\%$; $\alpha = 0.05$; $k = 2$) were determined to be enough for significance assessment. After this, the samples ($N = 36$) were collected and randomly measured. The net weights are shown in Table 1:

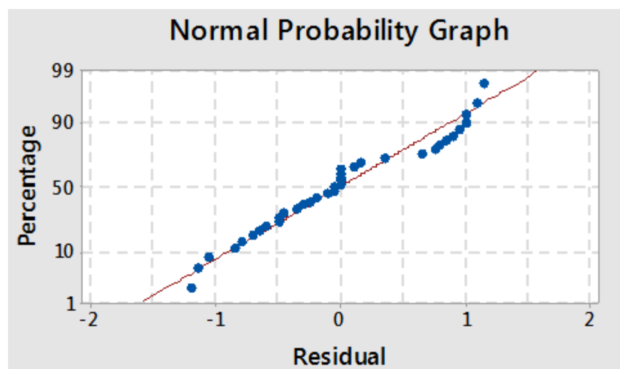
Table 1
Net weights of canned tuna under different combinations of Tomato Sauce Temperature and Conveyor Belt Speed

Tomato Sauce temperature (°C)	*Conveyor Belt Speed (rpm)*					
	135		*140*		*145*	
70 – 75	-4,4	-5	-0,2	-0,2	2,4	4,2
	-3,2	-4,8	-0,2	-0,2	2,4	4,6
75 – 80	-0,6	-1,8	-0,2	0,6	3,4	2,6
	-2,6	-0,8	1,4	0,2	1,4	2,4
80 – 85	5,4	4,4	1,6	1,2	2	1,4
	4,6	4	1,2	2,8	2,6	3

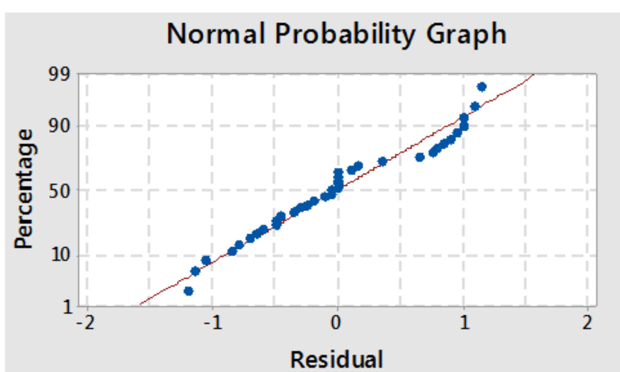
Considering the information from Table I, the residuals were obtained and analysed to validate the *Normality*, *Independence* and *Homoscedasticity* assumptions. First, an Anderson-Darling test was performed to validate the normality of residuals (refer to Figure 1a). With a P-value = 0.1 and AD = 0.61, the errors were concluded to be normally distributed (N~ [0, σ^2]). The Homoscedasticity assumption was also tested (refer to Figure 1b). In this case, there is no evidence to conclude that the variances are statistically different (All the p-values were found to be higher than 5%). Likewise, the independence condition was evaluated. In this respect, the residuals were found to be uncorrelated since they do not increase or decrease with the fitted values in a pattern.



(a)



(b)

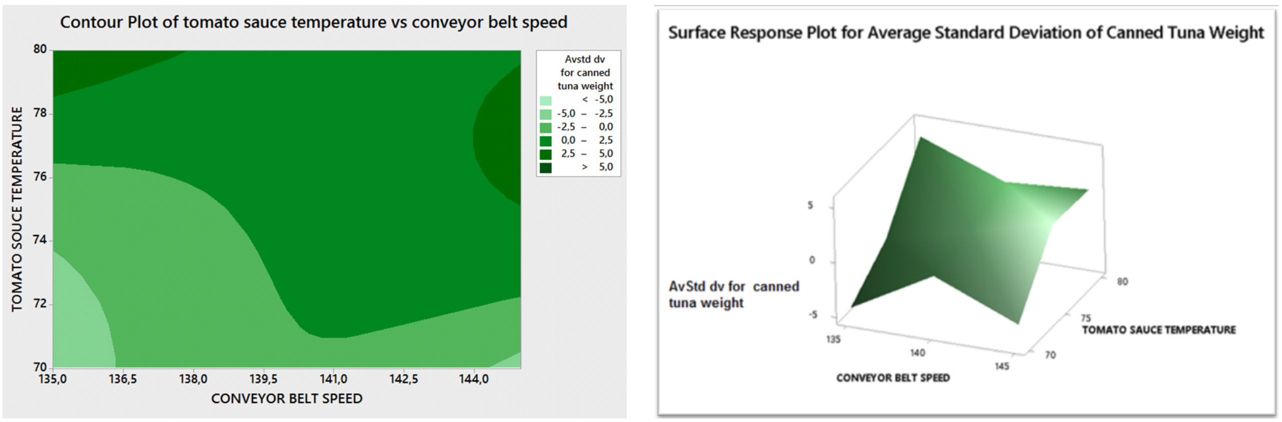


(c)

Figure 1: DOE assumptions: (a) Normality, (b) Homoscedasticity and (c) Independence

After checking the assumptions about the residuals, the ANOVA test was performed. The results demonstrated that both *Tomato Sauce Temperature* (P-value = 0; Observed F-statistics = 151.57) and *Conveyor Belt Speed*

(P-value = 0.006; Observed F-statistics = 6.26) were concluded to be statistically significant and thus, affect the *average standard deviation of net weights in canned tuna*. Besides, the interaction *Tomato Sauce Temperature* Conveyor Belt Speed* was also found to be statistically influencing on the response variable.



(a) **(b)**

Figure 2: Identification of optimal operating conditions for canning process: (a) Contour Plot and (b) Surface Response Plot

Being aware of these outcomes, 3D surface (Figure 2(a)) and contour (Figure 2(b)) plots were graphed to identify the operational conditions minimizing the variation of canned tuna weights. By analysing these graphs, the optimal operating conditions ($d = 0.9375$) for canning process are *Tomato Sauce Temperature* (70°C – 75°C) and *Conveyor Belt Speed* (135 rpm). Finally, a regression model was created to predict the performance of response variable using Eq. 4. The mathematical expression is shown below. In this case, the predicted R-squared-Q^2 was equal to 89.89% which indicates that the model has a greater predictive ability and the aforementioned factors effectively represent the variation of the response variable.

$$y = -399 + 5.17A + 2.56B - 0.033AB$$

4. CONCLUSION

Reducing variation of contents in the Fish Industry became an arduous task that must be addressed with accurate and effective statistical techniques. However, in reported literature, the studies concentrating on reducing variation in net weight of canned fish are largely limited. To cover this gap, the present paper proposed to combine Statistical Experimental Design and Response Surface methodologies which were concluded to be effective when facing process variation problem in the aforementioned industry. This framework can be extended and replicated with a high level of efficacy in other canning processes with considerable variability in product weight. This issue is even more important when improving company's profitability via reducing customer complaints, potential financial sanctions, and over-production.

Considering the case study, the results evidenced that both main factors (*Tomato Sauce Temperature* and *Conveyor Belt Speed*) and interaction were found to be statistically significant on the *average standard deviation in net weight of canned tuna*. Additionally, the optimal operating conditions for canning processes were: *Tomato Sauce Temperature* (70°C – 75°C) and *Conveyor Belt Speed* (135 rpm) which must be implemented to meaningfully minimize variations of net weights per can.

In future research, it is recommended to add more potential influencing variables in order to increase the accuracy of the predictive model. Additionally, it is proposed to combine these statistical methodologies with financial measures providing a deeper analysis of response variables.

Acknowledgment

The authors would like to thank the Specialization in Integral Quality Management of Universidad de la Costa CUC for its valuable contributions.

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