METHODS TO IDENTIFY, QUANTIFY AND MINIMISE VARIATION OF NET WEIGHTS IN CANNED FOODS

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Abstract

Using a 2^4 factorial design model, the methods to identify and quantify the major sources of variation of net weights in canned foods were investigated. A piston filler was selected using modified starch solution as the filling medium. The stroke length and speed of the filler and the concentration and temperature of the filling medium comprised the four factors. The data were transformed into means and variances of fill weights from both across filling heads and across consecutive filling cycles, and were used as responses.

The responses, which were derived across filling cycles for each of the filling heads, were used as blocks, to evaluate the head effects. The projection designs were used to optimise variation and fill levels at set piston-stroke levels. The factor level combinations required to minimise variation and maximise fill level which was computed through a model matrix using all important effects were found to be P+,S+,T-,C+ and P+,S+,T+C+ respectively. The contributions of factors and their interactions to the short-term variance of fill weights were estimated using variance across heads within consecutive filling cycles (88.5%). The analysis across filling cycles within individual heads estimated the deviation of fix factor levels within the trials and contributed to 44%, which appeared as factor effects. Most of this variation (52.3%) which was caused by the unstable filling mechanisms appeared as the residual error. The analysis of blocks using heads was successful in partitioning the variance due to head differences (3.6%).The high volume operations generated a higher contribution from unstable filling mechanisms to the total variance, and a lesser contribution from head differences to the total range of fill weights. The recommendations include methods and materials to reduce the error in the design. Future research is recommended in the areas of vacuum and single shot fillers, multi-filling processes, and particle size variation.

Dedication

I dedicate this thesis with love and appreciation to Piyadasa and Daisy Mary Vithange, my father and mother, and to Disinahami, my grandmother, for their inspiration, guidance and support in shaping my life.

Acknowledgements

My supervisors, Dr John Bronlund and Dr Nigel Grigg, not only did an excellent job of supervising the research which was carried out at the Heinz Wattie site but also stepped out of their line of duties to rescue and put me back on the right track when the going was tough. I deeply appreciate their invaluable help in accomplishing this task.

Working towards a master's degree amidst the pressures of a demanding career has been a difficult task. I deeply appreciate the selfless and unconditional support of my dear wife, Ajantha Vithanage, in motivating me to complete this thesis and for shouldering most of my share of the household responsibilities during this difficult time.

I give sincere thanks to Anthony Bennet, the manager of project engineering, for recognising the importance of the role of DoE in the food-processing environment of Heinz Wattie Ltd, Hastings and for providing the much-needed funds for this research. Further, I express my appreciation and thanks to Trixie Ackerly for her expert advice in helping to shape up the desktop document numerous times, and to Graham Danes for his valuable comments during the revising of this document.

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Glossary of Notations

ANOM	Analysis of Means
ANOVA	Analysis of Variance
AQS	Average Quantity System
Brix	Percent of soluble solids on w/w basis on sugar scale
DIKT	Data-Information-Knowledge-Technology
DoE	Design of Experiments (Planned Experiments)
HACCP	Hazard and Critical Control Points
IQR	Inter Quartile Range
LQ	Lower quartile
LSL	Lower Specification Limits
LSM	Least Square Means
MFw-Ac-Fc	Mean Fill weights Across Filling cycles
MFw-Ac-Fh	Mean Fill weights Across Filler heads
NPPOSE	Normal Probability Plot of the Standardized Effects
PCA	The principal component analysis
PCOSE	Pareto Chart of the Standardized Effects
PCR	Process capability ratio
PLC	Programmable Logic Control
Pre-fill	Any filling components involved prior to final filling
SD	Standard Deviation
SKU	Stock Keeping Unit
SPC	Statistical Process Control
SSB	Sum of Squares Between Samples
SSW	Sum of Squares Within Samples
TQC	Total Quality Control
TQM	Total Quality Management
UQ	Upper quartile
USL	Upper Specification Limits
Var-Ac-Fc	Variance of Fill weights Across Filling cycles
Var-Ac-Fh	Variance of Fill weights Across Filling heads

1 INTRODUCTION

Chapter

1-1 SCOPE OF RESEARCH

Heinz Wattie's Ltd. is a food company which manufactures about 1200 food products in the form of cans, pouches and frozen packs. In 1993, the author introduced Statistical Process Control (SPC), replacing the existing methods of control. The existing methods specified control of individual weights of cans within specification limits.

The initial stage of SPC (Statistical Process Control) involves the controlling of process averages within control limits. During the next stage, the variability of some processes was reduced by taking corrective actions for special causes. A total of over NZ$ 1.5m worth of "give-away" has been recovered. The proportion of time for which the process is in control has increased from 23% to 62% (Vithanage, 1994, 68). In spite of the initial success and ongoing improvements, the SPC programme was facing ever-increasing challenges from the following areas.

- Incapable production processes due to high variability of quantity and related quality parameters
- Control of weights while maintaining product safety and can integrity
- Control of weights while conserving product quality characteristics
- Expectations from overseas markets for tighter weight performance
- Increased consumer vigilance and meeting the regulatory requirements of different countries

A significant amount of direct and indirect saving will be made by meeting some of these challenges. For example, the cost of non-standard products due to under- and over-filling is around $ 500,000 per annum (Vithanage, 2003). The majority of quantity and quality related Nonstandard Products are due to the increased variations of output process variables. Although the total output variability could be reduced to some extent, a planned and systematic reduction was not possible for following reasons:

a) Lack of tools to identify and quantify the sources of this variability

b) Lack of knowledge of the optimum combination of the input variables, required to reduce the variation of net contents in canned products

Therefore, this study was aimed at developing methods to identify and quantify the contributing variations to the total variability of net weights. These process variables, which appear in the form of quality and other process parameters, would be identified and used as factors in the Design of Experiment.

Appendix 12 illustrates how the major sources, the factors within each of the major sources and the interactions among major sources, contribute to final and measurable net content variation in canned foods using the Japanese Beef Curry Process as an example.

1-2 PROJECT PROPOSALS

The overall goal of the project was to develop methods to minimise the variation of net weights in canned foods. The following two tasks were used to achieve this goal.

a) Identify and quantify the process variables, which contribute to net weight variability in canned foods using a liquid medium representing the key variables.

b) Develop methods to determine the optimum combination required of the contributing factors to minimise the variation of total net contents.

The optimum combination of the variables to reduce net weights variation, once quantified, provides a logical basis to optimise weights to reduce "give-away" and underweights.

These objectives were achieved by studying a representative medium through a selected filler. The information was then used to develop methodologies which are applicable to any product fill situation. The scoping of this study was therefore confined to the filler and product variability aspects represented in Appendix 12.

<u>Project Stages</u>

1) Process and Literature Reviews
2) Project approval from Heinz Wattie Ltd.
3) Screening of factors for planned experiment
4) Planned Experimentation
5) Data Collection
6) Analysis
7) Submission of Thesis

Chapter 2 LITERATURE SURVEY

2-1 REVIEW OF STATISTICAL METHODS

A literature survey was carried out to establish available statistical methods to reduce variability and to optimise processes in the food industry. The literature was reviewed to provide a general review of methods applied, the benefits of statistical methods, the role of Design of Experiments, building process knowledge using DoE as a tool, useful statistical techniques in DoE, and the application of DoE in reducing food process variability. Finally, the methodology of DoE was summarised as a tool for experimenting with multivariate processes and as a tool of analysis.

2-2 APPLICATIONS AND CASE STUDIES

2-2.1 STATISTICAL METHODS IN FOOD PROCESS IMPROVEMENT

Increased competition in the international market-place has prompted a revolution in quality control systems since 1980. Up to this period, relatively little was published on the application of SPC in the food industry. They included the use of control charts to monitor food processes, show trend analysis and for obtaining warning signals to control the process as the key statistical applications. Among examples of specific applications was the use of SPC in HACCP (Hazard and Critical Control Points) analysis, automated SPC monitoring in extruded products, use of control charts with suboptimal sampling in breweries and variance components applications in the biscuit industry. In recent times, the use of statistical methods such as multivariate analysis, regression analysis, time series and non-parametric methods has become more common. (Srikaeo *et al.*, 2005, 309-317)

In a paper dealing with industrial applications of Statistical Quality Control (SQC) (Grigg, 2005) provided a summary of academic articles which has been classified to show the subject and relevant industry product or sector. The key quality criteria were food safety and weight control and the industrial sectors involved were dairy, biscuit manufacture, meat, and poultry and drinks production.

The lead-time required for the successful launch of a product in the market-place can be greatly reduced by Design of Experiments. An article published by Arteaga & Peres (1994, 242-254), contains details of DoE applications available for optimisation work. Among them, Fractional Factorial Designs including Taguchi methods, Response Surface methodology and Mixture Designs, have been cited as effective.

The author has pioneered the use of statistical methods in food process improvements at Heinz Wattie, New Zealand since 1993. The methods used included the following:

1) Control charts for feed-back control

2) Modified acceptance sampling procedures for vendor/customer dealings

3) Challenge testing and validation methods for processing equipment

4) Component analysis for estimating measurement error and improving variation of weights during check weighing

5) Use of correlation, regression and ANOVA techniques to improve specific product quality-related issues

Srikaeo wrote about the use of ANOVA and ANOM (Analysis of Means) in conjunction with control charts, as means of identifying significant changes to mean process parameters. His efforts to separate the measurement error component of the observed variance from the true process variation, by the use of variance components methods, was a very useful contribution as this error factor has been found to be very significant. (Srikaeo *et al.*, 2005, 309-317)

2-2.2 *USE OF STATISTICAL METHODS*

2-2.2.1 Role of Statistical Thinking in Food Industry

Bjerke & Hersleth (2001,49-59) assert that the core elements of statistical thinking have been recognised as the generation of data, extraction of relevant information from data and utilisation of this information for optimal decision making. This paper also promoted the view, which was published by Ishikawa, (1985) that statistical thinking should be the basis for Total Quality Management (TQM) or Total Quality Control (TQC).

Statistical thinking plays a very important role in changing a company culture to accept statistical methods as an effective tool of process control and improvements. A model developed for Total Quality emphasised three levels of activities: strategic, managerial and operational and the responsibilities which are involved at each level. At the strategic level, the basic concepts such as acknowledging the universal presence of variation in processes, the interconnectedness of processes and the fact that reduction of variation improves quality, are established. At managerial levels, systems such as SPC, Design of Experiments and Robust designs are developed in order to bring together the tool kits for the application at the next level below. Although the list contained a random collection of tools, it is important to notice that most of the tools had origins in Designs of Experiments. These arguments further support the author's attempts to use methods in Design of Experiments to reduce variability in the net weight process in canned foods. (Snee, 1990, 116-121)

An investigation into the existing difficulties in applying statistical methods to the food industry has identified management involvement, systems for distribution of competence and some aspects of corporate culture to be among the main factors. (Bjerke & Hersleth., 2001, 49-59) The author of thesis also agrees with the idea (Grigg, 2005,10) of the existence of organisational filters (barriers) which need to be overcome before the use of statistical methods is effectively established. Grigg further presented a list of requirements for each of the six levels, which is required to be met in order to overcome each of these organisational filters.

Once the quality engineers have identified the factors and the optimum levels of those factors to minimise variability, the process can be redesigned for robustness. Snee (1990) highlights the importance of statistical thinking to make processes more robust. This derives from the quality principle published by W. Edwards Demings, urging for reduction in variation to improve quality. This form of thinking developed based on identifying, characterising, quantifying, controlling and finally reducing variations to provide opportunities for improvement. (Snee, 1990, 116-121)

One of the ways to reduce variation is to design and build processes that are not affected by unknown or uncontrollable variations. Snee used the term *rugged* or *robust* to recognise these processes. Design of experiments is an important tool to design rugged processes. A rugged product or process reduces variation, because it becomes insensitive to variations in components of manufacture, method of use and conditions of use. This is important in food processes where the net weights or a specific quality is affected by factors not directly involved in the food formulations but which arise from methods of handling such as filling.

2-2.2.2 Benefits of Statistical Methods

Grigg (2005) examined the existing statistical applications in the food industry and their benefits as well as the work needed to enhance the use of SQC techniques for effective realisation of those benefits. This paper further illustrates the benefits in a flow chart through a hierarchical format, which was reported using the research questionnaire (Figure 2-1). Although the flow chart looked somewhat complex, the list of benefits derived was a definitive proof of the validity of applications of statistical methods. The five main benefits, which appear at the top level of the hierarchy, were as follows:

a) Improved customer and producer confidence in product

b) Improved process visibility and understanding

c) Improved competitiveness

d) Facilitated continuous improvement

e) Cost savings

Further down the hierarchy were reduced process variability, enhanced control of product quality and consistency, reduction of waste and reduced giveaway due to overfilling.

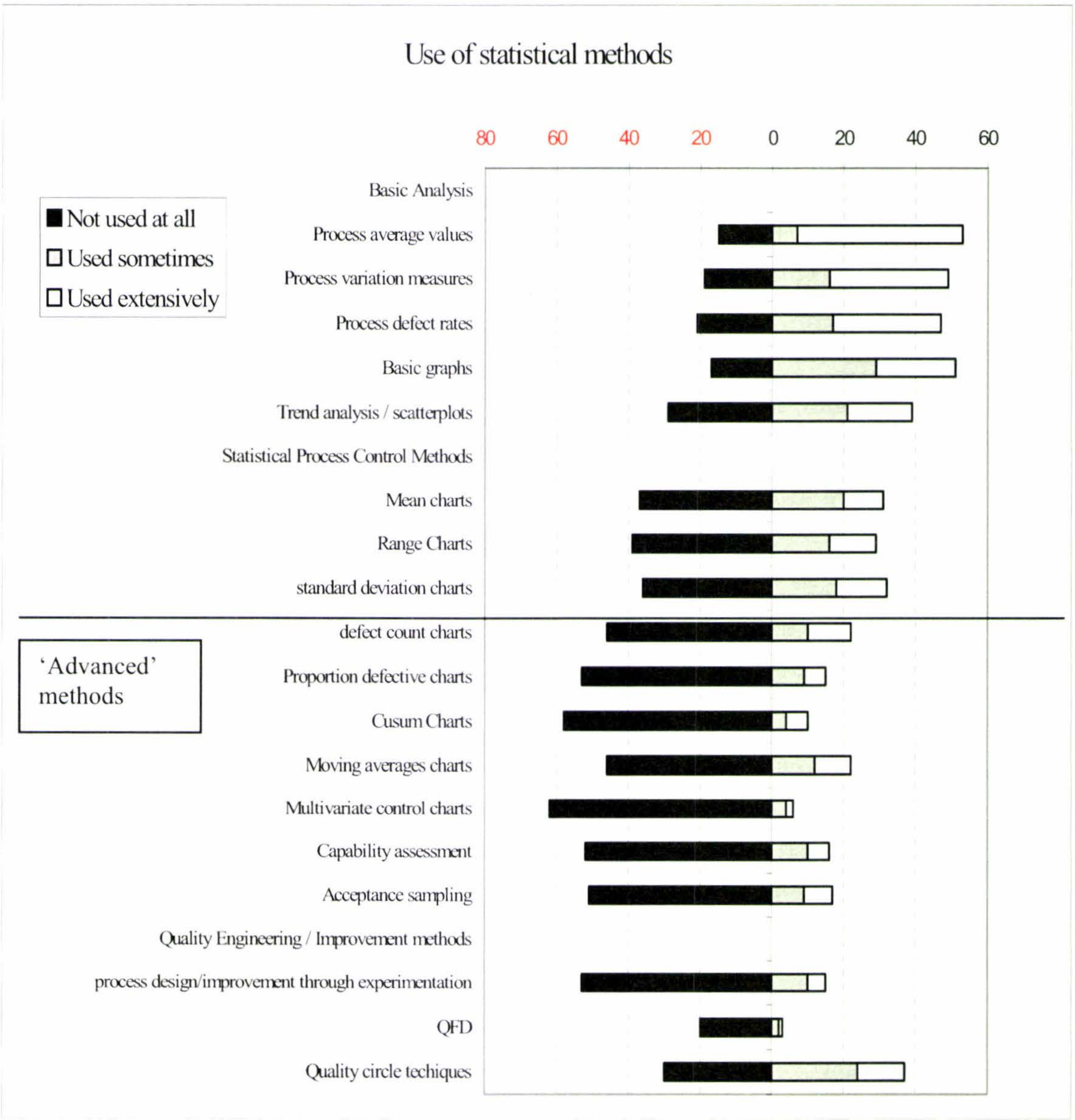


Figure 2.1 Use of statistical methods within responding organizations (Grigg, 2005)

The work of Srikaeo (Srikaeo *et al.*, 2005) demonstrated the use of SPC techniques to characterize a food process. He has quoted a definition for process characterisation as the "activity required to identify the key inputs and outputs of a process, collect data on their behavior, estimate the steady state behavior at optimal operating conditions and build models to describe the parameter relationship across the operating range". Although this is similar in context to the definition given by Montgomery (2001, Section 2-2.5), the latter highlights the essential features of the characterisation process. Montgomery's definition encompassed the identification of process parameters, both controllable and uncontrollable, that affect the response parameter concerned and the designing of an experiment that enables one to estimate the magnitude and the direction of the factor effects. The present author agrees with the latter definition and likes to allocate the activity of "the estimation of steady state behavior at optimal conditions and modeling" which Srikaeo quoted into the proper design of the experiment stage including the analysis. This activity would be more effective in my view, if done with a special emphasis on minimising the process variability.

2-2.3 *DESIGN OF EXPERIMENTS IN VARIABILITY REDUCTION*

Crow (2002) describes three sources of variation: manufacturing variation, environmental or deterioration variation and usage variation (Figure 2.2). The product can be designed to counter these sources of variation, depending on the extent to which we are aware of these potential sources of variation.

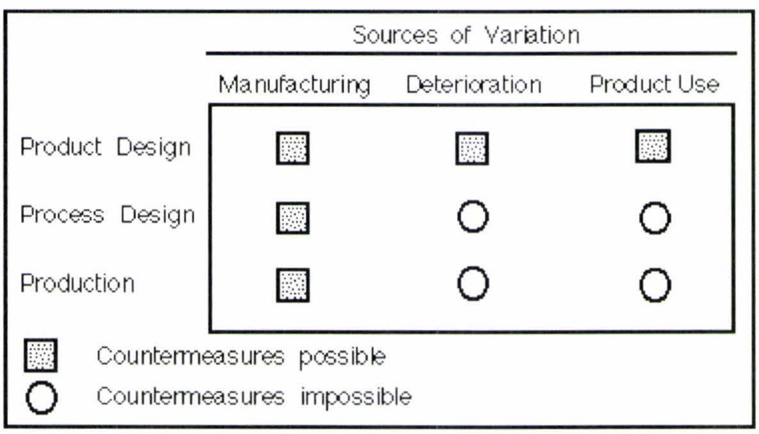


Figure 2-.2 Three major sources of variation in industries (Crow, 2006)

The concept of robust design is based on this. It is achieved primarily by the use of design of experiments to determine which factors (product and process parameters) are most sensitive to variation or noise and which factor level settings (parameter values) minimise the variability in the desired performance parameter (Figure 2.3).

Design of Experiments (DOE) can be used to counter all three sources of variation. In addition, other steps can be taken to counter manufacturing variation and usage variation. First, understanding the statistical capability of a process can help to either design within the capability of that process or determine when an improved capability is required. Second, by using SPC, special cause variation can be identified and attacked. Third, over the longer term, process variability from common causes can be systematically reduced through process optimisation, operator training, preventative maintenance, tool monitoring, standardisation of machine settings, climate control, power conditioning, and so on. Fourth, variability in usage can be countered by mistake-proofing, warning labels, easy-to-understand operating manuals and controls, and other, similar, measures.

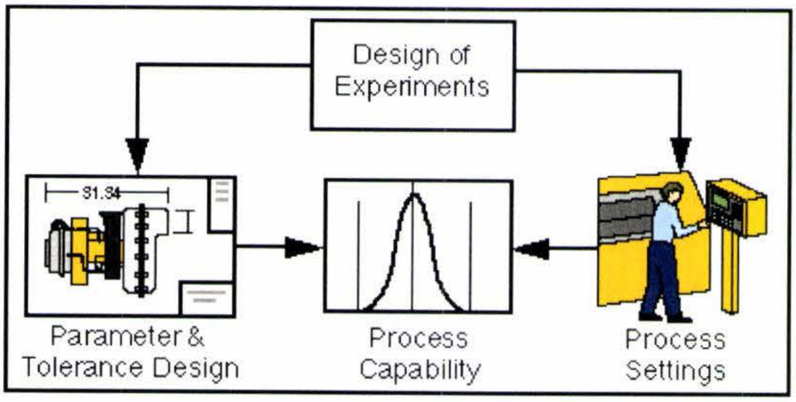


Figure 2-3 Concept of robust design (Crow, 2006)

Variability reduction involves understanding customer needs and developing a product and process design that balances these needs with process capabilities and potential sources of variation. Thus variability reduction is broader than SPC and DoE individually and more proactive than SPC.

A robust product is one that works as intended regardless of variation in its manufacturing process, variation resulting from deterioration, and variation in use.

Robust design can be achieved when the designer understands these potential sources of variation and takes steps to desensitise the product to these potential sources of variation. When the operation of the product or achievement of a performance characteristic can be mathematically related to a product or process design parameter, optimum product and process design parameters can be calculated. When these relationships are unknown, design of experiments (DoE) can aid in determining these optimum parameter values and, thereby, in developing a more robust design. Design of Experiments is based on the objective of desensitising a product's performance characteristic(s) to variation in critical product and process design parameters (Crow, 2002).

2-2.4 *DoE AS A TOOL OF BUILDING PROCESS KNOWLEDGE*

A paper published by Grigg & Graham. (2003), provides some valuable guidelines to use organisational knowledge, which is found to be equally applicable during the intended research. Specifically, this paper deals with aspects of building knowledge by the use of dynamics of knowledge creation. This knowledge has been classified as either existing or obtainable through planned experiments. The paper further examines the development of process knowledge, which normally exists within the company.

The approach described in this paper could be effectively used to challenge and test both the formal and informal knowledge among company personnel. It also recognises the value of process knowledge diffused within a manufacturing facility similar to Heinz Wattie's Ltd. Further, it recognises the need to develop this knowledge to be useful for practical applications using DoE.

The discussion on the process of creating process knowledge by using known concepts such as 'knowledge spiral', 'knowledge management landscape' and the 'DIKT (data-information-knowledge-technology) learning process', is of particular interest. It further stresses how DoE could provide an effective means of challenging and testing the competing hypotheses as well as existing tacit knowledge.

The paper stresses the need for an initial hypothesis that determines the variables to be included in the screening experiments. The problem is seen as the selection of key variables from a large domain of possible variables. This stage involves tapping into formal and tacit knowledge bases. Quality circles are seen as a means of tapping the tacit knowledge of the work force, with some limitations.

2-2.5 *USEFUL STATISTICAL TECHNIQUES IN DOE*

The process of quantifying variables contributing to the total variability of net weights requires an approach that is more fundamental than complex statistical systems. My approach is to review literature related to designs, in which screening techniques, methods of reducing experimental runs effectively and simpler but effective analytical techniques have been employed. The suggestion to use simpler techniques is essential; as such techniques could be repetitively applicable as a standard by technologists with low statistical knowledge.

One of the major difficulties encountered during planned experiments for multi-stage food processes is the occurrence of outliers. Of the numerous techniques presented, a very basic approach reproduced in the book by Clark and Randal (2004), appeals most. They have defined as an odd value that seems to be lying all by itself away from the main body of data and provided the following equation to identify an outlier.

An outlier is an observation

a) Above UQ + 1.5 x IQR or
b) below LQ – 1.5 x IQR

Where UQ and LQ denotes Upper and Lower quartiles and IQR denotes Inter Quartile Range.

When the factorials are un-replicated, outliers could affect the analysis. In a different approach, the experimenter does not actually have to remove the outliers because the this method helps to keep experimental error rate under control and at the same time improves the power to detect active factors. This method involves the combination of the rank transformation of the observation, the Daniel plot and a formal statistical testing procedure to assess the significance of the effects. (Aguirre & Peres, 2001, 637-663)

It is important to check whether or not a particular distribution of variables in statistical applications confirm to normal distribution. For example, the quality characteristics which control the beer-brewing process were found to be non-normally distributed using both Kurtosis and Skewness tests. The skewness measures the symmetry and the Kurtosis measures the tendency to deviate from the bell shape of the normal distribution. The application of transformed parameters using logarithmically transformed variables to construct control charts was found to be effective. (Ozilgen, M.,1998,57-60)

Gonzalez-Miret *et al.*, (2001) have used the Kolmogorov-Smirnov-Lilliefors Test to check the normality of the transformed data during their validation of microbiological variables using univariate and multivariate statistics. Alternatively, when variables do not fit normal distribution, the non-parametric Friedman Test model was used for analysing the effects as an alternative to ANOVA (Gonzalez-Miret *et al.*, 2001,261-268).

Split-plot experiments help to reduce the time and cost constraints as well as the size of the experiments in manufacturing environments having complex and busy schedules. A method of conducting sixteen run designs using fractional factorial and confounding was described by Kowalski (2002, 399-410).

One of the simple techniques of obtaining more information out of a factor analysis is to collapse or project the original design into another 2^k design with fewer variables by dropping one or more original factors if those factors and their interactions are less significant (Hines *et al.*, 4th ed., 384). Similarly, if one or more factors from a fractional factorial design can be dropped the remaining design will project into a full factorial design. The method requires the analyst to identify the largest estimated effects without regard to sign. If any of the factors under study are absent in the effect list, the analyst can assume that the factor has no significant effect or that the factor effect is distorted by error. Consequently, the analyst now could collapse the design into the next lower order. (Juran & Gryna, 1974)

The present author has experienced difficulties in targeting the process so that all the key responses meet within a desired set of specifications. An article dealing with correlating multiple responses details the design and analytical aspects required to achieve this. The procedure involved the modelling of distributional parameters in terms of experimental factors and finding a factor setting which maximises the probability of being in a specification region (Chiao & Hamada, 2001,451-465).

The lead-time required for successful launching of a product in the market place can be greatly reduced by Design of Experiments. An article published by Arteaga & Peres (1994, 242-254), contains details of DoE applications available for optimisation work. Among the methods presented, Fractional Factorial Designs including Taguchi methods, Response Surface methodology and mixture designs have been cited as effective.

It is important to look for corrective action when experiments could not be performed as planned. One of the common errors is the failure to reset all the factor levels during successive runs, violating the assumption of independent observations from run to run. This causes biased estimates of the coefficients in the model during least squares analysis, leading to incorrect conclusions.

Methods are available now to predict (Webb *et al.*, 2004,1-11) the variance, where the variance derived from the experiment was unrealistic against the expected variance. This paper explains how the failure to reset factor levels in successive runs leads to larger than expected variance and erroneous parameter estimates. Further, the paper provides methods of analysis for this type of experiment and recommendations to conduct DoE when one or more factor levels are not reset.

Another common obstacle in industrial experiments is the encountering of factors which cannot be completely randomised due to manufacturing restrictions. For example, complete randomisation of important factors, which affect the net weight variation such as concentration of product, temperature, filler speed and so on, will demand resources not usually available to the experimenter.

In a paper written about restrictions in complete randomisation, the authors (Arvidsson & Gremyr, 2003, 87-89) present consequences of incomplete randomisation. The paper achieves the objective of developing a pragmatic and user-friendly decision tree. The decision tree helps to select restrictions in complete randomisation. Further, the decision tree shows the importance of understanding the differences between randomisation and resetting, and therefore the consequences for the experimental results. Therefore, the decision tree offers a practical value in selecting restrictions.

Where we face factors that are hard to change, split-plot designs have become increasingly important. When factors cannot be fully randomised, researchers have demonstrated the use of the D-optimal first and second order split-plot designs (Goos & Vandebroek, 2004, 12-26) to overcome the problem. In fact, it has been shown that these designs could perform better in many cases than completely randomised designs.

2-2.6 *APPLICATIONS OF DOE IN FOOD PROCESS VARIABILITY*

A case study of the use of experimental design (Ellekjaer *et al.*, 1996, 29-36), in product development involved a study of the process quality of cheese to improve its sensory quality. A screening experiment was used to identify important variables that affect the sensory quality. Fractional factorial design with resolution IV was used to reduce the number of experimental runs. ANOVA and normal plots were used to evaluate the sensory quality due to factors involved. The principal component analysis (PCA) was found to produce similar results and therefore found to be important in identifying the improved sensory properties. The combination of experimental design and multivariate methods is thought to be effective in this situation.

The scores of the main principal component constituted the response variables during multivariate analysis. The design consisted of two levels of the selected seven factors in a 2^{7-2} fractional factorial design, where main effects and two factor interactions remain un-compounded. ANOVA was used to isolate sensory attributes which could differentiate between samples. Probability plots were used to study the effects of different factors and to isolate significant effects. Multivariate analysis was found to be more useful than univariate ANOVA for product improvements. Researchers were able to use conditions which have significant effect on quality such as grade of maturity and addition of dry matter and a cooling process to improve quality.

The use of nested designs will be considered for component analysis of net weight if the design can be converted to a nested design. We could have two different product temperature within each of the product concentrations and two filler speeds within each product temperatures and so on. Use of a Nested model was published by Ittzes (2001,119-125), who described how variance components were analysed in dry matter content in butter cream. The factors consisted of the compound itself, sample units chosen and the measurements within the sample. The variance of the process is estimated into these components using three control charts for averages, the sample-to-sample variability and the within-sample variability. The Nested model was applied to design the experiments and the ANOVA was used to separate variance components. However, adoption of a net weight variability model into a nested model of analysis must be compared with the analysis using factorial designs.

Where the analysis proves the mixture characteristics of a given product to be a significant factor contributing to total net weight variation, then more advanced mixture design and analysis could prove important. Bjerke at el. (2000, 22-36) described an application of a more advanced technique to optimise the food mixture. This design is called a *projection design* and takes into account the constraints among ingredients and is herefore more complex than factorial and fractional factorial designs. This paper discusses and compares the conventional mixture model approach with that of the projection design approach. It was mentioned that they have used the work published by Box at el. (1990) on this methodology as the basis for their work. He concludes that the projection design approach is more useful than mixture model designs. However, mixture model designs were seen as flexible in the design region and easier to analyse and interpret. The projection design approach seems to provide fractional versions for combined designs. If the factorial designs provide enough evidence that the recipe mix is a major source of variation, such as suspected in the case of White or Demiglace Sauce, then we could apply these techniques to minimise the variation.

Unlike classical factorial designs, the two methods allow for constraints among ingredients, in which ingredients are assumed to sum up to 100%. The possibility of combining mixture variables with other variables has also been mentioned. However, analysis was found to be more complicated and it may be difficult to perform without a statistical background. The objective of the experiment was to study the effect of different ingredients on the sensory quality of cooked sausages. The ingredients consisted of carrageenan, a type of whey protein, and different mixtures of milk powder, whey protein and sodium caseinate. For the purpose of this paper, only a single sensory quality was selected. The large number of experimental runs required in this experiment was reduced by using the design method available in projection design methods, rather than using fractional factorial designs. Data were also analysed according to projection design methods. The objective was to derive the regression coefficients such as would be obtained from a fractional factorial design in two levels (2^{5-1}).

One of the key issues, specifically in the food industry, is the losses that are incurred due to deviation of key quality characteristics from the desired target. This process could be reversed by reducing the variability, enabling the quality character in question to approach the target value. An application of the Taguchi method in optimising the milling process published by Ghani *et al.*,(2004,84-92) provides a good example of creating robustness in processes. The paper presents a case study on the end milling process at three levels. The DoE aims at finding the right combination of milling factors to achieve low cutting force and surface roughness. Although materials being handled in a milling process are very different from the food process in our study, the methods applied fit well with the intended research in which the reduction of net weight variability would lead to significant reduction of the cost of giveaway and underweights.

Much simpler statistical techniques found in the Taguchi methods can be used to replace approaches that are more complex. Two major tools are *signal to noise ratio* and *orthogonal arrays*. *Signal to noise ratio* measures *quality with emphasis on variation*. The orthogonal arrays can handle many factors simultaneously. Taguchi (1978 has developed a method for determining the optimum values of process variables which will minimise the variation in a process while keeping a process mean on target. Taguchi's approach uses statistical design of experiments economically to solve specific problems.

It quantifies the factor effect helping to identify the highest as well as the lowest influencing factors. At the same time, it is equally effective in investigating the effect of multiple factors on the process.

Ghani (Ghani *et al.*, 2004,84-92) suggests the use of the Pareto ANOVA technique, which requires minimum knowledge about ANOVA. It uses a simplified ANOVA in conjunction with the Pareto analysis principle. The significant factors and interactions can be chosen from the left hand side of the Pareto diagram. The Minitab statistical software, which we intend to use extensively during our analysis, is capable of creating a similar diagram called a Pareto Chart of the Standardised Effects.

Dr. Don Wheeler, who identified the "Four States of a Process", has introduced an analysis based on DoE techniques called "Scree Plot Analysis" (Santos & Clegg, 1999). This graphical approach was, in effect, a Pareto diagram similar to the above based on the factor sum of squares. The idea was to view the diagram as the cross section of a cliff, identifying the significant factors as standing out from the "scree" (rubble), at the foot of the cliff. This is a much simpler technique, which avoids the need for calculating variances and *F*-Ratios.

2-3 EXPERIMENTAL MODEL OF DOE

The Design of Experiment model as proposed by Montgomery (2nd ed., 1991, 454) which is illustrated in Figure2.2, shows its applicability to food manufacturing processes. Similarly, in the process of food manufacture, input variables are transformed into output variables, which are measured as quality and quantity characteristics. The specific set of output variables which characterises the food item during the manufacture can be grouped according to the unit operations involved. Following the trend in the model, some of these input process variables are controllable, while others are uncontrollable. The product and process improvement is usually achieved by improving one or more output responses. They are also called *dependent variables* since they are dependent on input process variables. Applying this model to our research theme, the target reduction and associated savings on "give-away" was proposed as the improvement objective and the variance and the mean of net weights were identified as output process variables.

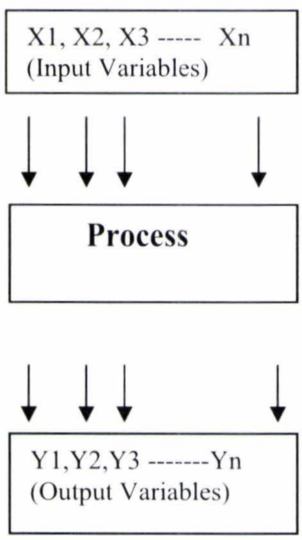


Figure 2-4 General model of a process (Montgomery, 2nd ed., 1991, 454)

Method of Experimentation

Planned experimentation is a test or series of tests in which measured changes are made to the input variables of a process and then the corresponding changes occurring in the output variables or responses are measured. Input variables that are used during planned experimentation are referred to as *factors*. Favourable changes to output or response variables are used to identify and quantify input process variables, for process improvement.

The aim of design of experiments is to identify important factors and to estimate or quantify the effect of those factors on the response variables. It is possible that during experiments, the effect of background and nuisance variables will be as great as the effect of selected factors on the response variables. The Experimental Design must therefore include methods to partition the total variation of the response variable into components due to factors, background variables, and nuisance variables.

Once the process is characterised and effect of factors and their interactions have been quantified the next step in the process is to optimise the important factors in order to deliver the best possible output or response. Depending on the nature of the process, the quality engineer may be interested in either maximum yield in a production unit or minimum variation of a selected character.

Shewhart (cited in Moen *et al.*,1998, 6) has introduced the concept of "degree of belief"to explain the extent to which an experimenter has drawn conclusions from an analytical study. The confidence on the effectiveness of the changes implemented as a result of a designed experimentation constitutes this degree of belief. The input variables, the range of their applications, type of DoE, and the tools of experiments selected determine the degree of belief required.

2-3.1 TOOLS OF EXPERIMENTATION

R.A. Fisher (cited in Moen *et al.*, 1998, 57) has recommended the following tools to ensure an effective planned experiment.

a) Experimental pattern
b) Planned grouping
c) Randomisation
d) Replication

2-3.1.1 Experimental Pattern

This is the plan of factor levels and combinations for the experiment. This plan should ensure that the desired output responses would be affected in a manner necessary to achieve the objective. There are several types of experimental patterns.

Factorial design is employed when the multiple factor effect needs to be studied. Although it is possible to study one factor at a time, this may lead to incorrect conclusions due to the following.

1) Presence of interactions between factors may distort the effect of a given factor on the response, as the response may also depend on other factors levels.
2) The study of the effect of one factor at a time takes longer.

Nested or hierarchical design deals with the study of factor levels which act within a higher set of factor levels in a hierarchical order. For example, when head-to-head variation of a filler is acting at a higher level then a set of valves within a given head becomes the second level of factors to study.

Incomplete designs consist of only a subset of a fully factorial or nested design.

Composite designs contain patterns made of combinations of factorial and nested designs.

2-3.1.2 Randomisation

Randomisation is used to determine the following using random numbers:

a) The factor combination of experimental units
b) The order of execution of certain aspects of the study.

Randomisation prevents the effect of unknown factors on the response variables. As explained previously, these unknown factors are called *nuisance factors*. During DoE, factors and background variables are built into the design to explore their effect on response variables. Randomisation separates the effect of factors and background variables from that of nuisance variables on response variables. Without randomisation, it is not possible to mask the effect of nuisance variables on response variables which could lead to the drawing of wrong conclusions. Random number tables should be used to generate numbers for the purpose of selection and ordering (Moen *et al.*, 1998, p. 63).

2-3.1.3 *Planned grouping (blocking)*

Planned grouping or block design is important in manipulating background variation to achieve the objectives of planned experiments. Objectives include controlling of background variation to minimise their effect on response variables of interest. The three ways of controlling background variation are as follows. (Moen *et al.*, 1998, pp 60-61)

1) Keep background variables constant
2) Measure and make adjustment to eliminate their effects
3) Use planned grouping to block their effects.

2-3.1.4 *Replication*

Replication involves repetition of selected parts of an experiment, which is used to gain increased confidence or degree of belief in the outcome of an experiment. Replication is carried out in different forms, which include: repeating of measurements, use of multiple experiments for each factor combination, partial replication and complete replication. Replication causes nuisance variables to be averaged out and allows the experimenter to study the interaction between the factors.

2-3.2 THE TOOLS OF ANALYSIS IN DOE

The aim of design of experiments is to identify important factors and to estimate or quantify the effects of those factors on the response variables. The classical method used to separate effects of these factors is called *analysis of variance* (ANOVA). It is a means of looking at the total variation in the data, breaking it into components, and running statistical tests to find out which components influence the experiment (Lorenzen & Anderson, 1993, 31)

More precisely, the analysis of variance serves to verify whether data from different samples provide sufficient evidence to indicate a difference among the populations (means) from which the samples were taken. When the variation among the sample means is large compared to the within-sample variation, it is apparent that a real difference does exist among population means. However, when the variation among samples is not too large compared to variation within it is not easy to make such a decision. The method of analysis of variance compares between sample variation (S_B^2) with within-sample variation (S_W^2) to determine whether or not the difference is significant. The S_W^2 represents the pooled estimate of the common variance 6^2 for the samples involved. The method involves the use of ratio $S_B^{2/}\ S_W^2$ as a test statistic to test the hypothesis of equal variance. The region above the tabulated value in the upper tail of the distribution thus becomes the reject region. If the calculated value $F = S_B^{2/}\ S_W^2$ falls in the reject region it is concluded that at least one of the population means is different from the others.

The Regression analysis is the other important statistical technique for estimating parameters which relate a particular variable to another variable or set of variables. This way regression quantifies a relationship between two quantitative variables, where a quantitative variable Y is related to a set of random quantitative variables X. Therefore, during the experiment it is possible to change one factor at a time and observe the effect on the response variable. With the results obtained, it is also possible to see the degree of effect on the response variable on an individual basis. The next step is to change the factors together in different combinations and observe whether or not such a change produces more favourable results. These experiments are called *screening experiments.* Since the Y variable (Factor) is dependent and predictable based on its relationship to x variables (Responses) it is also termed as *predictant* (Juran & Gryna, 1974, 23.97). The ultimate objective of regression analysis is to predict the quantity of dependent variable Y, in relation to independent variables, using a prediction equation derived using the Least Square method. The prediction equation finds a predicted value for Y by using estimated coefficients $\hat{\beta}_0$ and $\hat{\beta}_1$. The error of prediction is $Y-\hat{y}$ and is called *residual.*

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x$$

There are some important inferences about constants β_0, β_1, with which confidence intervals and statistical tests for slope (β_1) and intercept (β_0), can be performed. The confidence intervals for these constants reveal the reliability of the prediction equation. The Statistical tests about the slope in the form of $\beta_1 = 0$ are a useful tool to check the predictability of Y using X. The test statistic for the statistical test about the slope, β_1 is:

$$t = \hat{\beta}_1 / \sqrt{(S^2\epsilon / S_{xx})}$$

If the computed value above exceeds the table value, the Null Hypothesis ($\beta_1 = 0$) is rejected, to conclude the slope β_1 is positive and hence variable X is useful in predicting Y (Ott & Mendenhall, 1990, 399).

The Minitab software, which employs both ANOVA as well as the regression approach, will be extensively used in the analysis of factorial designs by this author. In the regression analysis section of the output, the effects of blocking, factors and interactions ("Terms") are estimated, along with the respective coefficients of the regression for the slope ("Coef") standard error of the coefficient ("SE Coef"), t-value for the statistical test ("T") and the corresponding significance ("P"). The latter section generates an ANOVA table in which the Degrees of Freedom (DF), Sums of Squares (Seq SS), Means of Squares ("MS"), F-ratio ("F"), and the Level of Significance (P) are tabulated against main effects, their interactions, blocks, and the residual error. The "Normal Probability Plot of the Effects" helps us to determine which terms are important. The terms that do not lie on the straight line connecting the points are probably important. Most importantly, the "Pareto Chart of the Effects" is used to identify the order of importance of the effects and interactions and to separate nonsignificant effects (Minitab for Windows, Release 14).

2-4 CONCLUSIONS OF LITERATURE SURVEY

The literature review section commenced by looking at the type of statistical methods applied and the key process areas published in the literature. It was revealed that apart from simple SPC applications, the methods such as variance component, regression, multivariate and time series analyses were used to improve product processes. The experimental designs used included Factorial Designs, Response Surface methods and mixture designs and combinations of control chart applications with DoE.

The discussion on the role of statistical thinking showed how to implement the statistical methods in food process improvement within the corporate environment. The discussion broadened into establishing the philosophies such as robust designing, and reduction of process variability as key drivers for process improvement. The results of the surveys published in the literature prove that application of statistical methods, including DoE, has contributed significantly towards process improvements, savings, customer satisfaction and the profitability of food industries. Specifically, use of these applications in process and product capability assessments, and follow-up corrective actions and in process characterisation to improve processes proves to be very useful.

The discussion of the role of SPC in DoE demonstrated the use of SPC as a screening test as well as means of controlling and holding the gains of DoE. Once the DoE delivers factor level combinations and directions to minimise variation of net weight, the author must not only implement them into relevant processes but must also hold these gains in future production activities using the effective control tools in SPC. Holding gains of the results of DoE could be achieved using the methods detailed under building of process knowledge. The discussion shows how we could utilise formal and informal knowledge using techniques such as "DIKT" and verify competing knowledge claims through DoE.

The literature provided case studies and some statistical techniques certain to prove invaluable in solving problems arising during experimentations. The reader will observe that some of these techniques had actually been applied during data collection and analysis. The survey presented techniques to remove outliers, methods of checking normality assumptions, alternatives to ANOVA when data did not fit normality assumption, and split plot designs to reduce time and costs. The projection design concept in particular was applied extensively throughout the analysis to obtain more information for optimisation efforts. The correlation of multiple responses, estimation of correct variance when there was a failure to reset factor levels as planned and the decision tree type approach to restrictions in randomising were among other useful techniques referred to.

The case studies provided the author with an insight into how to combine various designs and analysis combinations to find an appropriate pathway in dealing with net weight variability. They included conventional techniques, which commenced with screening experiments and used a combination of PCA and fractional factorial (2^{7-2}) for the design, and ANOVA and its multivariate version for the analysis. An experiment which employed a nested design using means and averages from control charts as responses provided an another option. The survey further provided a selection of tools to identify and quantify significant factors. They included the Pareto ANOVA technique and Scree Plot analysis. The Pareto ANOVA technique was found to be very effective during net weight analysis to find the optimum combination required to minimise variations.

The literature survey provided some useful information, guidelines and problem solving tools to empower the intended research. The review of the DoE model asserted its suitability as an experimental and analytical tool in the proposed research. However, the survey failed to reveal any published work done to reduce variation in net weight (pack weights) through control of contributing factors.

Therefore the proposal to build and apply an appropriate research model based on the knowledge presented in this survey is justified. The intended research should contribute to our understanding of the variability of the net weight process, by satisfactorily providing answers to our research questions. Not only should we attempt to answer, "Where does the net weight variation come from?" but also "What can we do to reduce this variation to optimise the net weight process to deliver the expected results"

Chapter 3 SOURCES OF VARIABILITY

3-1 SOURCES AND STATE OF CONTROL

The sources of process variables on the net weight variability and the means and extent to which such sources of variations are controlled are important in designing experiments. The quality and quantity control methods also serve as the means of establishing the levels of factors as revealed by DoE to optimise processes. The following section explores the dynamics of the food process, the composition of foods, packaging, filling and the weighing mechanisms for related variables, status, and methods of control.

3-1.1 VARIATIONS RELATED TO PROCESS DYNAMICS

The food manufacturing processes consist of unit operations, for example ingredient measuring, size reduction, mixing, preheating, filling, and thermal processing (Appendices 3-1 and 3-2). Although the bulk of ingredients are mixed up during the initial stages, further ingredients and functional additives may be added during subsequent operations.

During unit operations, the mixture is subjected to chemical and physical treatments such as: acidification, size reduction, and steam injection and so on, during specific points of the process. Such treatments lead to specific physical or chemical transformations such as gelatinisation of starch, caramelisation of sugars, and hydration of beans. These transformations in turn result in detectable or measurable changes in characteristics such as viscosity and %Brix levels. (The *Brix* is defined as *the percent* *soluble solids measured using refractometers*). These measurable changes manifest either as a shift in the process characteristics or as a change in the level of variation.

The operational fluctuations of unit-operations also create variations in these quality characteristics. While some of the unit operations are common to most foods such as batch weighing, mixing and preheating, other operations may be product specific such as steam injection or de-aeration. Appendix 2 shows a typical process layout on the factory floor with some of the common unit operation stations which are inter-linked via transfer lines.

Appendix 12 illustrates, using the Beef Curry Process, how the author had conceptualised the origin of net weight variability by using his own experience as well as the existing knowledge among operational staff. The net weight variability was seen as the net result of variations contributed by key process components. These components were identified as raw materials, processing methods, products, filler and containers. The variability arising from each of these components in turn is thought to be contributed by series of input variables characteristic of the particular component. Similarly, filler variability was shown to be caused by "come up time" for optimum filler operation, head-to-head variation, variations due to filler setup parameters and variation due to filler mechanics. Some of the filler mechanistic variations arise mostly from product uptake and a few from delivery related variables. They include degree of plug and valve fit, mechanical changes in the stroke guide assembly and so on.

The net weight filling process is a result of the combination of two separate processes namely, the product formulation and the filling where the former runs into the latter. Some of the variables in the filling process have their origins in the formulation process, while the rest of the variables are unique to the filling process itself as shown in Appendix 12. For example, the key input variables such as viscosity, concentration and temperature begin with product formulation while the speed of the filler and piston stroke length are unique to the filling process.

3-1.2 VARIATION RELATED TO PRODUCT COMPOSITION

The major components used in the manufacturing operations are classified into several groups. These groups mainly consist of Fresh or Frozen Vegetables, Meat and Fish, Dairy-based products, Condiments and seasonings, flavours and colouring agents, starch-based products, sugar-based products, oleoresins, oils and fat and functional additives. The functional additives commonly used in Wattie's canning sector include emulsifiers such as lecithin, pH modifiers such as citric acid, and bicarbonates. During the food process, blends and mixtures of various ingredients are added to the main recipe mix. Those frequently used include slurries made from starch, Roux made out of butter and starch, liquid sugars and tomato paste.

The variation of ingredient particle sizes, consistency, post-harvest age, climatic and topographical characters are the primary contributors to the product variability in food processes. A common example is the seasonal variation of % Brix level in Tomato paste and variation of fruit texture levels from the start to the end of the season. The original variation may be further increased by the variation contributed from the weighing and measuring of these ingredients prior to processing.

3-1.3 VARIATION RELATED TO PACKAGING

Besides being the deciding factor for quantity, can size contributes a significant amount of variability to gross weights due to variation of its weight and volume. The net weight of a product unit is calculated by subtracting the mean tare weight of the production lot from the gross weight. Therefore, this method produces only an estimated net weight of the package and, as a result, the total expressed variation of net weights in the production lot has a error component built into it. A constant headspace created by filler heads in a vacuum-filler controls filling volumes to a constant can height. Therefore the natural variation of can volumes during vacuum filling also could produce a net volume or weight variation, under a constant headspace. It is also possible to have several different can types under a single can size which create a weight or volume variation depending on the can neck type, lid type, beading characteristics, body thickness and the coating type. These variations could be characterised by their specific can codes.

The variability of net content inside the can produces a headspace variation above the fill level. The headspace variation causes variation in vacuum inside cans, under constant steam pressure exhaustion. In extreme cases overfilling creates a variation of positive pressure instead of a vacuum. This illustrates how the net weight variation could affect can integrity and safety related factors.

3-1.4 VARIATIONS RELATED TO FILLING OPERATIONS

The discussion below explains the mechanisms involved in vacuum and piston filling operations and how the specific mechanisms contribute to the variation of fill weights. Finally, a model for filler operations is presented combining the knowledge of those operation mechanisms and the knowledge of the possible forces involved from fluid dynamics.

3-1.4.1 Vacuum Filling operations

This machine is suitable for the filling of low viscous products into glass, metallic, and plastic containers. The cans, prior to filling, may be either empty or may already contain other product components in solid or liquid form. As vacuum filling eliminates most of the air present in the container, it ensures elimination of trapped air and maintains consistent filling. The effect of a vacuum combined with the headspace creating mechanism further ensures constant level fill. Vacuum fillers are the most efficient, accurate, and least variable of the four main types of fillers under discussion. As evident from the basic mechanism, the filler performs best when the food is liquid or when used as a final liquid fill of a multi-filling operation.

3-1.4.1.1 Mechanism of Vacuum Filling

A tabletop chain conveys the containers to a synchronisation screw, with variable pitch to facilitate can entry. This provides spacing between the cans and synchronizes them with a transfer star. The star then transfers the containers from the synchronisation screw to the filling station or valve tank where the cans are filled with the product. At the in-feed to the filling station, the cans directly activate the "no can-no fill" mechanism, which permits the first of three phases of the filling cycle to begin.

All these phases involved in filling take place during one filling cycle of the filler operation. One filling cycle is a single rotation of the filling table to which all the filling heads are attached. The phases of filling are controlled by a lever in contact with the cams located on a ring concentric to the filling station. Once the filling phase is completed, the containers leave the machine through a tabletop chain belt, which is tangential to the machine.

The filling station is essentially a series of filling valves (heads) attached to the bottom of a circular filling bowl through a valve, in the form of a circle at the periphery. The filler bowl with its filling heads is variously referred to as *filling station, valve tank*, or *filling table*. The filling table rotates above a can race that runs at the same speed, with all the filling heads directed at the open cans.

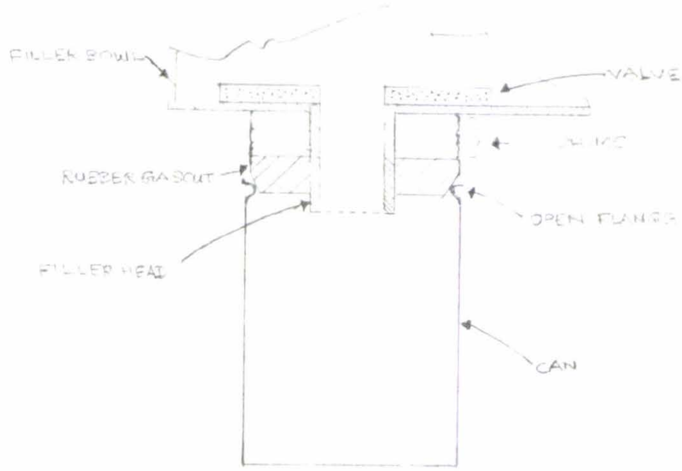


Figure 3-1 Can seal system comprising rubber gasket and open can flange

In the beginning, the can top is temporarily sealed, and the filling head is lowered into the can. The temporary sealing of the can top takes place when a rubber gasket, which is located around the filer head, comes into contact with the open flange of the can as shown in Figure 3-1. The headspace created inside the can is proportional to the depth to which the head is lowered inside the can. This is because during the filling process, liquid fills the can except for the volume occupied by the head. During the next stage, a vacuum is created inside the can and then the filler head opens the valve leading to the filler bowl containing filling medium.

Operating Cycle

1st phase – Valve Cleaning

The rubber gasket presses the can and a jet of steam cleans the valve passages.

2nd phase – Vacuum application

After the drainage of the valve, the "no can-no fill" device turns the distributor to a position which permits the evacuation of all the air present in the container. The container seat plates push the containers upwards until the flange is pressing against the gasket, assuring an airtight hold of the container. The filler creates a vacuum inside the can by connecting the inside of the can to a vacuum reservoir through a series of valves and pipes. The valve in the filler head opens up mechanically during rotation to enable this connection. Once the connection is established, the vacuum will stay until the head moves out of the can.

3rd phase – Filling

The distributor rotates further, opening the valve leading to the filler bowl. At this point the inside of the container meets the liquid in the filler bowl. The dual action of suction due the vacuum inside the can and the gravity of the liquid head fills the can. The filler bowl maintains a steady supply of filling liquid at a controlled height.

4th phase – Venting

The distributor rotates another fraction of the filling cycle, allowing the inside of the container to meet the outside atmospheric pressure. Once atmospheric pressure inside the can has been restored, the container is released from the filling valve.

The vacuum filler is connected to a vacuum pump through a vacuum tank. The vacuum tank is connected to the vacuum sliding block inside the filler through one or more plastic pipes. The sliding block is designed to draw the vacuum from inside the cans while the cans rotate past the block during the vacuum phase. A contact is made between the sliding block and the individual filler heads through a short pipe. The vacuum slide system is water lubricated by a connection from the main water network (Zacmi,1999, M 0255).

3-1.4.1.2 Head Space adjustment

Gross Headspace Adjustment:

The gross fill volume adjustment above 1mm is achieved by changing the spacer rings (shims) between the distributor and gasket to move the gasket up or down alongside the filler neck.

Medium Headspace Adjustment:

For headspace adjustment below 1mm, the filling valves must be lifted or lowered by regulating the head-wheel that moves the filling station vertically. This changes the thickness of the rubber gasket, making finer adjustments to the existing headspace.

3-1.4.1.3 Fine-tuning of fill-weights

A vacuum-breaking valve located on the outside of the vacuum tank can adjust the level of vacuum created inside cans. The valve is controlled to bleed air into the tank at different levels, thus changing the degree of vacuum inside the tank. The electronic or manual control of this valve enables fine adjustment of fill weights for a given set of spacer rings and the gasket.

The tank helps to maintain a uniform degree of vacuum inside the cans and facilitates separation of any product which may have been sucked in with the air. The tank is equipped with a level probe, which signals to the volumetric pump to start to remove product in the tank.

3-1.4.1.4 Selection Criteria

A vacuum filler is recommended where constant volume and headspace are preferred to constant weight. The vacuum filler produces consistent weights in cans where product density is uniform. This is due to the capability of the vacuum filler to produce a consistent headspace, and a consistent volume as a result. The vacuum filler is particularly good in delivering final liquid fill in a multi-filling situation. The use of other type of fillers for the final fill, in a multi-filling situation, may produce increased variability in the total net weight due to the variation of previous fill weights and volumes. However, the final net weight variation tends to come down when vacuum filling is used as the means of final fill, due to the final fill level is being maintained to a constant fill volume.

Another advantage would be the de-aeration of the product due to vacuum action of the filler. Additional net weight variation due to unintentional incorporation of air could be significantly reduced by the use of vacuum filling.

3-1.4.1.5 Limitations of vacuum fillers

The limitation of filling capability arises mainly due to failure to ensure that the required vacuum or variation of vacuum is achieved during filling. There are several reasons for variation of vacuum inside cans:

1) Vacuum loss due to malfunction of the vacuum pump
2) Inability to create the required vacuum due to leaking of air into an already-created vacuum from loose rubber gaskets used for sealing can tops
3) Improper valve seating
4) Product blocks in ducting which draw air from cans to the reservoir
5) Overfilling of products in vacuum reservoir due to breakdown of product-emptying mechanism
6) Temporary leak of air into reservoir during valve opening
7) Loss of horizontal alignment of the filler heads around the filler table, which causes loose fitting of rubber seal on the seam top
8) Worn or highly compacted spacer rings which pack the space between the rubber seal and the filler head
9) Inadequate water for lubrication of vacuum sliding block

The vacuum filler capacity is limited by its speed, and the number of heads and can size the filler has been designed to handle. Vacuum fillers are designed to work best in terms of fill variations with a specified range of speed, which is usually expressed in terms of cans per minute. The throughput of vacuum fillers depends on their speed and the can size.

3-1.4.2 *Piston Filling operations*

3-1.4.2.1 Operation Mechanism

A piston filler with vertical piston valves is used to fill liquid or semisolid products volumetrically. This machine is able to fill a wide variety of products into tinplate or plastic cans, and glass jars. The most commonly used products include tomato paste, tomato sauce, brine, jams, marmalades, fruit and creams, mineral and vegetable oils. This type of filler is capable of handling thin liquids with minimum leaks as opposed to the older generation of piston fillers with rotary piston valves, which are in operation on manufacturing lines such as Recipe-R1 and Seasonal-H1 lines.

A tabletop chain conveyer conveys the containers to a synchronisation screw. The screw separates and synchronises the containers through a transfer star. Then the star transfers the containers from the worm screw to the filling zone.

When the holding tank rotates, major operation phases follow one another. The phases are controlled through the position of the roller on the piston-lifting cam. The circle through which the pistons are rotating is divided into four parts, which correspond to the four phases of the operating cycle (Figure 3-2).

The height of the product-holding tank is adjustable by means of motorised screw columns, which are controlled by the control panel. The vertical closing valve with the piston-controlled cam ensures the total absence of dripping, and maximum closing

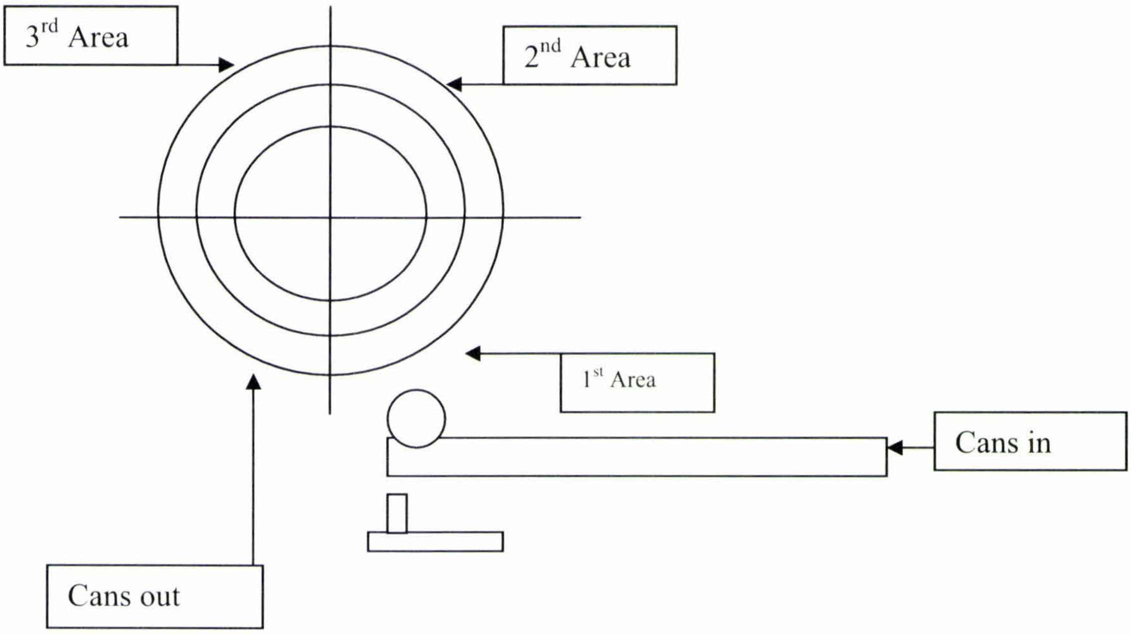


Figure 3-2 The four major areas of a piston filler operating cycle

Operating cycle (Figure. 3-3)

1st area – level cam

The valve rotates by a predetermined angle in order to close the connection between the filler bowl and piston cylinder. At this point, the passage between the piston cylinder and container opens up.

2nd area – downward sloping cam

The piston, whilst carrying out the downward stroke, transfers the previously sucked product into the container.

3rd area – level cam

This stops product transfer from the cylinder to the container and allows passage of the product from the filler bowl to the intake piston cylinder.

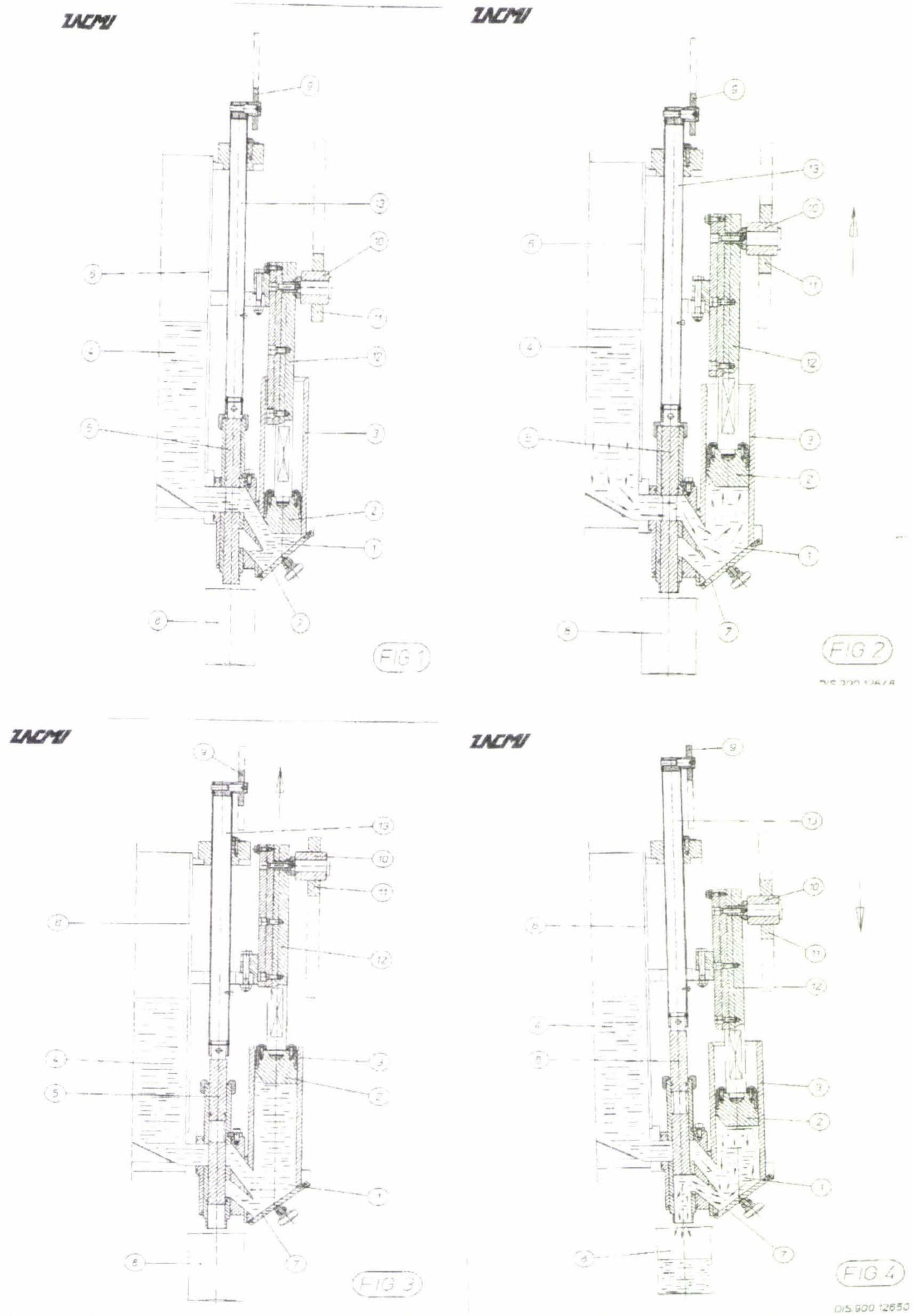


Figure 3-3 The cross-sections of piston strokes during the four major operations

4th area – upward sloping cam

The piston, during its ascending stroke, sucks a quantity of product which corresponds to the volume of the cylinder determined by the maximum height to which the piston plug ascends inside the cylinder.

The height adjustment level of the piston plug carrier guides determines the height to which the plug ascends. Each of the piston plugs is connected to a plastic roller through a long vertical slit in the upper part of the piston cylinder. Plastic rollers are secured within two guide rails and are able to ascend and descend through the lowest and highest points to which the rails have been adjusted in the beginning. The rails are adjusted vertically by turning a filler adjustment wheel manually. The duration of the upward and downward strokes, (fourth and second areas) corresponds to approximately half a revolution of the filler bowl. The table is moved up or down to accommodate the height of can plus the space for the cans to be lifted up to the filling head during the initial set up. This is done electrically. (Zacmi Food Processing Plants, 2001, Model 0290)

3-1.4.3 *Pocket Fillers*

The pocket filler is essentially a series of telescopic tubes where the inside volume of each tube can be adjusted to vary the fill volume or weight. Since the accuracy of the fill depends on the consistency of packing inside the pockets, fill weights and volumes are highly variable compared to vacuum or piston fillers. Since the pockets are not properly sealed, they cannot be used for liquid filling. Pocket fillers are generally used for meat varieties, baked beans or any other garnish fillings of larger particle size, such as vegetable mixtures, spaghetti shapes and ravioli. However, they provide a practical and economical way of weighing solid and chunk food as a part of a multiple filling process.

3-1.4.3.1 Mechanism of Filling

The pocket filler consists of a series of telescopic tubes (pockets) that open up to the top of the filling table. Each one of the telescopic units consists of a larger diameter top tube and a smaller diameter bottom tube that slide into each other during height adjustment. Top tubes are welded to the periphery of the circular filling table and the bottom tubes are connected to a bottom table which has the same diameter as the top table. The top table serves as a container for the filling material. Filling materials are transferred to the container by an appropriate conveyer system such as a slat belt conveyer. When the table rotates, the filling material is swept across the pocket entrances. The filling into pockets is guided by a system of converging partitions and a set of brushes as illustrated in Figure. 3-4.

Although the filler adjustment is incremental, fill weights are produced in discrete steps due to significant differences between weights of particles. For example, fill weights during sausage filling vary in steps of about 7 grams, due sausage-to-sausage weight difference.

Variation within given adjustment depends on uniformity of packing. The variation usually decreases with decreasing particle size. Other than the effect of particle size, the degree to which the frozen materials have been thawed also contributes to packing variation. Properly thawed materials such as sausages and meat become flexible enough to create a consistent pattern of filling compared to rigid frozen materials. Table 3-1 shows the relationship between the particle size of different meat fills and the estimated standard deviations for sample size =10.

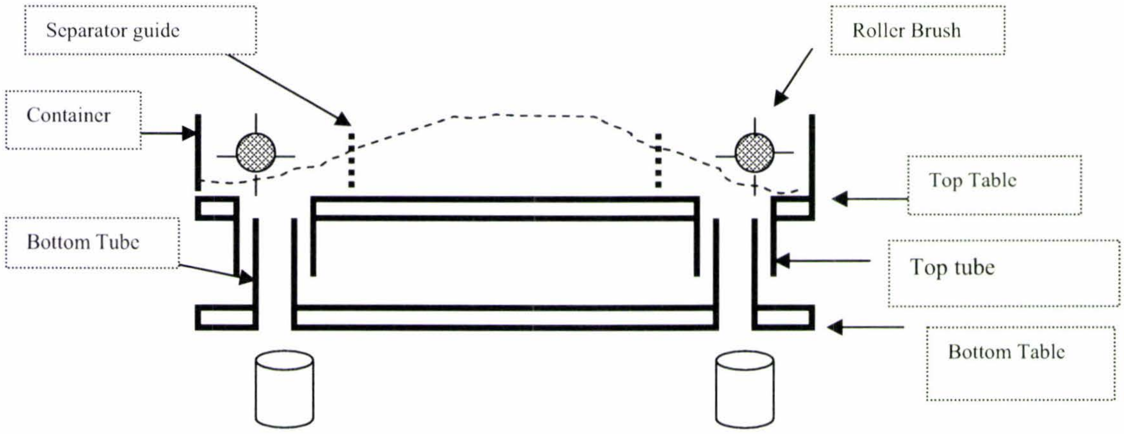


Figure 3-4 Cross-section sketch of a pocket filler

The use of pocket fillers is limited by several key factors:

- Diameter of chunk size should be smaller than 20% of the diameter of the pocket
- Length of the filling particles – Longer lengths of sausages increase the variability due to variation in packing
- Filling is more efficient with free-flowing and nonsticky particles

Table 3-1 Fill variations of various particle sizes using pocket filler

(SPC Data Base. (2005)

Fill Type	Mean Fill Weight in Grams	Standard Deviation in Grams	% SD
Baked Beans	177	1.60	0.9
Alphabet Spaghetti	44	1.05	2.4
Bacon	34	1.29	3.8
Meat Balls	60	2.90	4.8
Sausages	56	5.00	8.9

3-1.4.4 *Fillers as a contributor to variability*

Of the factors that contribute to filler variability, the head-to-head variability is a major contributor and is more prominent for piston fillers than for vacuum fillers. In piston fillers (Figure 3-6), the head-to-head variation is caused by defects in individual piston cylinders such as differences among piston stroke length, wear and tear of plugs, and volumetric changes in cylinder cavities and so on. For this reason, head-to-head differences are relatively consistent and measurable in piston fillers-whereas in vacuum fillers the variation due to any particular head is recognisable only when there is a gross defect in the filling head caused by leakage of vacuum from a rubber gasket or a valve block of a particular head. The volumetric filling of the vacuum filler is based on the fill volume created by the head gasket system. As such, the variables involved are minimum compared to the piston fillers whose fill volume is, to a large extent, based on the accuracy of its moving parts. Apart from the factors contributed by the mechanics and structural aspects of the filler, the variation of density and temperature in products produce a compounded variation of fill weights due to the volumetric characteristic of fillers. The changes in product density has been identified as a major contributor. This is because the changes in density produce corresponding changes in the weights due to the volumetric characteristic of the filler mechanism, which is common to most fillers.

A close analysis of filler mechanics as discussed reveals that their operations are based on similar fluid dynamics regardless of whether they are vacuum or piston fillers. They all have a filler bowl containing filling media, an orifice (valve) connecting the filler bowl to a cavity (piston cylinder or the can connected to the vacuum head) into which the medium is volumetrically measured, and external force which is applied in cycles to draw the filling medium into the measuring cavity. In a piston filler, the external force is applied through the motion of the piston and in the vacuum filler the same is applied by a vacuum created inside the can by the vacuum pump connector which joins the filling head between the valve and gasket (Figure 3.6). The variables affecting the filling process in and around the filler valve are as follows:

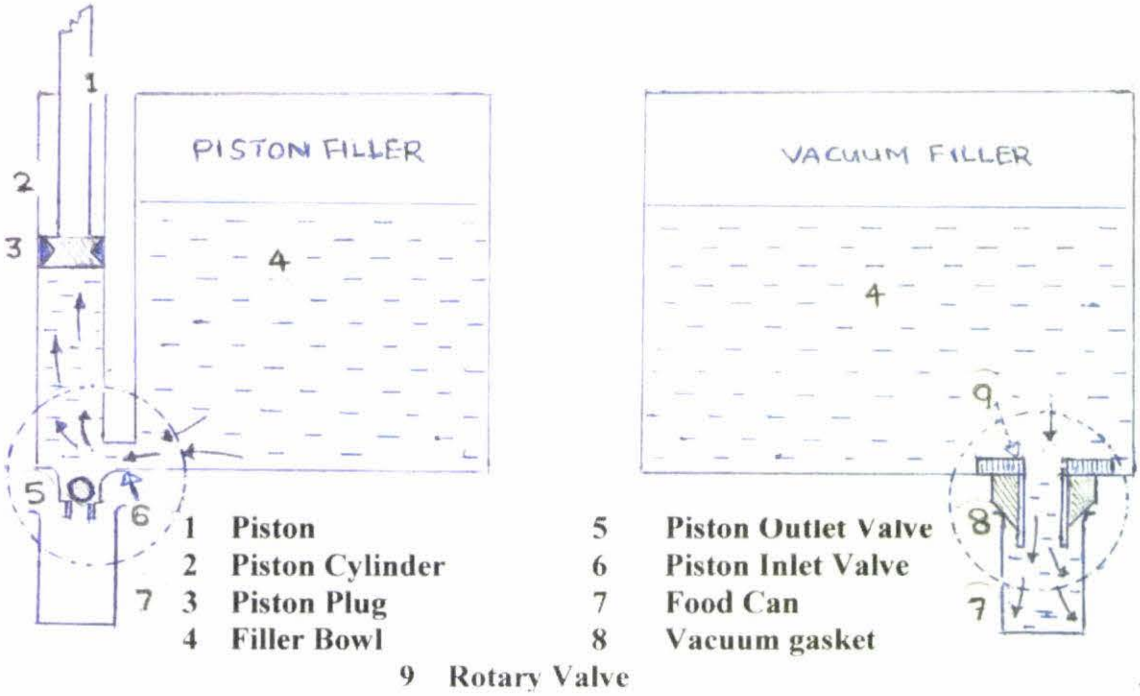


Figure 3-5 Fluid dynamics during piston and vacuum filling

- D	slot size of the valve unit:(L)
- μ	continuous phase viscosity units:(M/LT)
- ρ	fluid density units:(M/L^3)
- δ	surface tension units:(M/T^2)
- v	fluid velocity units:(L/T)
- ΔP	change in pressure in the filler valve units;(M/LT^2).

The product filling effect of the filler can be characterised by fluid dynamics involved in the incompressible flow in channels and therefore as a function of the Reynolds'(Re), and Friction Factor numbers (f) (Perry & Green, 1997)

Using:

Reynolds' number; Quantity of can fill = $f\{ v\rho/\mu \}$ is a ratio of a fluids inertia forces divided by a fluid's viscous forces.

Friction Factor number; Quantity of can fill = $f\{ \Delta P/\rho v^2 \}$ is a ratio of a fluid's viscous energy divided by a fluid's kinetic energy.

We have m = 5 variables and n = 3 dimensions

We seek for the solution to the mixing problem m – n = 3 dimensionless groups

$$\text{Quality of can fill} = f\,\{\,D v\rho/\mu,\ \Delta P/\rho v^2\,\}$$

Consider keeping the diameter of the filling valve/slot a constant.

$$\text{Quality of can fill} = f\,\{\,v\rho/\mu,\ \Delta P/\rho v^2\,\}$$

Therefore quality of fill becomes a function of the density, surface tension, viscosity of the product, the change in pressure across the valve, and the velocity of product through the valve.

The change in pressure across the valve is mainly a result of the suction force created either by the piston or by the vacuum and the pressure head of the filler bowl. The speed of the filler is reflected in the fluid velocity (v). If the filler operates at high speed and the velocity of filling approaches turbulent conditions then viscous forces become negligible and the quality of fill would be dependent on just the friction factor – that is, the pressure across the filling valve, product density and velocity through the filler valve. Most fillers have large filling orifices to reduce particulate damage, hence viscosity forces would be important. (Bounds, 2006)

3-1.4.5 *Control of Filler Variability*

The first step involved in reducing the variability due to piston fillers is the analysis of head-to-head variation to identify poorly performing heads. Once these heads have been identified and the amount of variability has been quantified, corrective action could be taken to adjust fill volumes or defects. A graphical presentation of a head analysis based on volume variation for different filling heads is shown in Figure3-6. It reveals individual heads that need adjustment to reduce the current range of 12 grams to the potential range of about 4 grams. Similar analysis on vacuum fillers may, or may not, reveal individual differences which are mainly due to gross defects of particular valves.

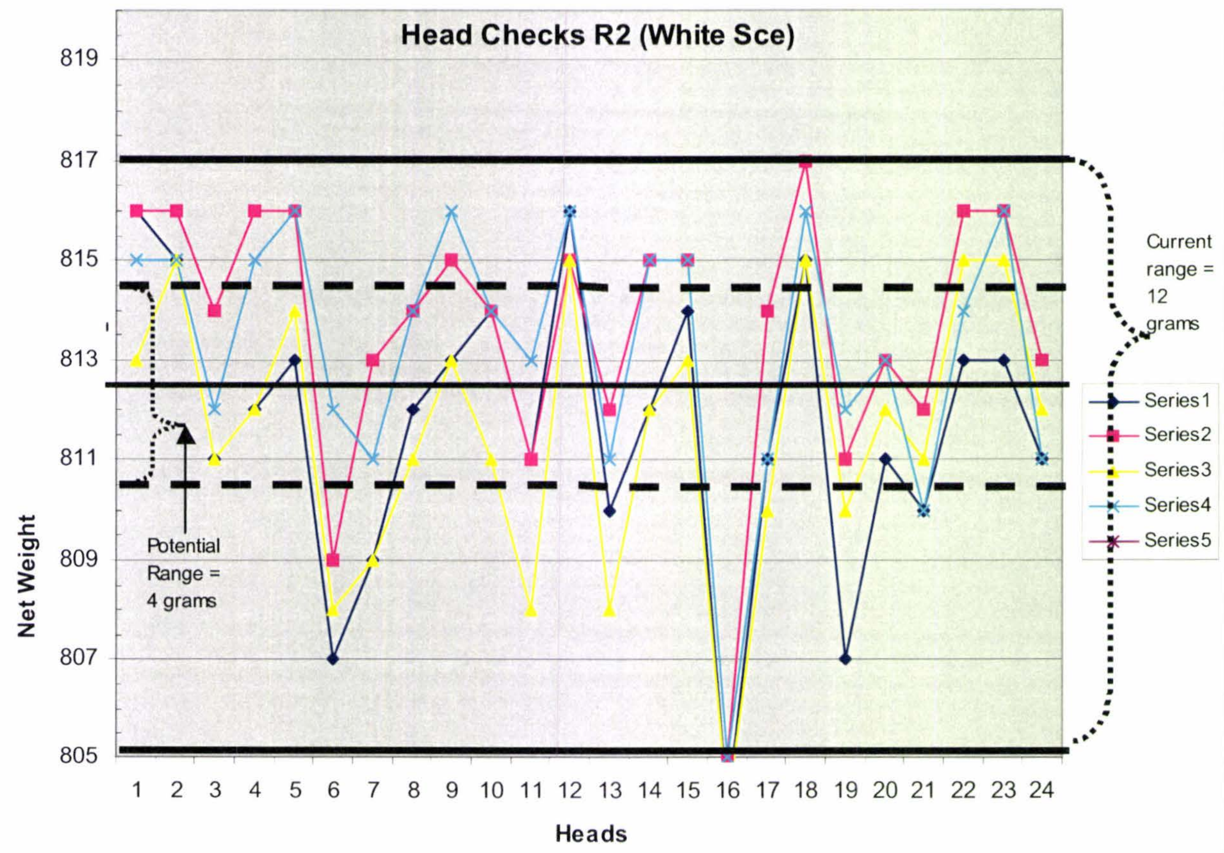


Figure 3-6 Head analysis using fill weights against each filler head for filler R2

However, comparison of the total filler variability with standard figures set up under good running conditions will reveal the need of overhaul or adjustments to valve seating, cams, and gaskets and so on in general. As discussed before, in a multi-filling situation where several fillers contribute to the total variation, use of a vacuum filler as the last filler produces considerably less total variation than the use of a piston filler. This is because the vacuum filler fills to a constant level whereas the piston filler does not. Therefore, use of a vacuum filler presents a better control of variability than does a piston filler.

3-1.5 EFFECT OF QUALITY CONTROL ON VARIATION

During volumetric filling, the net weight of a product becomes a function of its specific gravity. The specific gravity, in turn, depends upon the specific combination of physical characteristics of that product. The quality characteristic of interest, for example the texture of baked beans in canned baked beans, evolves during several stages within the stream of food processing. Usually these stages are associated with several distinct unit operations referred to in Appendices 3-1 and 3-2. Such operations may include, for example in the case of baked beans, blanching and final cooking (Thermal Processing). Therefore, it is evident that any given quality characteristic is present in distinct measurable levels at various stages of the processing stream. In the upstream of the process, the texture is controlled on the average to a target level, through control of unit operations. Therefore, the resultant variation of specific gravity and, in turn, the variation of net weights depends upon the degree to which these characteristics are controlled.

Of all the characteristics of products, the major ones, on which the quality of the product is dependent, are called *key quality characteristics* or *parameters*. These characteristics are measurable as well as controllable. Therefore, they are adopted as quality control parameters. Generally, if the selected key quality parameters are controlled within the specified levels called *specifications*, then it is accepted as a quality product. The degree of control varies from full automation to manual control.

The SPC, which is the most important manual methods of control, employs software based-process control system called Sentinel (Sentinel Software, 2000). Sentinel continuously monitors quality parameters and plots a variety of control charts or simple trend charts within specifications. The quality characteristic, which is measured in a fixed number of replicates called a *sample size*, is used to plot control charts for averages. The out-of-control signals are generated when a quality parameter has deviated from the limits as specified by the statistical process control rules. The feedback control may be activated automatically, semi-automatically or manually. During manual feedback control, the operator adjusts the process at the correct upstream point.

3-1.6 *QUANTITY CONTROL*

3-1.6.1 *As an essential Function of Food Processes*

The food package is sold based on its declared label weight or volume. The control of this aspect is important from economical, quality, consumer and legal points of view. Although quality control as described above affects the variability of net weights, it is not possible to use these methods directly to control net weights.

The quantity is treated as a part of the total quality. This is because of the important role which quantity plays in controlling some quality aspects. The control of volume is necessary to leave a minimum guaranteed headspace in order to achieve the specified thermal process. During rotary the cooker process, achieving the necessary thermal process depends on movement of a headspace bubble to facilitate heat transfer. The specified minimum vacuum ensures proper sealing of can, and reduces the presence of oxygen, which prevents oxidative deterioration of certain key quality aspects such as taste, colour and so on. Therefore, maintaining a minimum vacuum plays an important role in extending the shelf life of a canned product. Leaving a headspace during the filling process allows steam to be trapped within this space which, upon condensing, create a vacuum. On the other hand overfilling of cans due to insufficient control of net content has led to cooker jams and postprocess leakage at Heinz Wattle's Ltd. in recent years.

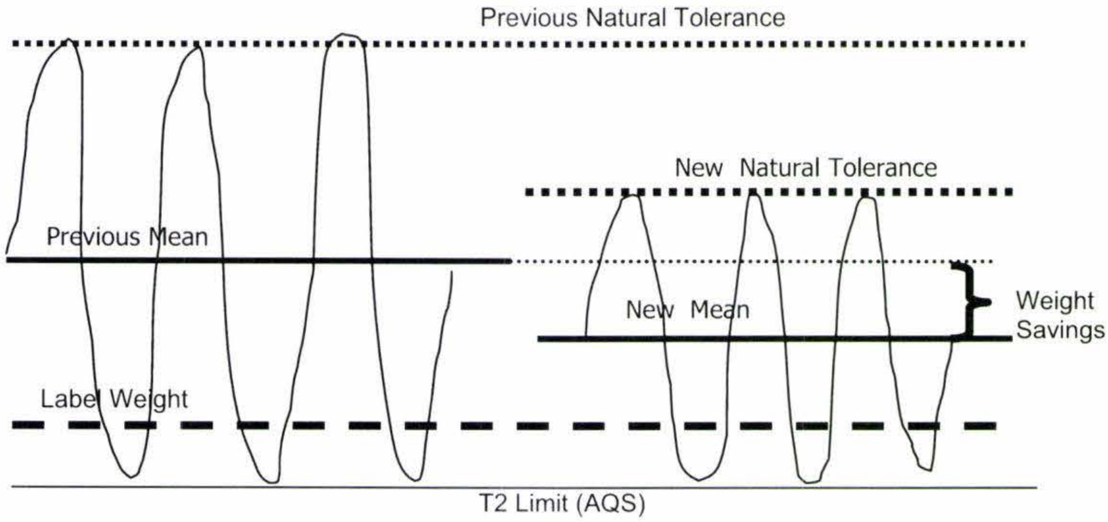


Figure 3-7 Potential for net-weight saving based on variation reduction

The consumer expects the net weight to meet the declared quantity stated in the label. The Weight and Measures regulations enable the manufacturer to implement complying control methods. The food manufacturers have to maintain their average fill level well above the label weight in order to fulfil this need. It is the standard practice to find methods to reduce the variation of net weights, so that the target could be set as low as possible above the label weight. Figure3-7, illustrates how savings on give-away could be achieved when the existing level of level of variation is reduced.

3-1.6.2 Methods of Quantity Control

3-1.6.2.1 SPC Methods

The control limits are calculated using an estimated standard deviation which is based on the average of both short-term and long-term standard deviations. This takes into account all the variation contributed by filling heads as well as a reasonable amount of natural product variability within a shift of production. Therefore, it allows for an acceptable amount of product variability arising from temperature, viscosity, product consistency and so on within a batch of production. The control limits are set around an optimum target selected for a particular product. This optimum target must not exceed the requirements dictated by criteria for can and product integrity as discussed earlier. The set target must also confirm to minimum legal limits for distribution of averages and individuals.

3-1.6.2.2 Regulatory Methods

The Label weight must first be verified for the adequacy of headspace after taking into account the variability of the product. The maximum possible target level is calculated based on minimum headspace requirements. The following criteria are used to evaluate these parameters:

- Minimum head space requirements
- Minimum vacuum requirements
- Average fill level and corresponding head space
- Product density at filling
- Legal requirements

The Optimum target could now be set between the maximum target level discussed above and the minimum target level permitted by weights and measures regulations such as the AQS. The minimum target is calculated to satisfy the "Three Packers' Rules" of the Average Quantity System (Carter,2002).

3-2 SCREENING OF SOURCES FOR MAJOR FACTORS

Having explored the sources responsible, it is required to identify the major factors on which the variation of net weights depends, so that the variation can be partitioned with respect to these factors. The following sections describe the methods employed and the results obtained in screening these factors for the DoE.

3-2.1 IMPROVEMENT FOCUS THROUGH PARTITIONING OF VARIATIONS

However, for the purpose of a study it has been agreed to narrow down the investigation into the area of net weight variability which is confined to the filling process. As illustrated in Appendix 12, the area of net weight variability in cans due to the filling operation, which encompasses variation due to heads, operational variables of the filler, key physical properties of filling media and random mechanistic variations, was identified as the scope of this study. The key objectives of the study were to find satisfactory answers to the following questions:

1) Where does the variation of net weight come from during the filling process?

2) What is the proportion of contribution from identified sources of variation to the total net weight variations?

3) What are the optimum levels of the identified sources (input variables) required to minimize the variability of net weights?

As discussed during the introduction, these questions have been formulated to reflect the net weight control and improvement priorities. It is important to focus on specific areas for improvement rather than to scatter the improvement efforts. A satisfactory answer to question two is expected to provide percentage or proportional contributions from the named sources. These percentage contributions provide a means of prioritising the improvement efforts in the selected areas. Finally, the answer to question three is expected to provide a mechanism for reducing the net weight variability.

It has been found that the delivered weight is not always directly proportional to the filler stroke adjustment. The filling process in the food industry always aims at filling to a set target weight within natural limits of variation. This target has been designed to achieve compliance with market and regulatory specification as well as to conserve the can and product integrity. Since a given stroke adjustment should theoretically deliver a constant piston volume it is important to find out whether any interactions among factor levels are responsible for this phenomenon. If these interactions between piston stroke and other factors are significant, then it is also important to find out the optimum factor combination which maximises the net weight for a given piston stroke adjustment.

3-2.2 IDENTIFYING THE FACTORS RESPONSIBLE FOR NET WEIGHT VARIATION

As an initial step prior to a systematic study of the net weight variability, the author organised a company-wide brainstorming sessions. Three important groups of employees were invited separately into these sessions. The groups consisted of process and maintenance engineers who design and maintain processes and machinery, technologists who are involved in developing and improving food processes, and finally the operational staff who possess a wealth of practical experience about net weight variations and contributory factors. The inputs from the brainstorming sessions were tabulated in the form of a fish bone diagram, which is shown in Figure 3-8. The factors contributing to net weight variation in products as revealed during brainstorming sessions can be grouped under raw materials, processing methods, product variables, filler variables and variables from the containers.

Further, the author is of the view that these variation components act in a hierarchical order in the process flow, from ingredient preparation to the filling of product into cans, to produce the final total variability. Figure 3-9 shows how basic variance components such as particle size, temperature and concentration alter the product density of the liquid which is inside the filler bowl about to be filled into cans. At the next level below in the hierarchical order, variation in product density along with the other components that effect the filling process namely-viscosity, variation due to differences in filling heads, temperature and speed of the filler produce a resultant weight variation of the liquid fill measured into the cans. Finally, the variation of this final fill, along with the variation in pre-fills which originated from prior filling processes such as baked beans or meat portions, and variation of tare weights of cans gives rise to the total net weight variability measurable using the gross weight of cans. Although the tare weight of cans is not an integral part of the food content, this variation-if significant-could affect the results of the automatic check weighing process and could be partially responsible for the net weight variation as computed by the check-weighers.

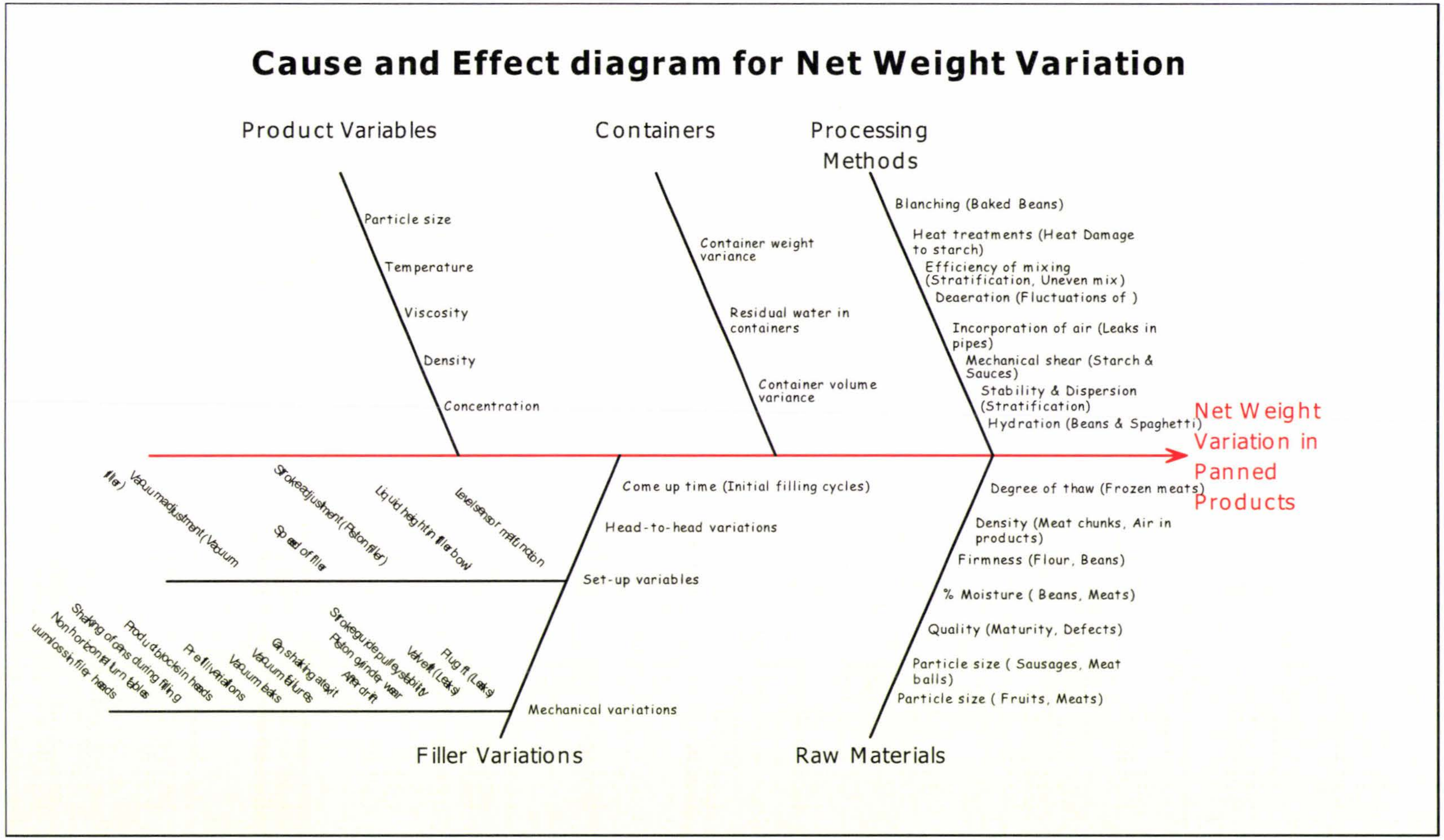


Figure 3-8 Cause and Effect diagram for sources of net weight variation in cans

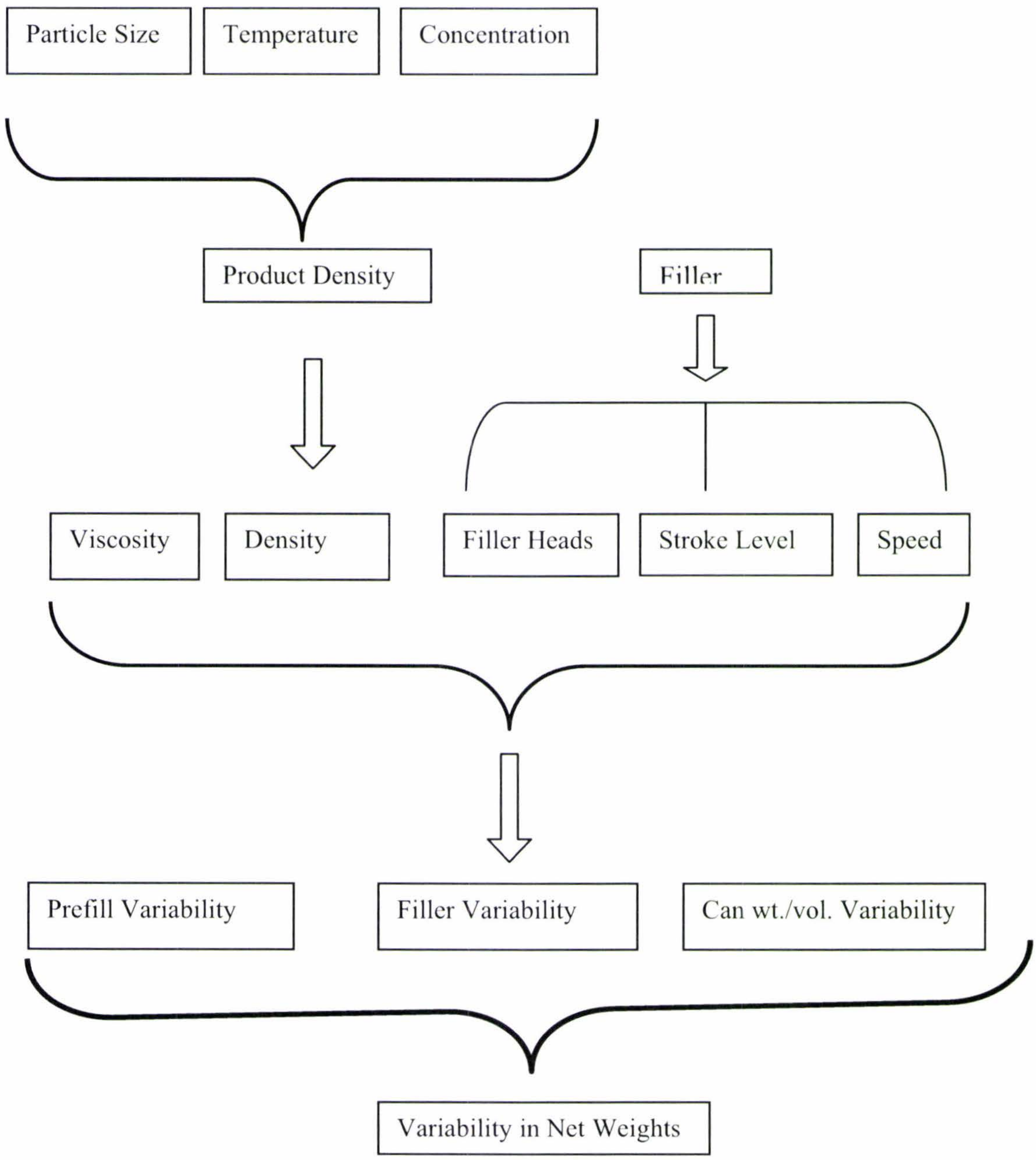


Figure 3-9 Hierarchy of variables in product filling process

3-2.3 *TIME-BASED CHARACTERISTICS OF VARIATIONS*

The variation of net weights during a filling process is measured in terms of standard deviation or variance estimated through a statistical sampling process. The net weight variation of products can be characterised by the duration of the filling process. Since the variation is a function of time, the size of the variation experienced is usually time related. Therefore, the variation experienced during a shorter period is smaller than that which is experienced against a longer period. However, the presence of special causes could result in a very high level of variation in a short period of time. A common example would be a product block in a single filling nozzle of a multi-head-filler for a few seconds. The both Long- and short-term variability are experienced by the process worker in a variety of ways:

Head-to-head variation of the filler

Random variations due to difference in product consistency from can to can

Random variation due to changes in filler mechanics

Long-term shifting of filler mechanics and fixings

Long-term variation due to shifting or trending of product characteristics

Sudden shift of product consistency

3-2.3.1 *Short-Term Variability*

In general, short-term variations arise within a relatively shorter period of time and are usually measurable within the period of time that it takes to empty a filler bowl full of product. Two main types of short-term variations may be included within this definition. The first type is the variation which the filler operator experiences within each of the filling cycles. This is mainly due to variation across a single filling cycle arising from head-to-head differences. Usually more or less the same amount of variation is repeated from cycle to cycle throughout the entire production when a consistent product is used in a well maintained filler.

However when the product is not consistent say-for instance-within a filler bowl, differences in terms of density, viscosity particle size so on of the product produce a second type of short-term variation on top of head to-head-variations. However, in the multi-head filling situations as planned for this study, the two types of short-term variation are hardly distinguishable from each other.

3-2.3.2 Long-Term Variability

When the data from each consecutive cycle are tabulated cycle-to-cycle differences of fill weights from the same head become evident (Table 4-3). It is possible that part of these differences arises due to differences in the consistency and time-based changes to the physical properties of the product, while the other part is due to random mechanical variations as shown in the cause and effect diagram above.

The tong-term aspect of time-based variance is also observed in two distinct ways, namely trending and shifting. The author uses the term "trending of variance" to explain a gradual increase of variance over a period. Likewise, term shifting of variance is observed as a sudden visible change of variance in one or more parameters of the process. These trends and shifts in the net weight process are usually detected in statistical process control charts where key quality and machinery related parameters are plotted at a fixed interval of time. Both of these types of long-term variation are monitored closely during production as they present a potential for producing Non-Standard Products (NSP). The statistical process control which provides limits for average control, a set of control rules and methods of process centring and targeting, has been rigorously applied to keep such trends and shifts within control limits (Section 3-1.6.3). As presented during the introduction, the necessity of reducing net weight variation of products is a key priority due to the savings potential in it as well as the legal and product quality implications.

3-2.4 SELECTION OF IMPORTANT FACTORS FOR THE PLANNED EXPERIMENTS

3-2.4.1 Effect of variation in the tareweight of cans

The variation of tare weight of cans as a contributing factor may be ignored if it is proportionally smaller compared to the variation of total net weight. The tare weight of the can must be deducted from the gross weight to determine the net weight of the product. The work involved in measuring the tare weights of over 4000 cans involved in the trial was found to be too time consuming. A sample of 200 empty cans were weighted and analysed to determine the variance of tare weight of cans. The table in Appendix 6 has shows that this variance was found to be only 0.08 grams for a mean tare weight of 47.5 grams. Compared to the mean variance of 4.1 grams across filling heads produced for all trials the variation in the tare weight of cans contributed only 0.5% to the total net weight variation.

Where Total Variance = 17.3 and Variance of Tare Weight = 0.08

$$(\hat{\sigma}_{\text{Total}})^2 = (\hat{\sigma}_{\text{Product}})^2 + (\hat{\sigma}_{\text{Tare cans}})^2$$

$$(\hat{\sigma}_{\text{Product}})^2 = (\hat{\sigma}_{\text{Total}})^2 - (\hat{\sigma}_{\text{Tare cans}})^2$$

$$(\hat{\sigma}_{\text{Product}})^2 = 17.3 - 0.08$$

Product Variance = 17.22

The percentage contribution of tare weight of cans to the total filler variation during the trials was estimated to be 0.5% (0.08/ 17.3 X 100 = 0.5%). Therefore, it was decided to ignore the variation of tare weight of cans and the gross weight (net weight + tare weight) as primary responses for all trials.

3-2.4.2 Process of Factor Selection

Identifying the factors which can effectively represent up-stream variables related to raw materials, and processing methods, presents another effective way of selecting the key factors for the design. The product variables identified-namely-concentration, viscosity, temperature and particle size-represent-most of the sources of variation originated in the upstream through raw materials and processing methods. For example, mechanical shear imparted through the high shear mixer can be represented by appropriate levels of viscosity in the liquid food and the density through appropriate levels of concentration and so on.

Further analyses of brainstorming sessions (Figure 3-8) along with the existing knowledge, has led to a conceptualisation of their mode of action, (Figure 3-9). This provided a logical basis on which to select the factors to represent net weight variation under the circumstances, leaving product variables and filler variables as the key areas to select the most important factors. Using a product variable list in the cause-and-effect listing, the author selected concentration of a specified starch solution as one of the factors to be used because of its ability to represent both density and viscosity if prepared to a standard method. Particle size can be eliminated if the test medium is homogenous. The temperature of the test medium has been selected as it is fundamentally important as concentration as a major source of variation. As for the rest, the critical filler-related factors have been decided after nominating the piston filler, which represented more than 80% of the filling processes company-wide. The speed in terms of cans per minute and the stroke adjustment level of the filler .constituted the rest of the factors. Finally, the planned experiment was designed using MAP-281 modified starch solution to represent the following four factors:

1) Concentration of the test medium measured by Kilograms per Litre (C)

2) Temperature of the test medium (T)

3) Speed of the filler expressed in cans per minute (S)

4) The filler stroke level measured from the scale in centimetres (P

Chapter 4 EXPERIMENTAL METHODS

4-1 EXPERIMENTAL DESIGN APPROACH

The reduction of net weight variation in food processes in the company has so far been attempted by the use of SPC methodology. These methods depended on watching the process and waiting for out-of-control signals to provide information leading to a useful change. This is usually achieved by improving the most outstanding source of variation related to the out-of-control signals. In contrast to passive observing of the process, in factorial designs, series of changes are introduced to process inputs and the corresponding changes are measured in the output (Montgomery, 1991, 453-455).

4-1.1 *WEAKNESSES OF ONE FACTOR AT A TIME DESIGNS*

As revealed during the brainstorming session, it was clear that the weight variation in liquid-based canned food is caused by more than one factor at the time of filling into cans. A commonly practised approach in the food industry would be studying one factor at a time. We in the food industry believe that experiments with more than one factor at a time may not help us to identify the factors which are responsible for changes in the response level.

The drawbacks of experiments with one factor at a time are twofold. One is the interaction between the factors. The interaction causes the effect of one factor on the response, such as variation of weight, to depend on the level or levels of other factors. During one-factor designs, each factor is changed in turn, and the data set collected will be used to study only the effect of this factor.

One of the key strengths in factorial designs is that they allow us to study the effect of interactions. In factorial experiments, all the data collected are used to study the effect of each factor (Moen *et al.*, 1998, 113-114).

4-1.2 AVAILABLE DESIGNS

It is important to investigate the most effective method to identify, quantify and finally to reduce network variability. The author has selected the following types of DoE for the investigation.

4-1.2.1 Nested Designs

Nested designs have been developed to deal with situations where factor combinations are not interchangeable. The combination of factor levels as required by factorial designs can be very expensive and time consuming when trialling under set operational flow in the industry. For instance, it was difficult to prepare a certain factor combination of a liquid food mix at one time and then follow up with preparing a different combination the next time. This is because of the work and time involved between the trial, and cleaning and machinery setting up to achieve the selected factor levels and trial replicates.

So a nested design could be applied to evaluate and quantify the sources of variations without having to change the operational set-up too frequently. However, they are limited in their capacity to estimate possible interactions between factors which were found to be very important as contributors to variation in the food industry.

4-1.2.2 Factorial Designs

Net weight variation of liquid-based food processes are complex and involve more than a single factor. Therefore, factorial designs provide tools of experimentation to produce effective results for statistical analysis. A full factorial design, consisting of all possible combinations of the factors and levels may become complex if too many factors are involved. However, factorial designs with up to four factors make efficient use of resources by using most of the data to estimate the effects and their interactions. Another advantage of using a full factorial design would be the possible projection of the parent design into replicates of a lower order design for effective use of information. This technique is called *projection design* where usually a factor which not significant is discarded (Section 2-2.5, 13)

The brainstorming sessions revealed four important factors affecting the filling process. A planning session showed that it is possible to conduct a full factorial experiment within facilities available at the factory (Table 4-1). It was further revealed that a two-level factorial design (2^k) would be adequate for the purpose of the experiment. They are easy to use in the design, and analysis can be performed graphically. Utilising factory facilities using mass production gear would not, in the first place warrant more than 2-factor experiments which demand more than 16 trials.

4-1.2.3 Fractional Factorial Designs

Factorial designs with up to three factors utilise most of the data to estimate factor effects and their interactions. However, when the number of factors involved in the design increases, an increasing proportion of data is used to estimate high order interactions, which are of little value. Alternatively, fractional factorial designs enable the experimenter to reduce the size of the experiment while allowing him to estimate its important effects. In this instance the author was able to allocate resources to run all 16 trials required for the full factorial, to study the effects of the four major factors identified.

4-1.3 SELECTION OF APPROPRIATE DESIGN

The nested designs were opted out, as they are not capable of measuring possible interactions. Although fractional factorials (2^{4-1}) could help to reduce the number of trial runs to eight, the author was not prepared to lose information which could arise from the compounding effect of certain 2-factor interactions. A fractional factorial 2^{4-1} uses only three factors in full design, and as such the effect of the remaining factor might be lost. Taking into account the relative merits and demerits of available design options, it was decided to run four full factorial experiment. The author had the time and the resources required to run the four full factorial, which also provided an opportunity of creating projection designs of lower order for detailed study under levels of a selected factor.

Table 4.1 Design matrix for 2^4 factorial design using selected factors

Test	Run Order	Trial Name	P	S	T	C
01	01	0101	-	-	-	-
02	03	0203	+	-	-	-
03	02	0302	-	+	-	-
04	04	0404	+	+	-	-
05	08	0508	-	-	+	-
06	07	0607	+	-	+	-
07	06	0706	-	+	+	-
08	05	0805	+	+	+	-
09	11	0911	-	-	-	+
10	09	1009	+	-	-	+
11	12	1112	-	+	-	+
12	10	1210	+	+	-	+
13	14	1314	-	-	+	+
14	15	1415	+	-	+	+
15	16	1516	-	+	+	+
16	13	1613	+	+	+	+

4-2 PLANNING FOR FACTORIAL DESIGN AND TRIALS

Having identified the major factors affecting net weight variation, the next task was to identify the two levels required for each of the factors. The two extreme levels of the operating range of each factor were selected as listed in the planning form below under section 4-2.1(3b).

4-2.1 PLANNING FORM FOR FACTORIAL DESIGN

1 Objective:

To study the effect of four important factors on the variation of net weights in (73/74 x110 mm cans) using MAF281 modified starch to fill through a piston filler. The results will be used to model partitioning of net weight variation in liquid-based food recipes.

2 Background information:

Information gathered during the brainstorming sessions and focus group discussions has helped to identify four major factors which, are thought to be affecting the weight variation during filling processes involving piston fillers.

3 Experimental variables:

A) Response Variables	Measurement Techniques
1 Mean fill weight of a single head across filling cycles	Lab Weighing scale
2 Mean of fill weight of a filling cycle across filler heads	
3 Variance of fill weights of a single filling head across filling cycles	
4 Variance of fill weights of a filling cycle across filler heads	

B) Factors under study	Levels	
1 Piston stroke height	140 Units	145 Units
2 Filler Speed	250 CPM	450 CPM
3 Product Temperature	60.0 ^{0}c	75 ^{0}c
4 Product Concentration	0.0.50 MAP 281	0.75% MAP 281

C) Background variables	Methods of control
1 Come up time for piston suction force	Wait for two minutes at can break after filler start
2 Come up time for temperature during start up	Drop liquid until temperature up to set level

4 Replication

Fill weights for a minimum of three filling cycles were collected in each trial for replication.

5 Blocking

Each of the twenty-eight filling heads in the filling station of the filler was used as a block during trials. The average fill weights produced by a single head through successive filling cycles in each trial constituted a block.

6) Methods of randomisation

The four trials belonging to each of the same concentration and temperature time combinations were randomised. The process layout did not warrant complete randomisation without wasting product and time. The randomised trial sequences are shown in Table 4-1.

7) Design Matrix

See Table 4.1 to view the matrix with factor levels applied.

8) Data Collection/ Summary form

See Tables 5.1 and 5.2 to view summary data in the form of response variables planned (3A).

See Appendix 1 to view trial data in graphics (Fill Weights in filling cycles against filler heads).

9) Planned Methods of statistical analysis

Minitab output using (Minitab Release 14):

1 Analysis of Variance for variances and means

2 Estimated Effects and Coefficients

3 Least Square Means

4 Pareto of the Standard Effects.

5 Main effects and Interaction plots.

4-3 METHODS AND MATERIALS

4-3.1 *PRODUCTION GEAR*

The processing line called H3 which is located in the simple recipe area was selected for the trials. The H3 line consisted of a piston filler, in and out can races, a can closing (capping) machine, and a product in-feed line from the Simple Recipe Kitchen. The Simple Recipe Kitchen consists of areas for paste cutting, baked bean blanching and spaghetti extrusion, ingredient weighing and recipe preparation. The recipe preparation area is equipped with a high shear mixing tank, bulk mixing tank, balance tank, steam injector unit, hot tank and a CIP cycle.

A piston filler was selected for the trials since it is capable of representing variation of fill weights contributed by the filler, product and major product components-namely-pre-fills. It also represents the most frequently used filling system catering for more than 60% of product filling requirements. The mechanism of a piston filler operation has been described in detail in Section 3-1.4.2. The piston filler on the H3 line, which has a filling station consisting of 28 filling heads, was used for the trials.

4-3.2 PRODUCT PREPARATION

A measured quantity of modified starch of the grade MAP 281 to make the required level of concentration (w/w basis) in thousand litres was weighed into skips. Each trial was planned to run for a minimum of eight consecutive filling cycles. As per trial plan below (Table 4-2) the quantity of starch solution required for a particular level of concentration was estimated to be approximately one thousand litres, (450 ml per can x 28 Heads x 10 cycles x 8 trial runs = 1008 Litres) based on the eight trials planned.

According to the tabular design in Table 4-2, 0.5% concentrated solution was prepared first, to provide for the eight trials planned under this concentration.

Next, the first half of the prepared solution was steam injected at 65 ^{0}c and transferred to the hot tank before pumping across to the filler bowl. The piston stroke-height was set to the planned low level mark (135cm) and one half of the hot (60 ^{0}c) solution was pumped to the filler bowl from the hot tank. The photograph in Appendix 4 shows the stroke level indicator beside the adjustment wheel. Finally, the two trials 11 and 32 planned at the low level of the filler stroke (135cm) were carried out at filler speeds of 250 and 350 CPM, respectively. The 2nd half of the 60 ^{0}c solution was used for trials 23 and 44 at the high filler stroke level (140cm) using filler speeds 250 and 350 CPM respectively.

Table 4.2 Tabular plan for filling process using starch solution

Design matrix for filling process using starch solution (Maps 281)

Trial date = 10/02/04 Trial medium : MAP 281 modified starch		Concentration			
		0.50% Viscol		0.75% Viscol	
		Filling Temperature		Filling temperature	
		60^{0}c **(1)**	75^{0}c **(2)**	60^{0}c **(3)**	75^{0}c **(4)**
Low Speed = 250 CPM	Low Fill level = 135 mm	**11**	**58**	**911**	**1314**
	High Fill Level = 140mm	**23**	**67**	**109**	**1415**
High Speed = 350 CPM	Low Fill level = 135 mm	**32**	**76**	**1112**	**1516**
	High Fill Level = 140mm	**44**	**85**	**1210**	**1613**

No. of cans required for a single filler cycle = 28
No. of can required for a eight filling cycles = 28 x 8
No. of cans required for the whole experiment = 28 x 8 x 16
No. of Litres of Starch solution required = 28 x 8 x 16 x 450 = 1613 Lit

The remaining portion of 0.5% solution was heated to 75^{0}c, and used for trials 85, 76, 67 and 58 in that order at the stroke and speed level combinations as shown in the plan.

The production line was drained of any remaining solution and the filters were cleaned before 0.75 % solution was prepared in the high shear mixer for the remaining trials. The run order was maintained as planned, and the trial was carried out in the same manner using the respective temperature, stroke level and speed combinations.

However only 15 of the sixteen trials planned were completed successfully. Trial 1516, which was deemed to be the last trial run, had to be abandoned because the supply of starch solution had been exhausted. The excessive draining of the solution to raise the temperature in the filler bowl to the set value had mainly contributed to this.

4-3.3 *TRIAL RUNS*

Before the start of a trial can breaks are released and cans are allowed to flow into the star wheel which creates the spacing among cans and aligns the cans into the filling station under the filling heads. As illustrated in Figure 4-1, the cans were marked with the respective filling head numbers when the can race had reached half way through the star wheel. Consistency in marking the cans was maintained by slowly rotating the filling station to align number one filling head in close proximity to the star-wheel position so that the first can to go under head number one could be identified and marked.

Once the marking of the first few cans with the respective filler head numbers was finished, the inkjet-coder located down stream after the can washer was set to print the cans with serial numbers starting with 001. This ensured traceability of the respective filler head numbers responsible for the fill weights in the cans as well as the counting of filling cycles.

Cans belonging to first three filling cycles were discarded after they were used to establish traceability. This ensured that the cans used for analysis had been filled once filler speed had reached the set value. During each trial the filler operation was monitored carefully to detect any abnormal filling, including missing cans. Corrective action was taken to remove any such cans, or cycles with filling deficiencies. Trials which were found not adequately meeting the standard filling requirements were repeated. During the trials the cans were allowed to roll into a bin. At the end of each trial the cans were collected from the bin and stacked in layers on a pallet which was labelled with the respective trial number.

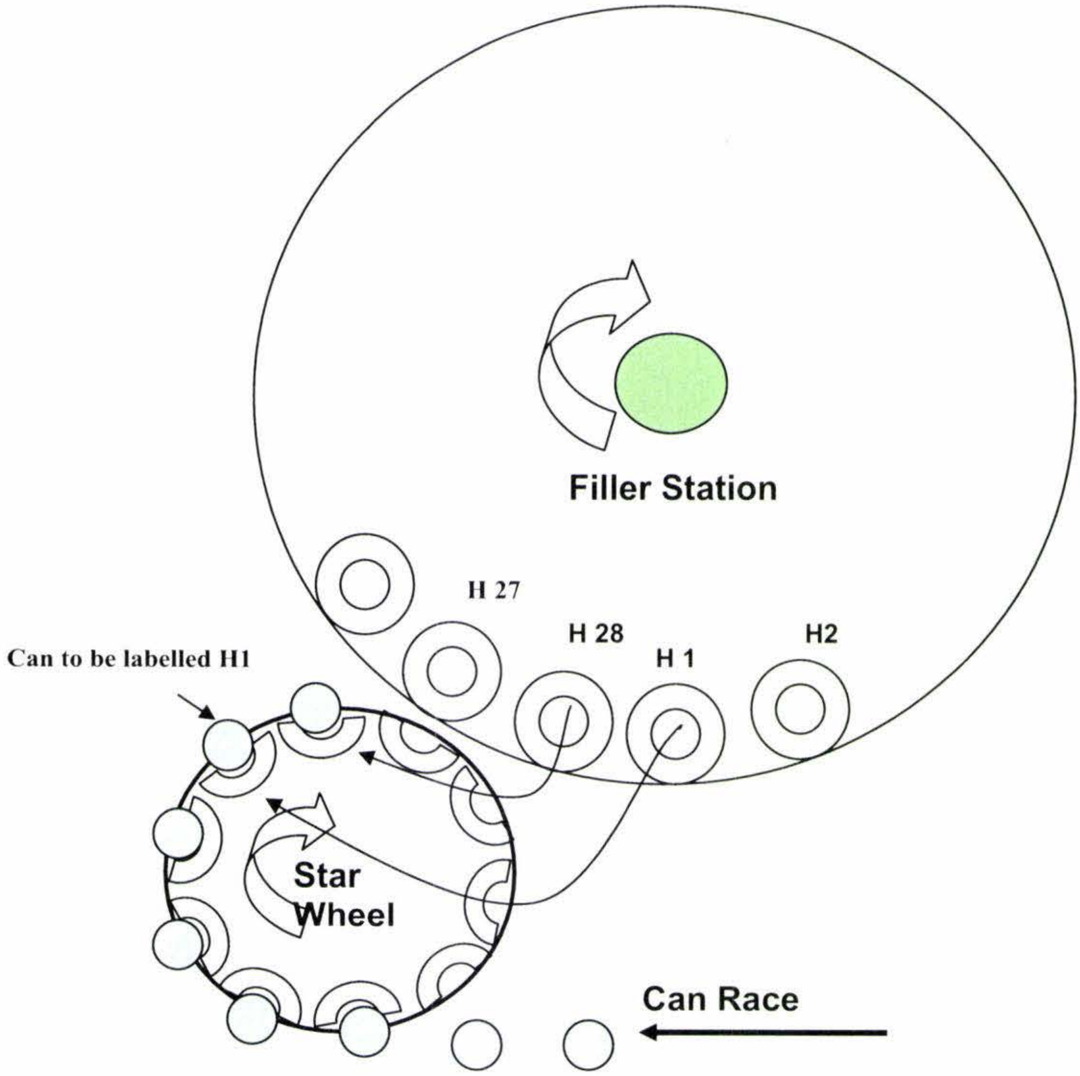


Figure 4-1 Can transfer from star wheel to filling station showing the can labelling method

4-3.4 *DATA COLLECTION*

4-3.4.1 *Collecting Response Data*

A weighting and data capture unit consisting of a weighing scale (Mettler Toledo and model P 5001-S) and a lap top computer was assembled for data collection. The weighing scale was serially connected to the laptop computer using an RS 232 interphase and the date was captured into a spread sheet. (Appendix 5)

The cans from each trial were weighed using the scale and the weights were transferred to the laptop programme by pressing the data output key on the scale. The serial number printed by the inkjet coder was manually keyed into the next column against each of the data points, which had been transferred to the laptop.

An Excel programme was used to sort the data into the run order of each trial, using serial numbers (SN). Further, the run order of can weights was partitioned into the sequence of filling cycles where each filling cycle consisted of twenty-eight can weights representing respective filling heads Once all the trial results had been tabulated, the fill weights were plotted against their respective head numbers using filling cycles in series (Appendices 1-1 to 1-5). Any data point which was well outside the common head-to-head weight ratio pattern was considered as an outlier and was removed from the data set. The author had used the original fill weight data to derive the mean fill weights and variances for each trial as shown in Table 4.3. Figure 5.4 further illustrates the process of collecting fill weight data from consecutive filling cycles during trials, tabulation and transformation of data into response tables for analysis.

Table 4-3 Tral 1314 b Gross Fill Weights, Means and Variances across cycles and heads

Head No	Cycle 2	Cycle 3	Cycle 4	Cycle 5	Cycle 6	Mean/Head.	Variance
1	407.5	407.9	406.8	406	406.3	**406.9**	**0.635**
2	404.3	403.1	407	402.2	401.7	**403.7**	**4.463**
3	405.1	403.7	402.8	402.3	402.1	**403.2**	**1.510**
4	408.6	409.8	408.1	406.4	406.5	**407.9**	**2.087**
5	404.9	404.2		404.6	402.8	**404.1**	**0.863**
6	405	403.8	402.4	401.8	401.9	**403.0**	**1.912**
7	405.1	404.1	402.9	402.4	402.3	**403.4**	**1.458**
8	409.9	409.7	408.7	408.6		**409.2**	**0.449**
9	404.9	409.2	408.4	408.2	407.8	**407.7**	**2.710**
10	404	403.3	402.7	402.4	401.6	**402.8**	**0.825**
11	409.7	408.6	407.3	407	407.4	**408.0**	**1.275**
12	404.3	403.6	402.6	402.5		**403.3**	**0.737**
13	404.7	404.4	403.2	403	402.9	**403.6**	**0.713**
14	404.2	403.3	402.6	402.4	402.6	**403.0**	**0.552**
15	404.1	403.6	403.2	405.1	404.1	**404.0**	**0.507**
16	405	404.1	402.8	402.5	402.7	**403.4**	**1.177**
17	405.9	404.5	403.7	403.6	403.6	**404.3**	**0.983**
18	406.3	406	404.9	403	402.9	**404.6**	**2.597**
19	409.6	405.6	404.7	405.9	405.5	**406.3**	**3.683**
20	408.2	407.2	406.6	406.6	406.2	**407.0**	**0.608**
21	403.6	402.4	402	401.6	401.5	**402.2**	**0.722**
22	405.3	404.3	410.3	407	404.9	**406.4**	**5.858**
23	409.5	408.9	408.4	407.7	407.5	**408.4**	**0.690**
24	405.1	404.5	403.9	403.5	403.4	**404.1**	**0.512**
25	404.3	403.1	403.2	402.5	402.6	**403.1**	**0.513**
26	403.8	403.2	402.4	402	402	**402.7**	**0.632**
27	403.2	401.8	401.3	401.5	401.3	**401.8**	**0.637**
28	406.7	405.8	406.3	406	406.4	**406.2**	**0.123**
Mean	**405.8**	**405.1**	**404.8**	**404.2**	**403.9**	**404.5**	
Variance	**4.24**	**5.54**	**6.53**	**5.13**	**4.50**	**5.43**	**4.8**

4-3.4.2 *Measurement of Factor Levels*

Before commencing the trials, factor levels were measured to ensure that the trial was carried out under planned factor levels. Table 4.4 shows the record of factor measurements against each trial. If the factor level was not reasonably within the factor levels as planned, the trials were repeated after the factor level had been adjusted.

Table 4.4 - Factor-level Meaurements

Concentration	Number of grams in 100 grams of solution	Cp	Unit of measure of viscosity
Temperature	Temperature at the filler bowl	SG	Product Wt. using 143 g bottle @ 100.22ml
Spindle size	Spindle size used for the viscometer	FBH	Liquid level in the filler bowl measured from top
Speed	Speed of the viscometer spindle	% Torque	Torque of spindle
Piston Stroke level	Top limit of the piston stroke	CPM	Filler Speed in terms of cans per minute

Trial	Concen tration.	Temp.	Spindle	Speed	% Torq1	Cp1	% Torq2	Cp2	SG	FBH	CPM	Piston Stroke
0101	0.50 %	61.5	2	100	20.2	80.8	20.8	83.2, 98.9, 97.5	97.5	100	250	140
0302	0.50 %	62.8	2	100	21.7	86.8	23.2	92.8, 99.0, 98.6	98.6	140	350	140
0203	0.50%	60.0	2	100	22.9	91.6	23.4	93.6	-	215	250	145
0404	0.50%	60.0	2	100	23.1	92.4	23.5	94.0	-	215	350	145
0805	0.50 %	70.5	2	100	13.7	54.8	14.7	58.8, 98.4, 97.6	97.6		350	145
0706	0.50 %	73.0	2	100	14.7	58.8	16.7	66.8, 98.1, 98.8	98.8	130	350	140
0607	0.50 %	77.9	2	100	14.8	59.2	15.7	62.8, 89.8	98	220	250	145
0508	0.50 %	75.5	2	100	15.2	60.8	16.0	64.0, 98.7, 98.4	98.4		250	140
1009	0.75 %	58	2	60	45.3	906	-	-		-	250	145
1210	0.75 %	54	2	60	52.9	1058	52.5	1050		60	350	145
0911	0.75 %	59	2	60	89.8	598	-	-		-	250	140
1112	0.75%	50	2	60	96.9	646	-	-		60	350	140
1613	0.75%	78	2	60	-	-	-	-			350	145
1314	0.75%	81.9	2	60	36.9	246	36	240			250	140
1415	0.75%	80	2	60	33.5	223	33	219			250	145
1516	Trial aborted											

Chapter 5 RESULTS AND ANALYSIS

5-1 METHODS OF TRANSLATING DATA FOR ANALYSIS

5-1.1 TABULATION OF TRIAL DATA

The term "filling head" will be used throughout this thesis to mean a piston assembly in a piston-filler and its components, which are involved in delivering the product into cans. The response data which consisted of gross weights (Net Weight + Can Tare Weight) of cans, were identified by three parameters. The most important one was the trial number representing the factor combination applied. Next was the head number from which the contents were filled into the can and the last was the consecutive number of the particular filling cycle. Since the variation of can tare weights was not significant (Appendix 6), the gross weight data were treated as responses to treatments consisting of factor combinations. Therefore these gross weights will be termed "fill weights" for the purpose of analysis of the results.

Tables 5-1 and 5-.2 summarise responses from all fifteen trials. The data in each horizontal line represent responses calculated from fill weight data for each trial. Trial-1516, has been missed out and therefore no data were available for this. Table 5-1 contains mean fill weights and variances of fill weights across filling heads in each filling cycle which have been copied from the last two rows of each trial data table such as Table 4-3. Similarly, data in Table 5-2 contain mean fill weights and variances across filling cycles for each head which have been extracted from the last two columns of each trial data table.

Table 5-1 Mean fill weights and variances across filling heads

	Factor Levels				Mean Fill Weights Across Heads for each Filling Cycle					
Trial	**P**	**S**	**T**	**C**	**Fill Cycle 2**	**Fill Cycle 3**	**Fill Cycle 4**	**Fill Cycle 5**	**Fill Cycle 6**	**Grand Mean**
11	-	-	-	-		**421.6**	**421.2**	**420.8**	**419.5**	**420.8**
23	+	-	-	-		**433.5**	**432.5**	**432.6**	**431.7**	**432.6**
32	-	+	-	-		**413.9**	**413.6**	**413.7**		**413.7**
44	+	+	-	-		**426.9**	**426.8**	**426.3**	**426.8**	**426.7**
58	-	-	+	-		**410.9**	**409.3**	**410.8**	**410.2**	**410.3**
67	+	-	+	-		**434.3**	**434.8**	**435.6**		**434.9**
76	-	+	+	-		**406.0**	**405.9**	**405.2**		**405.7**
85	+	+	+	-		**435.2**	**434.8**	**434.8**	**434.5**	**434.8**
911	-	-	-	+	**418.3**	**418.1**	**418.0**			**418.1**
109	+	-	-	+		**446.5**	**446.0**	**445.8**		**446.1**
1112	-	+	-	+	**418.2**	**419.1**	**418.7**			**418.6**
1210	+	+	-	+	**446.3**	**446.8**	**446.5**	**446.4**		**446.5**
1314	-	-	+	+	**405.8**	**405.1**	**404.8**	**404.2**	**403.9**	**404.8**
1415	+	-	+	+	**447.1**	**445.1**	**443.7**	**443.2**		**444.8**
1613	+	+	+	+	**447.4**	**447.2**	**447.5**			**447.4**
Trial	**Factor Levels**				**Variance Across Heads for each Filling Cycle**					
11	-	-	-	-		**40.45**	**12.62**	**11.59**	**35.12**	**24.9**
23	+	-	-	-		**18.55**	**9.00**	**23.10**	**15.06**	**16.4**
32	-	+	-	-		**7.89**	**4.94**	**6.4**		**6.4**
44	+	+	-	-		**7.08**	**6.33**	**6.15**	**6.60**	**6.5**
58	-	-	+	-		**50.79**	**56.32**	**69.78**	**51.97**	**57.2**
67	+	-	+	-		**9.50**	**12.02**	**11.63**		**11.1**
76	-	+	+	-		**16.30**	**13.56**	**12.62**		**14.2**
85	+	+	+	-		**8.37**	**7.96**	**8.31**	**8.74**	**8.3**
911	-	-	-	+	**10.78**	**6.62**	**6.65**			**8.0**
109	+	-	-	+		**6.75**	**5.97**	**5.62**		**6.1**
1112	-	+	-	+	**15.27**	**7.82**	**7.86**			**10.3**
1210	+	+	-	+	**9.95**	**5.27**	**5.41**	**6.16**		**6.7**
1314	-	-	+	+	**4.24**	**5.54**	**6.53**	**5.13**	**4.50**	**5.2**
1415	+	-	+	+	**6.20**	**10.19**	**7.46**	**6.62**		**7.6**
1613	+	+	+	+	**15.16**	**13.96**	**4.89**			**11.3**

The run charts in Figures 5-1 to 5-3 represent means and variances of trial data in the order in which the trials were carried out. Figure 5-1 shows the run chart of mean fill weights across filling cycles for each filling head for each trial. The mean fill weight differences between high piston and low piston strokes are clearly evident. Detailed observation reveals that the head-to-head filling ratios are not consistent from trial to trial. At the same time, no fluctuations due to special causes were found throughout the sequence.

Table 5-2 Mean Fill Weights & Variances Across Filling Cycles

Mean Fill Weights Across Filling Cycles for Each Filler Head (MFw-Ac-Fc)

Trial	Head 1	Head 2	Head 3	Head 4	Head 5	Head 6	Head 7	Head 8	Head 9	Head 10	Head 11	Head 12	Head 13	Head 14	Head 15	Head 16	Head 17	Head 18	Head 19	Head 20	Head 21	Head 22	Head 23	Head 24	Head 25	Head 26	Head 27	Head 28
11	419.2	419.4	423.0	419.8	421.3	417.2	417.2	419.4	422.7	416.2	421.0	417.9	422.7	424.1	418.0	424.1	427.1	418.6	424.0	424.8	418.2	422.1	426.2	425.1	420.5	422.1	414.6	414.7
23	432.2	427.2	436.2	435.7	433.5	436.1	430.3	429.5	430.8	437.7	429.2	432.7	429.8	434.2	434.3	428.5	433.4	438.4	430.5	428.8	433.4	430.8	434.6	438.2	436.6	431.9	430.8	427.9
32	411.4	412.9	413.7	417.9	415.0	412.1	411.1	411.9	416.4	411.0	415.2	411.7	413.1	413.7	412.1	414.1	416.4	414.1	414.6	416.0	409.1	417.1	418.9	415.7	412.6	412.2	410.8	415.5
44	424.3	425.4	426.5	431.1	427.8	424.7	424.0	424.8	427.2	425.1	429.8	425.6	425.8	426.9	424.4	426.3	428.6	430.0	426.0	429.6	424.5	430.8	430.0	428.0	425.1	424.8	423.6	425.7
58	405.1	408.7	409.2	411.6	410.6	406.0	411.5	410.9	408.3	416.5	410.9	401.5	406.4	414.7	416.3	410.1	414.2	411.6	410.4	408.9	413.9	407.7	415.4	413.9	411.5	410.2	408.5	404.6
67	440.8	432.2	437.0	435.5	431.4	435.5	431.7	435.0	437.2	436.8	436.2	436.8	438.1	439.6	439.3	434.0	432.3	431.8	429.8	436.2	429.6	432.1	433.7	436.3	434.3	432.5	431.6	431.3
76	401.6	402.5	405.3	406.5	408.3	403.2	402.4	402.5	409.6	406.3	404.1	404.1	402.5	405.5	410.6	404.0	408.1	409.9	408.8	408.1	407.6	409.6	409.7	407.5	404.5	403.1	400.7	403.0
85	431.5	433.9	434.6	438.6	433.9	433.1	431.9	433.3	440.6	432.2	439.2	433.1	432.8	433.4	432.4	433.2	435.8	437.4	439.3	437.2	432.7	438.3	439.4	435.4	433.2	432.8	431.6	435.4
911	419.1	419.6	419.6	419.9	418.3	415.3	414.6	418.2	421.4	419.1	419.2	420.2	419.7	414.2	417.4	416.2	417.3	420.7	420.5	419.8	415.4	418.8	419.5	420.4	416.9	415.0	414.7	418.2
109	443.3	447.4	446.6	448.5	446.9	443.1	443.8	449.7	449.2	444.0	449.4	448.7	444.7	444.0	447.5	443.9	445.1	448.8	446.7	448.3	442.9	444.9	448.9	445.5	443.0	443.6	443.0	448.3
1112	420.2	420.8	420.1	420.8	418.0	415.6	416.1	422.2	421.4	413.1	421.4	421.1	418.7	414.9	419.6	415.3	416.9	421.4	419.2	420.7	413.1	417.1	421.5	421.7	416.6	416.3	415.8	421.2
1210	448.0	447.2	448.6	448.4	448.5	448.0	442.7	448.9	446.8	445.6	448.5	447.4	442.4	445.1	448.1	444.4	444.9	448.4	448.0	447.3	442.1	448.5	448.1	448.1	442.1	442.6	446.9	448.1
1314	406.9	403.7	403.2	407.9	404.2	403.0	403.4	409.2	407.7	402.8	408.0	403.3	403.6	403.0	404.0	403.4	404.3	404.6	406.3	407.0	402.2	406.4	408.4	404.1	403.1	402.7	401.8	406.2
1415	446.6	443.4	443.7	448.4	444.0	441.3	442.7	448.5	449.1	443.1	448.0	447.2	443.4	443.1	443.5	443.7	444.0	446.8	445.9	445.6	442.1	442.9	448.6	442.0	440.4	439.9	443.4	448.1
1613	448.3	448.1	444.6	442.1	449.4	447.7	442.8	450.0	450.6	444.4	450.0	449.6	440.7	446.6	448.3	445.2	448.8	449.8	448.8	448.5	447.0	448.8	450.1	450.2	443.6	444.1	447.8	446.7

Variances of Fill Weights Across Filling Heads (Var-Ac- Fhs)

Trial	Head 1	Head 2	Head 3	Head 4	Head 5	Head 6	Head 7	Head 8	Head 9	Head 10	Head 11	Head 12	Head 13	Head 14	Head 15	Head 16	Head 17	Head 18	Head 19	Head 20	Head 21	Head 22	Head 23	Head 24	Head 25	Head 26	Head 27	Head 28
11	17.36	0.47	0.94	20.25	0.06	2.28	0.29	0.21	8.39	0.13	25.74	2.06	0.28	25.05	27.41	83.94	1.72	0.74	83.73	50.71	19.26	47.24	3.98	7.12	0.04	39.22	16.98	42.81
23	13.24	0.70	2.70	4.50	14.92	22.51	0.31	0.41	0.29	39.60	0.28	21.41	0.54	1.62	4.91	1.47	5.03	27.92	4.14	46.65	0.17	0.46	0.605	1.56	2.12	0.05	0.53	4.22
32	0.50	0.12	0.00	0.12	0.60	0.05	0.02	0.08	0.00	0.02	0.00	0.01	0.02	0.18	0.01	0.72	8.00	14.05	0.85	0.605	7.61	0.18	0.40	0.08	0.01	0.13	0.02	0.32
44	7.99	0.46	0.38	2.963	14.89	0.26	0.01	0.18	0.13	0.46	0.29	0.73	0.40	0.49	0.34	0.26	0.58	3.15	0.61	0.18	0.07	0.02	0.31	0.34	0.37	0.25	0.09	0.50
58	33.06	77.36	17.97	4.68	9.94	63.89	142.05	11.78	67.46	92.64	94.53	36.22	117.10	22.49	217.60	98.58	18.61	65.98	2.30	16.03	73.10	46.66	28.68	73.83	48.03	35.49	54.39	27.12
67	12.36	0.01	0.18	1.003	0.04	0.323	0.245	0.045	1.083	7.213	8.32	0.003	8.71	0.93	0.063	0.023	0.013	0.323	0.503	0.19	0	0.5	0.005	5.445	36.13	0.005	1.28	0.18
76	0.85	2.54	3.89	12.60	25.00	1.77	1.56	1.26	36.21	39.24	2.42	24.44	1.14	6.43	34.45	5.22	6.49	1.42	0.16	0.09	4.75	9.40	1.00	5.30	1.33	0.13	1.80	10.24
85	0.04	0.60	0.48	0.16	0.00	0.41	0.05	0.26	0.09	0.14	1.45	2.75	4.33	0.13	1.18	2.40	0.06	0.32	0.06	0.06	2.42	0.40	0.35	0.70	0.19	0.39	0.04	3.21
911	0.19	0.34	0.10	0.18	0.52	2.20	2.50	26.65	0.07	12.92	13.74	0.13	15.70	3.76	7.39	13.51	6.24	0.64	0.16	0.16	19.41	0.24	1.96	0.27	8.67	0.30	0.04	12.32
109	5.33	0.49	1.56	0.24	0.12	0.18	0.12	0.30	0.19	0.07	1.01	0.37	0.69	0.58	3.24	0.36	0.37	0.37	0.61	0.36	0.32	0.16	0.26	1.80	2.59	0.37	0.30	0.02
1112	0.10	0.12	1.05	0.03	0.72	0.31	0.16	0.21	0.22	19.57	0.27	0.04	13.08	6.17	7.36	6.49	12.09	0.02	40.09	0.08	4.21	0.25	0.04	0.01	0.61	0.24	0.18	0.41
1210	0.383	0.687	2.58	1.03	0.813	0.457	0.409	0.223	10.62	0.02	0.02	3.203	0.253	6.736	0.71	2.483	10	0.437	0.117	0.069	0.042	0.169	0.207	0.227	0.069	0.349	0.323	0.72
1314	0.64	4.46	1.51	2.09	0.86	1.91	1.46	0.45	2.71	0.83	1.28	0.74	0.71	0.55	0.51	1.18	0.98	2.60	3.68	0.61	0.72	5.86	0.69	0.51	0.51	0.63	0.64	0.12
1415	6.48	11.52	15.68	12.00	3.51	0.09	4.52	3.15	4.60	3.31	4.46	0.97	5.44	5.60	2.52	3.31	6.30	3.68	1.19	14.88	6.60	7.37	5.08	0.04	1.13	4.50	9.68	5.78
1613	0.045	0.125	0.98	87.12	0.253	0.18	0.605	0.37	0.37	0.063	1.09	0.223	58.41	3.063	0.36	1.29	0.61	0.863	0.023	0.125	9.263	0.413	0.243	0.13	0.125	0.16	0.045	10.46

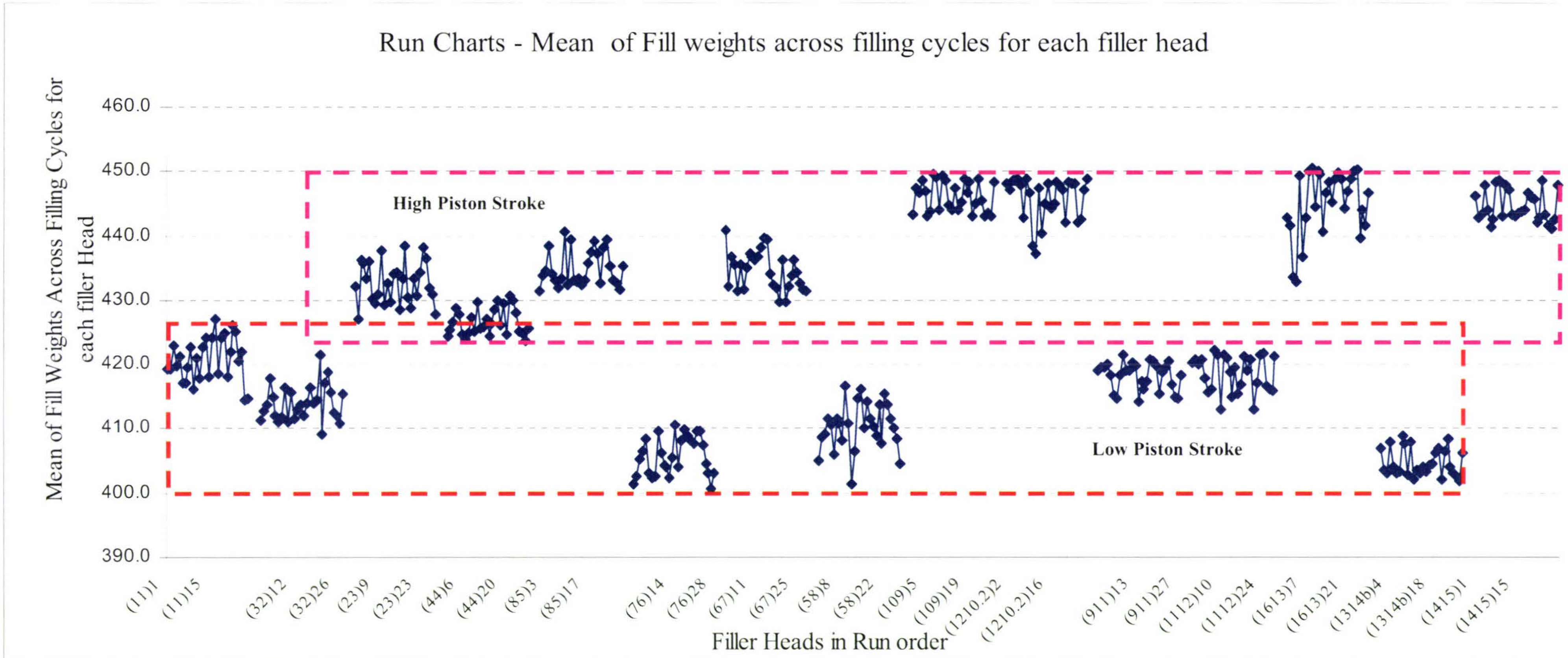


Figure 5-1 Run Charts for Mean of (Original) Fill Weights Across filling Cycles for each filler head

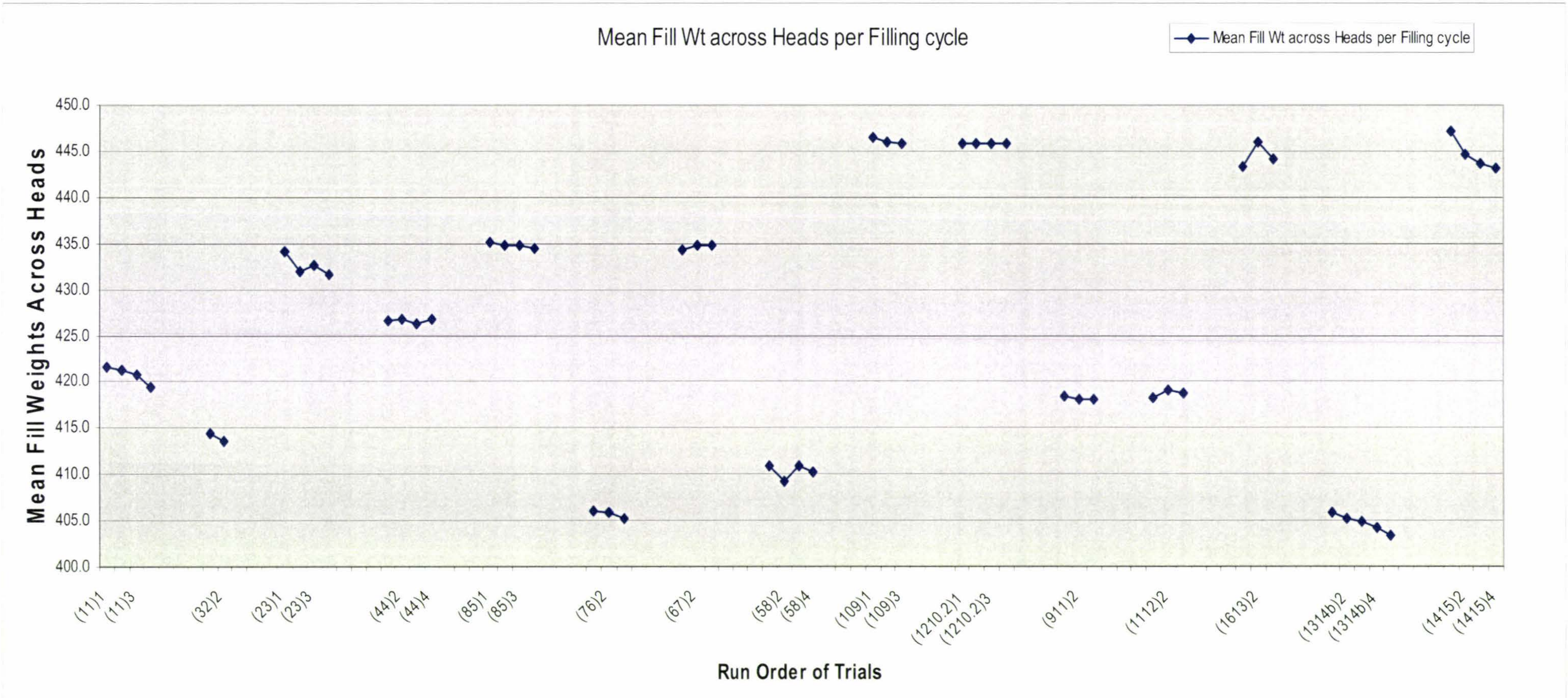


Fig. 5-2 Run Charts for Mean (Original) fill-weights across filler Heads for each Cycle

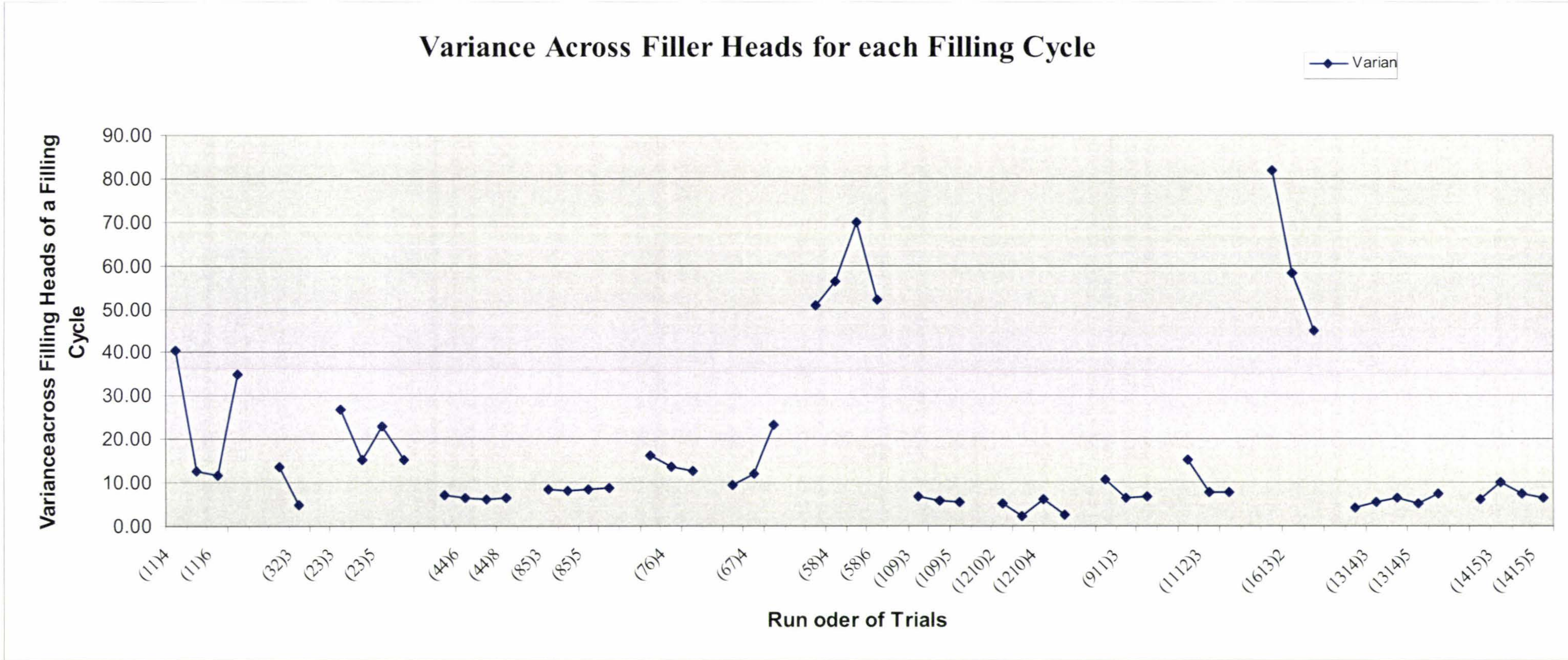


Figure 5-3 Run charts for variance of (original) fill-weights Across filler heads

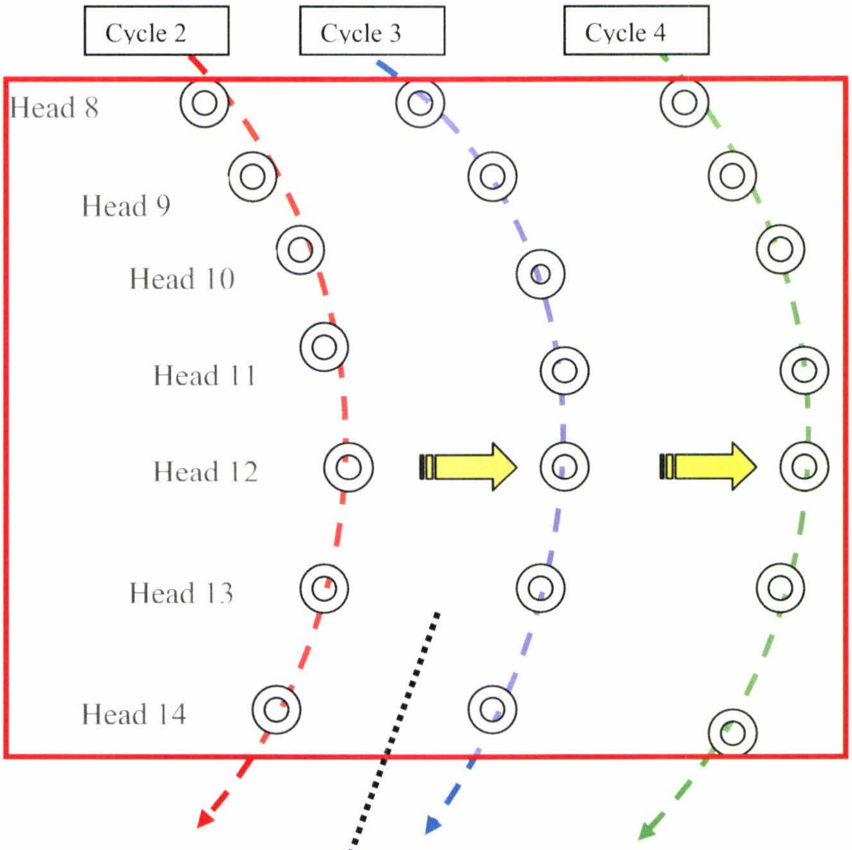
The run order in Figure 5-2, is shown as the order of consecutive filling cycles. Each point in the plot represents the mean of fill-weights across twenty-eight filling heads of each filling cycle. Each trial is represented by three to five filling cycles. Once again no special trends could be spotted. However, the mean fill weights within certain trials seem to trending downwards for half of the trials. An important observation was that the variation of mean fill weights from trial to trial is evidently larger than the differences within the trials themselves. Figure 5-3, on the other hand, shows the variance of fill weights across the filler heads in each filling cycle. For most of the trials the variance value for each cycle remained more or less the same within the trials. However, for few a trials, namely, 11, 58, and 1613 the values within the trials varied considerably. The high variance figures in trial 1613 (Figure 5-3) may warrant further investigation to find any possible special causes.

5-1.2 *RESPONSE TYPES USED FOR ANALYSES*

The author used the fill weight results of the trials to derive the following four types of responses to be used in four different analyses. Figure 5.4 illustrates how the fill weight data form the trials have been transformed into the response variables described below.

a) <u>Mean of fill weights across filling cycles (MFw-Ac-Fc) for each filling head</u>

It is evident that different factor combinations could produce different filled weights off a given head into cans. (Figure 5-1) Therefore, the mean of fill weights from a particular head during consecutive filling cycles in each trial would be effective as a response to evaluate factor effects. Even under the same piston stroke (P+ or P-), where the volumes are supposed to be same, differences of filling characteristics among trial solutions could result in weight differences. All twenty-eight heads were used as separate blocks rather than replicates, to evaluate the significance as well as the contribution from head-to-head differences.



Head No	Cycle 3	Cycle 4	Cycle 5	MFw-Ac-Fc.	Var-Ac-Fc
1	407.9	406.8	406	**406.9**	**0.635**
2	403.1	407	402.2	**403.7**	**4.463**
3	403.7	402.8	402.3	**403.2**	**1.51**
4	409.8	408.1	406.4	**407.9**	**2.087**
5	404.2		404.6	**404.1**	**0.863**
6	403.8	402.4	401.8	**403**	**1.912**
7	404.1	402.9	402.4	**403.4**	**1.458**
8	409.7	408.7	408.6	**409.2**	**0.449**
9	409.2	408.4	408.2	**407.7**	**2.71**
10	403.3	402.7	402.4	**402.8**	**0.825**
11	408.6	407.3	407	**408**	**1.275**
12	403.6	402.6	402.5	**403.3**	**0.737**
13	404.4	403.2	403	**403.6**	**0.713**
14	403.3	402.6	402.4	**403**	**0.552**
15	403.6	403.2	405.1	**404**	**0.507**
16	404.1	402.8	402.5	**403.4**	**1.177**
17	404.5	403.7	403.6	**404.3**	**0.983**
18	406	404.9	403	**404.6**	**2.597**
19	405.6	404.7	405.9	**406.3**	**3.683**
20	407.2	406.6	406.6	**407**	**0.608**
21	402.4	402	401.6	**402.2**	**0.722**
22	404.3	410.3	407	**406.4**	**5.858**
23	408.9	408.4	407.7	**408.4**	**0.69**
24	404.5	403.9	403.5	**404.1**	**0.512**
25	403.1	403.2	402.5	**403.1**	**0.513**
26	403.2	402.4	402	**402.7**	**0.632**
27	401.8	401.3	401.5	**401.8**	**0.637**
28	405.8	406.3	406	**406.2**	**0.123**
MFw-Ac-Fh	**405.1**	**404.8**	**404.2**	**404.5**	
Var-Ac-Fhs	**5.54**	**6.53**	**5.13**	**5.43**	**4.8**

Figure 5-4 Transformation of filler trial data into four main response variables

b) Mean fill weights across heads (MFw-Ac-Fh) for each filling cycle

The mean of fill weights across heads within filling cycles would represent factor effects but were expected to be corrupted somewhat due to head-to-head variations. If head-to-head variation is constant throughout all the trials then the total variation across the heads is a function of the effect of factor combinations. The common knowledge that the head-to-head variation was not constant seems to be the main concern in these trials, which was further confirmed in the run order chart for mean fill weights across filling cycles (Figure 5-2). The MFw-Ac-Fh in each filling cycle were used as blocks rather than replicates to reduce the residual-error in the analysis as well as to check if there was any significance in the cycle-to-cycle differences. Since the Var.-Ac-Hds is as same as the variation across a single filling cycle, this statistic also represents the short-term variability of each of the trial runs of the factorial experiment.

c) Variance of fill weights across filling cycles (Var-Ac-Fc) for each filling head

The Var.-Ac-Fc in each head has the potential to represent the long-term variability due to shifting of factor levels arising from both product and filler related factors used. It is unlikely that the data would reveal this, as the filling liquid during any given trial is considered to be homogeneous and the number of cycles used was minimal. Therefore it allows the assumption that any observed variance across cycles for the same head could mostly be due to noise variations arising from the filler mechanism and due to unwarranted and uncontrollable changes to set factor levels. Therefore, the filled volumes of a given head between filling cycles within the same trial should be the least variable. Variation within a given head for a single trial is expected to be less than the variation from the entire filler head assembly. The Var-Ac-Fc in each head was used as a block to evaluate the contribution from head-to-head differences to the total variation and the significance of this contribution.

d) Variance of fill weights across filler heads (Var-Ac-Fh) within each filling cycle

For a given factor combination, the variance across filler heads in a single filling cycle (Figure 5-3) represents mostly the variation due to the difference among all the heads. However, when applied to trial runs, it is also expected that different factor combinations would cause either an increase or a decrease in the magnitude of variance across filler heads. This enables these statistics to represent the effects of factors and their interactions. The Var-Ac-Fhs in each filling cycle were used as blocks, rather than using them as replicates, to reduce the residual error in the analysis as well as to test the significance due to cycle-to-cycle differences.

For each of the above response types, three separate analyses were carried out using the full factorial matrix, one half matrix which contained factor combinations under the high piston stroke and the other half matrix which contained factor combinations under the low piston stroke (Figure 5-5). Table 5.-3 shows the planning schedule for all the 12 analyses. The summary results of experimental analyses as per the planned schedule, which were calculated using the Minitab programme (Mintab for Windows, Release 14) are listed in Table 5.4. These results will be used in Sections 5-2 to 5-5 to explore the sources of net weight variations and to quantify these sources.

Table 5-3 Schedule of planned analyses

	Mean of Fill Weights						Variance of Fill Weights					
Response Type	From each head across filling cycles			Across filling heads in each filling cycle			From each head across filling cycles			Across filling heads in each filling cycle		
Matrix Type/ projection used	Full Matrix	Half Matrix with P+ Projection	Half Matrix with P- Projection	Full Matrix	Half Matrix with P+ Projection	Half Matrix with P- Projection	Full Matrix	Half Matrix with P+ Projection	Half Matrix with P- Projection	Full Matrix	Half Matrix with P+ Projection	Half Matrix with P- Projection
Blocking	28 Heads	28 Heads	28 Heads	3 Fill. Cycles	3 Fill. Cycles	3 Fill. Cycles	28 Heads	28 Heads	28 Heads	3 Fill. Cycles	3 Fill. Cycles	3 Fill. Cycles
Section	6-2	6-2.1	6-2.2	6-3	6-3.1	6-3.2	6-4	6-4.1	6-4.2	6-5.	6-5.1	6-5.2
Reason for Analysis	Partition of factor and head to head effects	Partition of factor and head effects at high P	Partition of factor and head effects at low P	Effect of Factors	Effect of Factors at High P	Effect of Factors at Low P	Quantify head-to-head variances, factor effects & unstable filler mechanism	Quantify head-to-head variances, factor effects & unstable filler mechanism at high P	Quantify head-to-head variances, factor effects & unstable filler mechanism at low P	Short term variance due to factor effects & interactions	Short term variance due to factor effects & interactions at high P	Short term variance due to factor effects & interactions at low P

Table 5-4 Summary analysis of trial responses using Minitab output

Response type used	R-Sq%	R-Sq (Adj) %	% Contributions				Effects in the order of significance Effects	Factors not significant	Important interactions	Factor combination to maximise	Factor combination to minimise
			Blocks	Main Effect	2-way interact	3-way interact					
MFw Ac Fc in Fh (Full matrix) using Fhs as Blocks	97.74	97.49	1.06 P<0.05	84.50	12.00	0.18	P> P*C> P*T> C> T> T*C> S*C> S> P*S> S*T> S*T*C> P*S*T	None	P*T & T* C	P+, S+, T+, C+	P-, S-, T-, C-
MFw Ac Fc in Fh (Half Matrix @ P+) using Fhs as Blocks	92.5	91.15	3.87 P<0.05	81.41	06.78	0.43	C> T*C> T> S*C> S*T> S*T*C> S	None	T*C & S*C	S+, T+, C+	S+, T-, C-
MFw Ac Fc in Fh (Half Matrix @ P-) using Fhs as Blocks	89.00	86.76	6.99 P<0.05	72.50	09.51	-	T> S*C> S> T*C> S*T	C	S*C & T*C	S+, T-, C+	S+, T+, C-
MFw Ac Fh in Fc (Full matrix) With Fc in Blocks	99.88 99.9	99.83 99.85	P>0.05 0.02	87.28	12.38	0.22	P> P*C> P*T> C> T> S*C> T*C> S> S*T*C> P*S> S*T>P*S*T	None	P*C & P*T	P+, S+, T+, C+	P-, S+ T+, C-
MFw Ac Fh in Fc (Half Matrix @ P+) With Fc in Blocks	99.39 99.49	99.13 99.16	P>0.05 0.10	91.93	06.86	0.60	C> T>T*C> S*C> S*T> S*T*C> S	None	T*C and S*C	S+, T+, C+	S+, T-, C-
MFw Ac Fh in Fc (Half Matrix @ P-) With Fc in Blocks	99.55 99.64	99.36 99.39	P>0.05 0.09	88.47 88.39	11.53 11.51	-	T> S*C> S> S*T> T*C	C	S*C and T*C	S+, T-, C+	S+, T+, C-
Var. Ac Fc in Fh (Full matrix) Fhs in Blocks With out Blocking	47.68 44.09	42.00 42.16	3.59 P>0.05	16.79	17.05	10.26	S> P*C> C> P*T*C> P*S> T*C> P*S*T> S*T> S*C>P	T	P*C	P-, S-, T+, C-	P+, S+, T-, C+
Var. Ac Fc in Fh (Half matrix @ P+)	19.27	4.74	10.85	01.35	06.72	0.36	T*C> S*C> S> S*T	S, T, C	T*C & S*C	S-, T+, C+	S+, T-, C+
Var. Ac Fc in Fh (Half matrix @ P-)	53.15	43.60	08.92	24.05	20.18		C> S> T*C> S*T> S*C	T	T*C	S-, T+, C-	S+, T-, C+
Var. Ac Fh in Fc (Full matrix) With Fc in Blocks	88.47 89.06	83.09 82.80	P>0.05 0.59	33.67	34.35	20.45	C> S> P*T*C> P*C> P*S> T*C> P*S*T> S*T> S*C	T & P	P*C & T*C	P-, S-, T+, C-	P+, S+, T-, C+
Var. Ac Fh in Fc (Half Matrix @ P+)	58.57	40.44	P>0.05 1.80	15.57	41.07	01.92	S*C> T*C> C> S*T	S, T, C	S*C & T*C	S-, T-,C-	S-, T-, C+
Var. Ac Fh in Fc (Half Matrix @ P-)	89.12	84.46	P>0.05 0.89	45.68	43.44		C> S> T*C> S*T>S*C>T	T	T*C	S-, T+, C-	S+, T+, C+

5-2 ANALYSIS USING MEAN OF FILL WEIGHTS ACROSS FILLING CYCLES

The design matrix consisted of four factors; P,S,T and C representing piston stroke, speed of filling, temperature and concentration of fill liquid respectively. The 28 blocks in the blocking column represented 28 filling heads. Therefore any single head was an experimental unit in which all trials were conducted. The estimated effects and regression coefficients for fill weights, obtained from Minitab output in Appendix 13, show significant effects of factors and blocks. Accordingly, looking at p-values for the slope test, only a few blocks (heads) namely; 4,6,7,9,13,18,20,21 and 23-27were found to be significant. All four factors and all two-way interactions were significant. Of the three – way interactions only two, namely P*S*T and S* T*C, turned out to be significant.

As per R-Sq, 97.7% of the variations can be explained by listed terms. Further a very narrow gap between former and R-Sq (Adj.), explains that most of the listed terms are significant. Analysis of variance results in Table 5-5 have further confirmed these observations through respective P values for the F-tests. The percentageage contribution of each factor and their combinations to the total SS (Sums of Squares) for the model is considered as a guide to the relative importance of each of these terms (Montgomery, 2001, 234). The SS for factors and their interactions themselves represent the order of magnitude of their relative importance. As per this indicator, the main effects and 2-way interactions contribute 96.5 % of the total variation in net weight. Though significant, the contributions of blocks (filler heads) to the explained variations amounted to only 1.0%.

5-2.1 MEAN OF FILL WEIGHTS ACROSS FILLING CYCLES AT HIGH-P

The R-Sq value being 92.5% shows only a slightly high residual error compared to the parent design using all the factors. The design matrix consisted of only three factors; S,T and C representing speed of filling, temperature and concentration of fill product respectively. The 28 blocks in the blocking column represented 28 filling heads. Appendix 15 shows that all the factors and blocks were significant at $p<0.05$. Inspection of p-values for the slope test, for the coefficients, shows that the number of blocks (heads) which were significant was very close to the parent analyses which included the piston stroke. But the contribution to the responses from heads, calculated using SS, was found to be about four times as high. The effect of concentration is shown to be dominant at the high piston stroke level, which is clearly shown in the Pareto chart of the standard effects. This is followed by effects of interaction T*C and then temperature. The effect of temperature appeared to indicate an opposite trend in which significantly high fill weights were produced at high temperature. However, analysis of interaction plots reveals an increase of fill weights with high concentration at both high and low temperatures, diminishing the effect of temperature as a single factor. The effect of the speed seems to be the least, showing only a slight increase of fill weights at low speed. The interaction S*C, however, confirms that fill weight increases at both high and low levels of speed when combine with high concentration but the rate of increase was found to be higher at high speed.

5-2.2 MEAN OF FILL WEIGHTS ACROSS FILLING CYCLES AT LOW-P

The design matrix consisted of only three factors; S, T and C representing speed of filling, temperature and the concentration of fill liquid respectively. The 28 blocks in the blocking column represented 28 filling heads. Out of eight runs required for the full factor combination, results of only seven runs were obtained due to one missing trial. From p-values for the slope test for the coefficients, only nine blocks (heads) namely, 6,7,9,12,20,21,23,24 and 27 were found to be significant at $p< 0.05$ compared to twelve in the full factor analysis, which included the piston stroke. The persentage of the variations which could be explained by the listed terms is slightly less at 89% compared to 92.5% for the projection at the high piston stroke (Appendix 16).

When the piston stroke is low, the contribution to the responses from the filling heads which-is calculated using SS-is found to be seven times higher than the parent analysis and one point eight (1.8) times higher than the P high projection analysis. As clearly shown in the Pareto chart of the standard effects and main effects charts, the effect of temperature was dominant but negative at the low piston stroke level. Although higher speeds tend to reduce fill weights, the interaction of speed with concentration reverses the this trend, indicating that speed exerts a positive effect at high concentration levels, and when combined with low speed fill weights it dropped showing an interaction between the speed and the concentration. This was further strengthened by the fact that the S*C interaction was dominant over the effect of speed in this instance. In contract to its dominant and positive effect during high P projection, the effect of concentration in the low P projection failed to contribute significantly. The T*C interaction plot reveals that high temperature reduces the fill weight at both levels of the concentration.

5-3 ANALYSIS USING MEAN FILL WEIGHTS ACROSS FILLER HEADS

The design matrix consisted of all four factors, P, S, T and C. The mean fill weights of the first three effective filling cycles for each trial were selected for analysis. The filling cycles were used as blocks, in order to determine whether or not there was any significant difference between filling cycles. Each one of the three filling cycles formed a block containing all the fifteen trials. The first section of Appendix 17 shows the estimated effects and regression coefficients for fill weights from Minitab output. All the factors and 2-way interactions and one 3-way interactions were significant. The main and interaction effects are in the same order of significance as for analysis across filling cycles up to the first five effects.

The fact that the value for R-Sq is 99.9% explains that most of the variations in the fill weights were contributed from the listed terms. The ANOVA table confirms that the contribution from the main effects and two-way and three-way interactions were significant at $P<0.05$. The contributions to the total variation from the main effects and 2-way interactions were 87.3% and 12.4 % (99.7%) respectively, which are approximately the same as shown in the analysis across the filling cycles (96.5%). Tests of significance from both estimated effects and ANOVA proved that effects between filling cycles (blocks) were not significant and contributed only about 0.02% to the total variation of fill weights.

The Pareto chart of Standardised Effects illustrates that the effect of the piston stroke length contributes most to the observed responses. The next step was to investigate the effects of the factors other than the piston stroke. This was to find out the sources of variation of fill weights when the filler adjustment is set constant. This was achieved in the same way as we did for analysis across cycles for mean fill weights. The method used was to sort high stroke responses from the low stroke responses and to run them as two separate trials. This converted the analysis into two new 2^3 designs.

5-3.1 MEAN FILL WEIGHTS ACROSS FILLER HEADS AT HIGH-P

At 99.5%, the R-Sq value is only slightly less than that in the parent analysis and therefore shows only a slightly high residual error compared to the parent design. (Appendix 18)

The design matrix consisted of only three factors; S, T and C, representing speed of filling, temperature and concentration of fill liquid respectively. There are only three blocks in the blocking column, which represented the three filling cycles. In terms of p-values for the slope test, all the main factors and two-way interactions are significant at $p < 0.05$.

The p value for the blocks (0.294) in the ANOVA table indicates that the block-to-block effect is not significant. Once again, similarly to the P high projection using fill weights across filling cycles, the effect of concentration is shown to be dominant at the high piston stroke level, followed by the effect of temperature which is also clearly shown both in main effects and Pareto charts. The effect of two-way interactions-namely T*C, S*C and S*T-line up next in decreasing order followed by the 3-way interaction S*T*C. The effect of the speed seems to be the least among the main factors. The interaction plots are also very similar to P high projection using fill weights across filling cycles, which reveals that at high concentration fill weight increases considerably against both levels of speed and temperatures. Therefore, main effects of speed and temperature are challenged by their interactions with concentration (T*C and S*C).

5-3.2 MEAN FILL WEIGHTS ACROSS FILLER HEADS AT LOW-P

The design matrix consisted of only three factors; S,T and C representing speed of filling, temperature and concentration of fill liquid respectively. There are three blocks in the blocking column representing the three filling cycles. Appendix 20 shows that the speed, temperature and all 2-way interactions are significant at $P < 0.05$. The p-values for the slope test show that the block-to-block effect is not significant as was expected. The effect of temperature once again was shown to be dominant at the low piston stroke level, which is also clearly shown both in main effects and Pareto charts. The effect of the 2-way interaction namely S*C lines up next in decreasing order, followed by the effect of speed, S*T and T*C. Similarly to its counterpart, which is a P-low projection of mean fill weight across filling cycles, the effect of concentration turned out to be nonsignificant.

The trends in main effects and interaction plots are also very closely similar to the analysis across cycles at the low piston stroke level. However, the main difference between analysis of mean fill weights across filling cycles and across heads at P low was that the latter produced an R –sq value of 99.6%, whereas the former produced a value of only 89%. This represents a drop of the residual error from 11% to under 0.5%.

5-4 ANALYSIS USING VARIANCE OF FILL WEIGHTS ACROSS FILLING CYCLES

The design matrix consisted of all four factors, P, S, T and C. The variances of fill weights across first three effective filling cycles from each trial were selected for analysis. Each of the twenty-eight filling heads formed a block containing all the fifteen trials. The first section of Appendix 21 below shows the estimated effects and regression coefficients for variances of fill weights from Minitab output.

The value for R-Sq being 47.68% coupled with high residual error, shows that most of the variations contributing to the observed response remain unexplained. The R-Sq Adj. was 42% showing a gap of more than seven points between them. This indicates that the level of contributions from factors and their interactions to variations that are significant ($P<0.05$), are considerably less when compared to similar contributions to mean fill weights levels. The effect of temperature turned out to be non-significant, while that of the piston stroke was just within the line of significance. Both the speed, concentration and all the two-way interactions were significant except P*T.

The ANOVA table shows that although the effect of blocks (Filling Heads) contributes 3.6% of the observed variance, it failed appear as a significant effect ($p<0.05$). The 2-and 3-way interactions are significant and therefore partly responsible for the observed variations. The contributions to the total variations from the blocks, main effects and 2-way and 3-way interactions were 3.6%, 16.8%, 17%, and 10.3%. Nevertheless, the contributions from the same effects to the explained portion of variation of the responses were 7.5%, 35.4%, 35.8% and 21.5% respectively.

It was decided to carry out a projection analysis under the two levels of piston stroke as done previously. This was to find out sources of variance of fill weights across filling cycles when the filler adjustment is set to a constant to deliver the required target weight.

This was achieved in the same way as we did for the analysis across cycles for mean fill weights. The method used was to sort high stroke responses from the low stroke responses and to analyse them as two separate trials.

5-4.1 *VARIANCE OF FILL WEIGHTS ACROSS FILLING CYCLES AT HIGH-P*

The R-sq is only 19.27% and none of the main factors were significant. Of all the effects and their interactions, only T*C and S*C were found to be significant. The contribution from factors and interactions to the total variation was only 8.4% and the contribution from the same to the explained portion of variability in this analysis was 43.7%. The contributions to the explained portion of variation of the responses from the main effects and 2- way and 3-way interactions were 6.99%, 34.8 % and 1.8 % respectively. Although the effects of blocks (heads) are not significant, they account for 10.85% of the variation of responses, which is more than the sum total of all the other effects. These observations confirm that P-high projection analysis is not as effective in estimating the main effects as it was for the parent analysis. A high residual error of 80.7% of total SS shows that most of the variations contributing to the observed responses remain unexplained. The R-Sq (Adj) being only 4.74% highlights a very low level of contribution from significant factors and their interactions to the observed variations (Appendix 23).

5-4.2 VARIANCE OF FILL WEIGHTS ACROSS FILLING CYCLES AT LOW-P

In contrast to P-high projection, R-sq was high at 53.15% and concentration and speed were significant at $P<0.05$ and their effects are considerably higher. R-Sq (Adj.) value at 43.6% confirms a higher contribution to the explained portion of the variation from terms that are significant in contrast to the P-high projection above.

The effects of concentration and speed were dominant while that of temperature was non-significant. The two-way interaction, namely T*C and S*T, were also significant. These observations confirm that the effects of factors and interactions of the P-low projection analysis were higher in comparison to the parent and P-high projection analyses.

The ANOVA table confirms these observations. The contributions to the total variations from the main effects and 2- way interactions were 24.0% and 20.2%, and contributions of the same effects to the explained portion of variation were 45.24% and 37.9% respectively. The contribution from blocks was not as high as in the P-high projection and as seen from ANOVA, and the blocks contribute only 8.9% of the total variation (Appendix 24).

5-5 ANALYSIS USING VARIANCE OF FILL WEIGHTS ACROSS FILLER HEADS

The design matrix consisted of all four factors P, S, T and C. The variances of fill weights across heads within each filler cycle for each trial were selected for analysis. In the analysis with blocks, each of the three filling cycles formed a block containing all the fifteen trials. The first section of Table 5-14 below shows the estimated effects and regression coefficients for variances from Minitab output for the analysis without blocking.

The value for R-Sq being 88.47% explains that almost twice the amount of the variations of fill weights across the filling heads (short-term) were contributed from the listed terms compared to analysis across filling cycles. The R-Sq (adj.) value of 83.09% indicates that contributions from the significant terms were satisfactory. The concentration, speed, all the two-way interactions except P*T and two of the 3-way interactions, namely P*S*C and S*T*C, stand out as important effects. The effects of P and T were non-significant ($p > 0.05$). The ANOVA table shows that the contribution from the main effects and 2- and 3-way interactions were significant. The contributions to total variations from the main effects, 2- and 3-way interactions were 33.7%, 34.3% and 20.4% respectively. The effect of cycle-to-cycle differences as determined by blocking was non-significant and contributed only 0.59%. The order of significance as per Pareto chart of Standardised Effects was C> S> P*T*C> P*C> P*S> T*C> P*S*T

The effects of concentration and speed on net weight variation were negative, while the effect of temperature was positive, indicating that variation could be reduced by high levels of concentration and speed and a low level of temperature. It is once again important to investigate the possibility of better partitioning of variability by using 2^3 factorial projections, while keeping the piston stroke constant at its high and low levels. Since most the of filling operations are carried out at fixed piston stroke levels, the project studies are expected to provide further information useful in minimising variations under such circumstances.

5-5.1 *VARIANCES ACROSS FILLER HEADS AT HIGH-P*

The results of 2^3 factorial experiments under high piston stroke are shown in Table 5-15. The R-Sq is 58.6%, pointing to a considerable reduction in contribution from listed terms compared to the parent analysis. The gap between R-Sq and its adjusted value is about 18%. Although this difference is considerably high, it is still proportionately less than the same gap for the P high projection using variation across filling cycles.

A similar P+ projection for Var-Ac-Fc, using only two-way interactions has significantly contributed (41%) to the total response variation. This amounted to 70.1% of the explained portion of variation, while none of the main effects were significant. The order of effects in their decreasing significance was found to be S*C> T*C >C>S*T> S.

5-5.2 VARIANCES ACROSS FILLER HEADS AT LOW P

The exercise was repeated this time by selecting the mean variances for the filler stroke at low level, and analysing the factorial results. The results of 2^3 factorial experiments under high piston stroke are shown in Table 5-16.

It is important to note that 89.12% of the fill weight variation is accounted for by the factors and their interactions under study. The analysis indicates that speed and concentration are the significant contributors to variation, which is similar to counterpart analysis using variations across filling cycles at low P. Among other similar trends were the order of significance of factors and interactions and the non-significance of temperature. The residual error is significantly less and the share of significant contributions to the explained portion of responses has also increased as shown by the R-Sq (Adj.) value compared to the counterpart analysis across cycles.

Chapter 6 DISCUSSION OF RESULTS

6-1 ANALYSIS OF THE PLANNED EXPERIMENTS USING MEAN FILL WEIGHTS AS RESPONSES

The analysis of both mean fill weights across heads and filling cycles produced very similar results in estimated effects, coefficients, and for analyses of variance. Both analyses have produced high R-Sq (Adj.) values. Both types of analysis have produced identical results for the order of significance up to the first five effects, important interactions and for the factor combinations required to maximise fill weights.

However, there is about a 2.3% unexplained residual error present in the analysis of MFw-Ac-Fc, as against less than 0.2% of residual error in the analysis of MFw-Ac-Fh. The analysis across cycles using heads as blocks serves to partition response variation due to effects of factors as well as to differences among filler heads. Therefore this excessive residual error points to the presence of unknown nuisance variables which are partly responsible for the observed variation of the responses. The cycle-to-cycle changes in the filler mechanisms and deviation of fixed factor levels are shown to be responsible for this error (Section 6-2.11). Hence the efforts taken to analyse both forms of variations (across cycles and across heads), were justified as the exercise helped to select the correct model to analyse and partition the variability of fill weights due to factors and their interactions, head-to-head differences and unstable filler mechanisms.

From the main effect plots the dominant effect was seen to be the Piston Stroke. The speed of the filler in terms of cans per minute does not seem to exert a major effect on fill weights at this stage, even though this effect was significant and was supported by interaction S*C. The filling at low concentration leads to lightweights and vice versa. Interaction of Piston Stroke with concentration (P*C) accentuated the positive effect of concentration, increasing the fill weights. Although the effect of temperature as a main factor was negative, the trend was reversed when temperature interacted with the piston stroke (P*T), causing the fill weight to increase at high temperature and high piston stroke. The interaction of temperature, with concentration caused the fill weights to increase more at high temperature than at low temperature, with increasing concentration. The combination of high concentration and high filler speed also produced higher weights.

The careful study of factors, interaction plots, and least square mean values enables us to predict the combination of factors required to reduce or increase the level of fill weights. The combination required for maximising fill weights was found to be P+ S+ T+ and C+ for both types of responses used (Table 6-1). The combination to minimise fill weights was found to be low levels of piston stroke, concentration, temperature and speed (P-,S-,T-,C-) during analysis across filler cycles. However, the analysis across filler heads showed the speed and temperature to be on the positive side (P-, S+, T+, C-). The Cube plots of data means for both analyses, however, confirmed the latter results. These findings illustrate that the factors other than the filler stroke do play a significant role, apart from the obvious contribution of the piston stroke in changing the fill level.

Table. 6-1 Modelling of factor combination for Fill Weight optimisation

Response type used for analysis	MFw Ac Fc in Fh (Full Matrix)							
Order of effects as per PCOSEO	Minimising Model				Maximising Model			
	P	S	T	C	P	S	T	C
P	-				+			
P*C	-			-	+			+
P*T	-		-		+		+	
C				-				+
T			+				-	
Required Combination	-	-	-	-	+	+	+	+

Response type used for analysis	MFw Ac Fh in Fc (Full Matrix)							
Order of effects as per PCOSEO	Minimising Model				Maximising Model			
	P	S	T	C	P	S	T	C
P	-				+			
P*C	-			-	+			+
P*T	-		+		+		+	
C				-				+
T			+				-	
SC		+		-		+		+
TC			+	-				
S		-				+		
Required Combination	-	+	+	-	+	+	+	+

6-1.2 *PROJECTION OF DESIGNS WITH MEAN FILL WEIGHTS*

It is well known among operators that the fill weights tend to deviate from the set value under constant filler stroke settings. Figure 5.1 shows significant differences in mean fill weights within the same level of piston stroke. This observation warrants our examining the effect of factors other than the piston stroke on the variation of fill weights.

This was done by separating high stroke responses from low stroke responses and analysing them as two separate trials. This method of creating two replicates of lower order design (2^3) from a single replicate of higher order (2^4) design is called *projections* (Section 2-2.5, 16). Figure 6.1, illustrates how the parent design could be split using piston stroke (P) to generate two replicates.

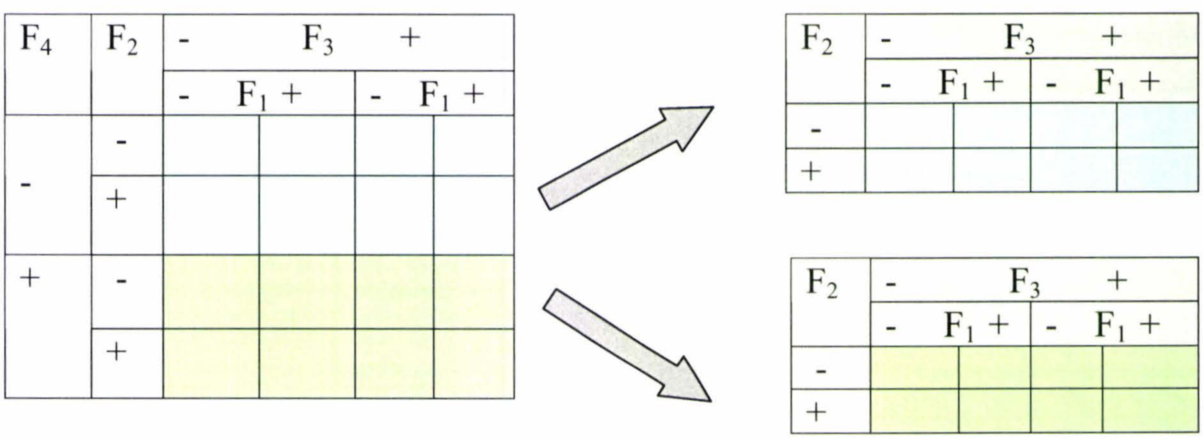


Figure 6-1 Projection of 2^4 into two replicates of 2^3 designs using F_4

6-1.2.1 *Projection Designs (2^3) across filling cycles and across filler heads*

The analysis of the mean fill weights across filling cycles using 2^3 factorial analyses for high stroke and low stroke produced R-sq values of 92.5% and 89.0% respectively. This indicates a slightly high error term for low stroke. The two 2^3 projection designs, which used mean fill weight across the twenty eight heads, had returned better R-sq values for both high and low stroke replicates. They were respectively 99.4% and 99.6%. Both projections of MFw-Ac-Fh confirm the trend in the parent design, that the factors and their interactions account for most of the changes in fill weights (99.4% >) observed across filling heads compared to analysis of MFw-Ac-Fc. In the latter analyses, the head-to-head effects and unknown error effects reduce the percentage contribution from factors and interactions.

The dominant effect of concentration in P-high projections seems to follow the trend in the analysis of the full matrix, where the positive effect of P*C was the second important effect. It may be argued that at high stroke operations, the positive effect of P*C interaction, which is already present, may have accentuated the effect of concentration to the dominant level. The factor combinations required to maximise fill weights under high piston stroke in both types of projection designs, namely across cycles and across heads, were identical and had high levels of speed, temperature and concentration (P+) , S+, T+ , C+. In P-high projections, the effect of temperature is positive and significant and its interaction with speed also supports high temperature to increase fill weights. On the contrary, in P-low projections temperature plays a dominant and negative role, which is supported by its significant interactions with both concentration and speed. This causes low temperature along with high levels of speed and temperature to maximize fill weights (P-) , S+, T- , C+.

6-2 ANALYSIS OF THE PLANNED EXPERIMENTS USING VARIANCES AS RESPONSES

6-2.1 *ANALYSIS FOR VARIANCE OF FILL WEIGHTS ACROSS FILLING CYCLES*

The analysis of variance of fill weights within individual pistons across the filling cycles (Var-Ac-Fc) is of particular interest. A very low R-Sq of 47.7% which accompanied a high residual error demonstrate a high level of unexplained variation in this particular design. The use of filling heads as blocks enabled the estimation of the proportion of variation due to head-to-head differences and was found to be 3.6%. The next important observation was the value for R-Sq (Adj), which is almost 50% less than the same value obtained for the model which used variances across filler heads in filling cycles when analysed with blocks. It is important to investigate whether or not there is any obvious reason for the observed statistics before using projection designs to separate high and low strokes.

The response used was the calculated variance of fill weights within the same piston across selected filling cycles for a given factor combination (Trial). Each of the pistons in the filling station (filling cycle) was regarded as a block, in which all the trials would be carried out. It is reasonable to expect a homogenous solution, having the characteristics of a particular factor combination used throughout a given trial. As such it is not logical to expect the observed variation to be a proper function of the particular factor level combination used in the trial.

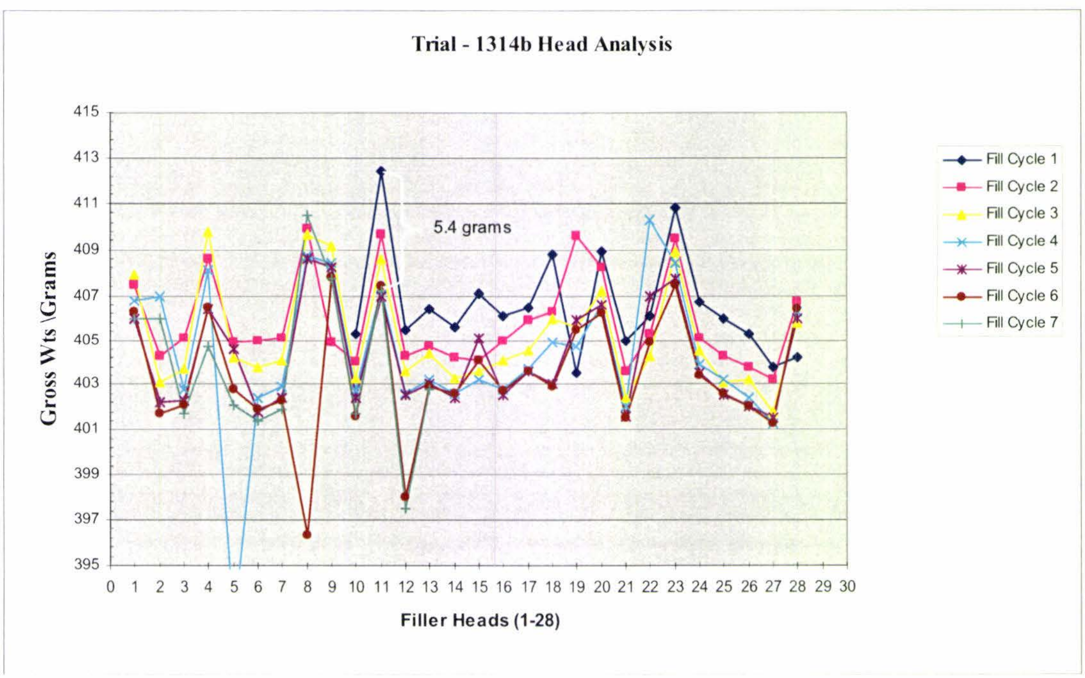


Figure. 6-2 Fluctuation of Fill Weights within each head during filling cycles

Nevertheless, the variation of fill weights due to changes in the set factor levels across consecutive cycles is hard to avoid. Table 4.4 shows evidence of such changes in the set values for temperature, specific gravity, viscosity, and liquid level in the filler bowl. It is important to notice that some factor combinations were proved to produce more variation than others (Figure 5-3). Therefore, the variation due to factors and their interactions attributable to these reasons was found to be 44.1%. Further, during the analysis the portion of variation which did not originate either from factor combination or from head-to-head variation appeared as the variation due to residual error. A considerable portion of the variance across the filler cycles, therefore, could be due to the variation of the mechanical aspects of a particular piston assembly. Therefore the observed variance of fill weights across filling cycles may not be representative of particular factor combinations, rather it may represent the combined instability of the volumetric of the filling heads and instability of the factor levels. The variation due to these nuisance factors will be dealt with in detail in the next section. This explains why the residual error contributes a very high 52.3% of the total SS.

6-2.1.1 *The contribution from the unstable filling mechanisms*

Given the fact that the trial speeds used were 250 and 350 cans per minute, an average four-cycle trial would be completed within 20 to 28 seconds. However, up to 5.5gram differences among fill weights between cycles from the same head have been observed during a single trial. Figure 6-2 further shows that there was cycle-to-cycle and directional shifting of fill weights in some heads as well as random fluctuations in others.Although there was some evidence of deviation in the set factor levels such as temperature, and concentration as discussed earlier, it was obvious that such changes were not significant enough to account for the above differences among fill weights within such a short space of time, unless special causes were present. The data related to any known special cause variations, such as initial unsteady filling cycles and factor levels which were set differently from the planned level of measurements, have been eliminated. Therefore the sources of this background variation were not fully known at the time of the experiments. However, during an investigation the following factors were found to be contributing to the background variations.

a) Time taken to reach optimum suction force for pistons
b) Short-term variance in product properties within filler bowl
c) Uneven rotation of warn-out pulleys during the upward stroke of the piston

d) Differences in valve opening and closing (Appendix 9)
e) Worn-out piston "o" rings (Appendix 10)
f) Worn-t valve body "o" rings
g) After drift (Appendix -11)
h) Excessive clearance between valve housing and valve body
i) Downstroke not quite reaching the minimum cylinder depth
j) Product leaking out due to lack of fit in valves and plugs
k) Air leaking into piston cylinders during upstroke
l) Vertical vibration of guide rail during upward stroke of run of guide pulleys
m) Filler bowl level fluctuations to about 60 mm range during filling

It is also noteworthy that P high analyses of both types had returned considerably low R-Sq values compared to P low analyses. It is also evident that the factors involved were non-significant and that contributions to variations were mainly from two-way interactions.
It is reasonable to expect more involvement of unstable filler mechanisms as shown above, during high volume operations (P+) than during low volume operations (P-) of the filler. However, it is not completely clear whether this phenomenon is related to high stroke operation or due to the loss of information from the missing trial (P-, S+, T+, C+). It is recommended that future research into sources of variation of net weights using piston fillers should investigate this phenomenon.

6-2.2 *ANALYSIS USING VARIANCE OF FILL WEIGHTS ACROSS FILLER HEADS*

The mean variances across filler heads for each trial were higher than the mean variances across filling cycles for the respective trial. The analysis of the variance of fill weights across all the filler heads (28) in separate filling cycles has produced valuable information for partitioning the total variability due to factor effects. In contrast to the previous variances across filling cycles, 88.5% of the response variances were explained by the main factors, their interactions and blocks. The blocks are non-significant and contribute to less than 1% of the variations of the listed terms. A relatively high R-Sq (Adj.) shows that the rest of the listed terms, namely main effects and interactions, are significantly contributing to the total variability of fill weights. The unstable filler mechanisms, as discussed earlier, also could play a role in changing the consistency of head-to-head volume ratios from trial to trial as evidenced from head analysis charts of each trial shown in Appendix-1. Therefore this lack of consistency in head-to-head volume ratios could contribute to a significant proportion of the observed variance of fill weights across heads, which appears in the form of residual error (11.5%)

The contribution from filling cycles (as blocks) to the observed variance is smaller compared to the contribution from filler heads (as blocks) for the analysis of variance across filling cycles. The results of the full design turned out only a contribution of less than 1% from the filling cycles compared to 3.6% from the filling heads. This confirms that each filling cycle acts more or less as a replicate consisting of fill weights across all the twenty-eight heads. However cycle-to-cycle differences, which were characterised by shifting of the mean fill weights from cycle to cycle, were visible in head analysis charts.(Appendix 1) Therefore the use of filling cycles as blocks was justified as they confirmed that the observed cycle-to-cycle differences had not significantly contributed to the variance of fill weights.

Contrary to the effect of factors on fill weights, the effect of factors on variance in fill weights was not dominated by piston stroke level and in fact the effect of the piston stroke level was non-significant, within the range tested. The effect of temperature was also non-significant and failed to play a major role except in its weaker interactions with other factors. This is an important finding as it helps to isolate speed of the filler and concentration as the key factors that control the variability of fill weights.

6-2.3 *FACTOR LEVEL COMBINATIONS REQUIRED TO MINIMISE VARIATION OF FILL WEIGHTS*

The combinations of factors required to minimise fill variations derived from both types of analyses were found to be the same. The combination of factors required to minimise the variation of fill weights, which was computed through comparison of the effects of factors and interactions and their significances, was high piston stroke, high speed, low temperature and high concentration (P+, S+, T-, C+). Although the effects of both piston stroke and temperature turned out to be non-significant, their interactions P*T*C, P*C and P*S, dictate the sign of these factors in the combination required to minimise variations (Figure 6-2).

Both projection design analyses for variance across filling cycles shows that the combination of factors required to minimise variation are the same as for their parent design (S+, T-, C+). The projection design analyses using variance across filling heads failed to reproduce the factor combination required of the parent design to minimise variation.

Table 6-2 Modelling of factor combination for variance optimisation

Response type used	Var Ac Fc in Fh (Full Matrix)							
Order of effects as per PCOSEO	Minimising Model				Maximising Model			
	P	S	T	C	P	S	T	C
S		+				–		
P*C	+			–?	–			–
C				+				–
P*T*C								
P*S	+	+			–	–		
T*C			–	+			+	–
P*S*T								
S*T		+	–			–	+	
S*C		+		–		–		–
P	+				–			
Required Combination	+	+	–	+	–	–	+	–

Response type used	Var Ac Fh in Fc (Full Matrix)							
Order of effects as per PCOSEO	Minimising Model				Maximising Model			
	P	S	T	C	P	S	T	C
C				+				–
S		+				–		
P*T*C								
P*C	+			+	–			–
P*S	+	+			–	–		
T*C			–	+			+	–
P*S*T								
Required Combination	+	+	–	+	–	–	+	–

6-3 PARTITIONING OF VARIABILITY DUE TO FILLING HEADS

The effects of blocking, which represent head-to-head differences, were significant for both parent and projection design analyses of fill weights across filling cycles. The analysis of the MFw-Ac-Fc showed that the head-to-head differences accounted for 1.06% of the observed responses. Obviously, the contribution from the heads has been dwarfed by the dominant volume effect of the piston strokes. Since the operators carry out the filling operations at a set piston stroke for a targeted volume, it is important to investigate the effect of head-to-head differences on fill weights at both sides of the piston stroke.

Once the effect of the piston stroke is removed by the projection designs for the Mfw-Ac-Fc, the contributions to the final fill level differences increased to 3.87% and 6.99% respectively for high and low strokes. These block effects were approximately 3.5 and 7 times higher than the block effect of the parent 2^4 designs, respectively, for low and high piston strokes. Since these block effects reflect head-to-head differences, this indicates that when filling at the low piston stroke, the head-to-head variation is higher than when filling at the high stroke.

The analysis of Var-Ac-Fc using heads as blocks, on the other hand, has revealed the contribution from head-to-head differences to the total variance of fill weights. Figure 6.1 shows a total mean fill weight range of 50.6 grams and mean range across heads of about 9.5 grams for all the trials. This proportion amounts to approximately 19% of the total variation. The figures for P-high and P-Low were 33.2% and 33.6% respectively. The observed proportion of total range to head-to-head range can be converted to approximate the proportion of variances using the following calculations. The percentageage contributions to the total variance from head-to-head differences were 3.59%, 10.85% and 8.92% respectively, for the full matrix, P-high and P-low projection analyses (Var-Ac-Fc) which used heads as blocks (Table 6.3).

Table 6-3 Partitioning head variation using range method

	Full Matrix	P-High	P-Low
Total Trial Range / Range Across Heads	19%	33.2%	33.6%
6 x SD $_{\text{Across All Trials}}$ / 6 x SD $_{\text{Across Heads}}$	0.19	0.332	0.336
SD $_{\text{Across All Trials}}$ / SD $_{\text{Across Heads}}$	0.19	0.332	0.336
$SD^2_{\text{Across All Trials 1}}$ / $SD^2_{\text{Across Heads}}$	$(0.19)^2$	$(0.332)^2$	$(0.332)^2$
Variance Across all Trials / Variance Across Heads	3.61%	11.0%	11.3%

The blocking experiments therefore produced close but slightly lower contributions, confirming that the use of heads as blocks for data across consecutive filling cycles is effective in partitioning the variability due to filling heads.

A close inspection of graphs for fill weights against filling heads of each trial shows that it was possible to reproduce a similar proportional pattern for head-to-head volumes in successive filling cycles within each trial to a reasonable degree of consistency for some trials (Trials 23, 32, 44, 76, 5, 109, 1210 and 1314). However, the head-to-head proportions among different trials were found to vary and failed to follow a consistent and fixed pattern. The analysis using blocks requires consistent differences among heads throughout the trials to bring out these differences in full. This observation is important when trying to quantify causes of fill variability. It points to the importance of fixing the random fluctuations of the fill volumes within heads prior to fixing the differences between heads.

Chapter 7 APPLICATION OF RESULTS

7-1 RELEVANCE TO THE EXISTING FOOD PROCESS

The planned experiments carried out enabled us to estimate the degree of variance when the levels of factors were changed by measurable quantities. Some of these factor combinations caused significant changes to the variability and the mean fill level of the net weight process, whereas others failed to make any significant impact. We could relate these observations to actual food processes, where significant but unwarranted changes to the direction and degree of factor levels take place for several reasons. These reasons include, errors in recipe mixtures, changes in ingredient quality, erroneous process settings, excessive and unwarranted tweaking of process settings, and mechanical shifts of process parameters. The shifts of parameters are of particular interest as they include the temperature of the filling media, particle size of recipe components, vacuum levels of fillers, levels of deareation, mixing of ingredients and speed setting of machinery, all of which have a direct bearing on the factors. The analyses carried out above using starch media, showed that while changes to the concentration and the speed of the filler affect the variability significantly, changes to the piston stroke and temperature were almost non-significant. However, similar changes to any of these parameters significantly affected the fill weights. This constitutes a brief answer to the question "Where does the variation of fill weights come from?

The object of DoE however transcends understanding the process. However, this understanding helps to prioritise improvement needs of the process. Where the partitioning of variability indicates that most of it arises from poor performance of machinery, then we need to improve the machinery. This understanding also helps us to deal with sources variation caused beyond factor effects, as in the case of unsteady filler mechanisms revealed in this study.

Our theses as proposed are based on the hypothesis that it is possible to:

- Identify and quantify the sources of variation of fill weights
- Find methods of optimising the effect of factors (minimise variation and optimise fill levels).
- Identify the sources of background variations and their effects
- Use the information to reduce fill variability and to optimise the fill weights.

It is important to assess the effectiveness of the methods and the experimental model applied in order to meet these objectives in individual product processes.

7-1.2 *APPLICABILITY OF THE EXPERIMENTAL MODEL*

The analyses confirm that when factor levels of interest are maintained at specific levels and directions, then it were possible to produce a predictable level of variation or level of fill weights This author also has used the analytical models for optimising variance and fill weights to derive the combinations required to optimise these (Tables 6-1 & 6-2). However, the predicted combination of factor levels and directions required would serve only as generalisations as they are dependent on the product type, factor levels, and filler type selected for the specific product. For example, the variation contributed through a vacuum filling process may not be fully exposed, as the delivered volumes off the heads also depend on the pre-fill-weights as discussed in detail in Section 3-1.4.5.

The selection of a proper experimental medium for planned experimentation to represent varied net weight processes was a difficult task. Although we justified the use of modified starch solution as a suitable medium to represent the four major factors revealed through brainstorming, it was not capable of representing some other key aspects of filling processes in the company. These aspects include the following.

1) Multi-filling processes

Table 7-1 below shows statistics from a Beef Curry process. It is evident that variation arises not only from attributes related to the curry source but also from attributes related to beef filling which is a process prior to the piston filling of curry source.

Table 7-1 Component Variation of three different Beef Curry types in R2 - Piston Filler

Component Variation of three different Beef Curry types in R2 - Piston Filler						
Trial No.	Beef Curry Trial 1		Beef Curry Trial 2		Beef Curry Trial 3	
Meat Fill	Meat 95 +/- 8.5		Meat 72 +/- 8.5		Meat 72 +/- 8.5	
Product	European Beef Curry		Fruit Beef Curry		63 -72-81 HBBL	
Sample Size	Sample Size = 100		Sample Size = 100		Sample Size = 100	
	Mean Fill t	Std. Dev.	Mean Fill t	Std. Dev.	Mean Fill t	Std. Dev.
Meat	94.8	3.5	73.7	5.0	70.6	5.4
Curry	754.2	5.4	769.8	6.3	768.7	6.6
Net Wt	849.0	7.1	843.6	8.2	839.3	8.3

2) Particle size and density variation

It is important to include particle size and perhaps the fat content when analysing, for example, chunky soup categories as against creamy soups.

However, the use of a modified starch solution in a single stage filling environment enabled us to sort out the effects of fundamental product characteristics as well as the effects of the filling mechanism without complicating the analysis. The study was able to explain the sources of variation of net weights adequately. The experimental methodology, techniques of analysis, and lessons learned from the planned experiment can now be used in future studies to explore the broad spectrum of the net weight process.

The main outcomes of the analysis of results are as follows:

- Methods of transforming the fill weight data to calculate responses for the analysis were confirmed as being effective
- The use of a statistical model to find factor combinations to optimise weights and their variations was shown to be successful
- The use of blocking to identify effects due to, head-to-head differences, shifting of fill weights with time and unstable filling mechanisms was shown to be effective
- The role of the factors and the interactions of factors in controlling the net weight process were clarified
- The use of projection designs to obtain more information under controlled conditions of a particular factor was proved be useful

7-2 COMBINATIONS REQUIRED FOR LEAST VARIANCE

The food industry seeks to find out the best combination of factors possible under various product and process constraints to minimise variations. There is a secondary need to optimise fill weight to achieve the target weight as well. Once the combination of different factor levels has been successfully applied to reduce the variation, then the question of process targeting can be worked out as already discussed.

The results of this study show that the two processes mentioned above are independent of each other and also show the need to be cautious in sorting out conflicting combinations. As illustrated, the factor combination to minimise fill variations (P+, S+, T-,C+) has the level of temperature (T-) conflicting with the level of temperature (T+) which is required for maximising fill weights. The factor level combination required to maximise fill weights follows a logical pattern predictable from basic laws of physics-whereas, the combination required to minimise variation was more complex, and was not entirely dictated by the direction of main effects themselves. This was due to conflicts between effects of factors and their interactions on level of fill variations. For example we have seen how piston stroke has become the dominant factor in deciding the fill level for obvious reasons, but the effect of this factor on variation is not even significant ($p>0.05$). The concentration and the speed were the highest and most significant effects that controlled fill weight variations, whereas the effects of piston stroke and temperature were much less significant.

The direct effects of piston stroke, concentration, temperature and speed on the fill weights could be explained to a degree through the application of basic laws of physics as shown below in Table 7-2. However, as we could observe from this table, the effects of the significant interactions which the piston stroke has with concentration and temperature may influence the direct physical effects as calculated to produce the effects measured through the analysis.

Table 7-2 Comparison of direct physical effects versus actual process effects of factors

Factor	Low level	High level	Calculated direct effect per 430 grams	Measured effect through DoE
Piston Stroke	40mm	45mm	+21.00 grams	+27.2 grams
Temperatue	60^0c	75^0c	-03.59 grams	-04.52 grams
Concentration	0.50% W/W	0.75% W/W	+01.03 grams	+06.38 grams
Speed	250 cpm	350 cpm		+02.06 grams

These observations corroborate the idea that the inherent variation of net weights may be either enhanced or diminished depending on the strength and the direction of the factors and their interactions.

This illustration of effect estimates also shows the dependence of the magnitude and significance of these effects on the limits of levels selected. For this reason we need to apply caution when the effects are used as guidelines to optimise food processes. It is the author's view that separate planned experiments must be designed to suit particular operational limits, as these results provide only approximations and guidelines.

An example would be the behaviour of liquid food media having similar densities but capable of producing very different levels of viscosities when heated up to a constant temperature. This is attributed to the different rheological properties of those liquids. We would expect similar situations to arise when dealing with versions of soups having tomato bases versus starch bases when subjected to similar heat treatments. Since viscosity is known to affect the filling performance, we would expect these two liquid food media to produce significantly different levels of variances even if we keep all the four factor levels (P, S, T, C) the same.

7-3 LONG- AND SHORT-TERM VARIABILITY OF PRODUCT PROCESSES

The magnitude of the changes to process parameters, such as viscosity or density, depends on the length of time the process is exposed up to the time of measurement. Depending on whether such a change is sudden or gradually shifting with time, the resultant variability manifests either as short- or long-term variation. The variation which is measurable within a short period, is defined as *short-term variation*. It is possible to look at these modes, namely short- and long-term variations experienced in food processes, in the light of the results obtained from planned experiments.

During the planned experiments, controls were put in place to maintain constant factor levels during each trial, and no significant variation of fill weights was expected from the same filler heads. However, a measurable variation has been recorded in each filling head across consecutive filling cycles. We have already argued that this portion of variation is due to background factors not included in the design. Figure 5-1 illustrates how the mean fill weight and the level of variation change when the factor level combination changes from trial to trial. Let us assume that this run-chart represents an actual product run, over a similar period of time, and the planned changes to factor combinations from trial to trial represent actual changes which characterise the filling process. These changes to the product and filler characteristics (factor levels) of the hypothetical product could be due to either chance or special causes. It is apparent that the total variability of all the data across the trial series was much larger than the variability experienced during any individual trial. Therefore we could argue that the long-term variation of the net weight process of a product arises more or less in the same manner.

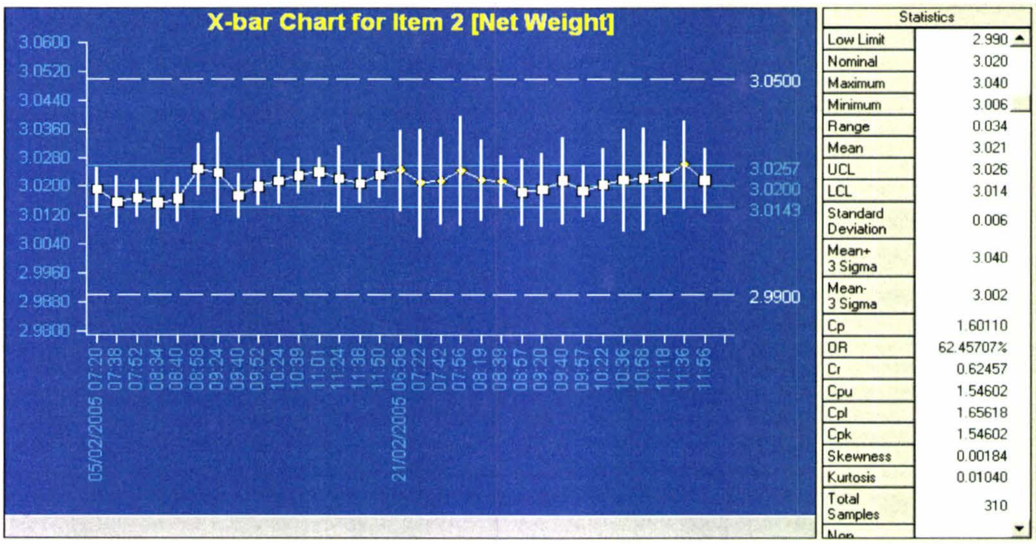


Figure 7-1 Effect of temperature on fill variations

Figure 7-1 illustrates how short-term variation measured in terms of standard deviation (estimated using sample mean range) has increased from 4g for 3020g of mean fill on the 05th, to 7g. for 3022g of mean fill on the 21st, within the same month, for 3Kg Demiglace Sauce. The long-term variation which is the total standard deviation of all the fill weight samples for each day has increased from 5g to 7g. The error bars represent the range of fill weights within ten samples taken from ten consecutive filling heads. The averages were in control (within control limits) and no significant difference was observed between average fills for different days. Further investigations had revealed that average closing can temperatures of the two days involved were 80^{0}c and 85^{0}c, respectively. The prevailing knowledge among experts reveals that the viscosity of this product is dependent on the temperature. Therefore it is reasonable to conclude that the accompanied change in the viscosity could have raised the level of variance of fill weights. Therefore, besides the direct effect of temperatures on weight delivered per constant head volume, its interaction with the viscosity of the product could change the level of variation. This real time evidence substantiates the finding of the experiments which demonstrated that a change of factor levels within the limits of the experiment could alter the level of variance of fill weights.

During the planned experiments the change of concentration from 0.50% to 0.75% w/w led to a change of viscosity from 73 Cp (at a spindle speed of 100) to 612 (Speed 60) Cp for MAP 281 starch solution (Table 4-4). The effects of concentration has been rated as one of the dominant factors which caused the variation to increase considerably in response to a relatively small change in concentration (0.5% to 0.75% w/w) during the trials. Significant changes in viscosities which are recognised as being "too runny" or "too thick" is a common occurrence in food processing. Accordingly potential fluctuations in concentration of viscous food media such as creamy soups, premium baked bean sauces, and tomato and curry sauces, would create increased variability in their respective net weight processes.

Raw materials, which inherit significant amount of natural variation due to maturity, size differences, varietal differences and climatic factors, eventually pass some of them into food products during recipe-making stages. Eventually they, along with other sources of primary variations, are translated into identifiable major factors such as we experimented with.

7-4 APPLICATION OF DOE IN DIFFERENT FILLING AND MEASURING ENVIRONMENTS

Although both piston and vacuum fillers are based on volumetric measurements, the resultant level of variability for a given product was found to be significantly different (Appendix-7). These differences can be attributed to their modes of operations (Section 3-1.4.4). During piston filling, the product is measured during its up-stroke whereas during vacuum filling, the product is measured inside the can. depending on available can space and the amount of vacuum which has already been created before filling commenced. There is a reasonable amount of uniformity of the distribution of vacuum and space inside cans within a single filling cycle of a vacuum-filler. This enables the filler to produce a low level of variation across cans. Because of this, variation of fill weights within filler cycles of a vacuum filler is caused by random fluctuations due to vacuum operations, valve operations, and product blocks and so on. Therefore, the use of filling heads of a vacuum filler as blocks in DoE may fail to reveal any head-to-head variation. The main factors of importance relating to the vacuum filling mechanism are the speed of the filler and the level of vacuum. Usually the vacuum is set to the maximum possible level to minimise fluctuations. Piston fillers, on the other hand, suffer from head-to-head variation for reasons already explained. And in most cases these head-to-head differences maintain a fixed ratio, enabling us to predict the level of variability within a filling cycle (short-term variability). However the filler that was used for these trials failed to produce a fixed ratio for head-to-head differences across the trials due to the instability of the filler mechanism. (Appendix 1)

The second major difference between the two types of fillers is based on respective volumetric mechanisms involved during multiproduct filling. The vacuum filler fills only the leftover space in the can after initial fills during multifilling operations. As seen from the filling statistics presented, during multifilling situations using vacuum fillers, total final net weight variation, in most cases, is much less than the pooled variation of components. The net variation after piston filling always remains higher as the contributions from components are independent and additive. The DoE application to partition the sources of variation due to filling components in multifilling situations during vacuum filling may not be as straightforward as for piston filling operations. The speed, after-drift, filler bowl height, temperature, trapped air and so on also affect the performance of the two types of fillers in different ways.

8 Chapter SUMMARY AND CONCLUSIONS

8-1 SUMMARY OF INVESTIGATION

The food industry is seriously short of adequate research into variability of net weights in canned products necessary in order to develop methods to increase capability, to ensure the safety of consumers, and to comply with regulatory, trade and consumer requirements. This thesis describes how the above research needs have been met by developing a DoE and an analytical model with the following objectives:

a) To develop an experimental model and methods of analysis
b) To identify and quantify responsible factors and their interaction in terms of percentageage contributions to the total net weight variations
c) To establish the combination of the levels of input variables (factors) in order to minimise the net weight variation and to optimise net weights in order to maintain the target quantity

It is hypothesised, therefore, that the variation of net weight-which is dependent on multiple factor processes-may be reduced by applying optimum levels of those factor combinations derived by analysis of design of experiments.

The use of brainstorming sessions helped to identify factors that significantly affect the net weight process. The piston stroke, speed, temperature and the concentration were identified as the main controllable factors. Considering the available resources and the potential for the expected outcome of the analysis, the full factorial design was selected as the most appropriate among the types of DoE scrutinised for this application. The full matrix for the 2^4 factorial design using the four factors consisted of 16 runs. The experiment was conducted with limited randomising of experimental runs using a piston-filler with twenty-eight heads. MAP281 was used as the filling medium and the factor levels were set as per +/- configurations of the matrix. The two levels of each factor were carefully selected to cover the limits of manufacturing conditions. The order of trial runs was obtained by randomising the four trial runs under each temperature and concentration combination, as the full randomisation was not possible due to operational constraints. The fill weights for approximately ten consecutive filling cycles for each trial were collected in 76 x 110 mm cans. After having removed all outliers for fill weights, gross weight data of the cans were recorded into tables.

The original response data were transformed to derive the means and variances which were to be used as responses. Two types of means and variances were derived depending on how the net weight data were transformed. The mean fill weight and variance of data across filing cycles were used to investigate the effect of factors on the variation visible in the long-term (across consecutive filling cycles) in each filling head. The second type of transformed data consisted of mean fill weights and variances of data across the filling heads in each filling cycle. This allowed the author to study the effect of factors on the short-term (across heads in the filling station). Therefore, four main types of transformed responses were presented for analysis. Each of the full matrices for the four main response types once again used to produce two replicates of projection designs. Projection designs were used to explore further optimisation opportunities under high or low levels of piston strokes and to confirm the results of the analysis of the full matrix. Finally, along with their two projection designs, the four main response types produced twelve analyses.

Data were analysed using the Minitab statistical programme using Estimated Effects and Coefficients for Variants, Analysis of Variance (ANOVA), Least Square Means (LSM), Normal Probability Plot of the Standardised Effects (NPPOSE), Pareto Chart of the Standardised Effects (PCOSE), Main Effects, Interactions, Cube Plots and. Residual Plots.

8-2 MAIN FINDINGS

Analysis of mean fill weights

The contribution from the listed factors and their interactions to the levels of fill weights ranged from 89-99%, when mean fill weights were used as responses for both types of analyses (across filling cycles and across filler heads). The order of the significant effects was identical up to the first five effects. The effects of all the significant factors and interactions were approximately the same. However, the main difference between the two analyses was that the former revealed a significant block effect due to head-to-head differences in fill weights

The analysis of both types of mean fill weights is justified in spite of the similarities, as the exercise helped the author to select the correct model to partition effects due to factors and interactions, head-to-head differences, as well as-to a lesser degree-the unstable filling mechanisms.

Projection designs of mean fill weights

Figures 5-1 to 5-3 show a presence of substantial differences among mean fill weights of different trials, although they were under the same stroke level. The use of projections for mean fill weights provided additional information on how to fine tune fill weights to deliver the target quantity when the piston stroke level has already been adjusted. It further enabled the estimation of factor effects, other than piston stroke, when the effects of piston stroke were removed by P projections.

The subsequent analysis of MFw-Ac-Fc shows that both projections returned higher percentage contributions from head-to-head differences to the total range of fill weights (3.9 and 7.0% respectively for P+ and P-) than that from the full design. This indicates that the projection designs accentuate contributions from the head-to-head differences, due to removal of the dominant effect of the piston stroke. The statistics cited above also confirm that there is less contribution from head-to-head differences to the total range of fill weights at high volume operations (P+) than at low volume operations(P-). The projections using Mfw Ac Fh confirms that the effect of consecutive filling cycles did not significantly contribute to variation of fill levels.

Factor Combinations to maximise fill levels

Both analyses (MFw Ac Fc and MFw Ac Fh) generate the same factor level combinations to maximise fill weights for the full design and P + projection designs. This required high levels of speed, temperature and concentration (P+), S+, T+, C+. The high stroke projection shows that high volume operations are dominated by the effect of concentration, which warrants the same combination of factor levels as for the parent design to maximise fill levels. On the contrary, the negative effect of temperature seems to be dominant in P- projections. Therefore at low piston stroke operations, the factor combination to maximise fill levels across filling cycles as well as across filling heads required high levels of speed and concentration and a low level of temperature (P-), S+,T-,C+. These dominant effects during projections seem to follow the effects of powerful interactions (P*C and P*T) present in the full analysis, depending on which one of the interactions could exert influence based on the direction of stroke. The concentration did not have any significant effect during low P operations for either type of analysis.

Analysis of Variance of Fill weights

Var-Ac-Fc

The analysis of variance of fill weights across filler cycles showed a poor contribution from the factors and their interactions (44%). In ideal factorial experiments, the response variation expected here would be limited only to a noise variation in the fixed levels of the factor combination for a given trial. Therefore, it is reasonable to expect a less efficient contribution of factor effects to the variance across filling cycles. However, the analysis across filling cycles contains fill weight data for a longer period of time compared to data across all the heads within each filling cycle and therefore these fill weights could result in some time-based shifting from the same head. In fact, the observed contribution from factor effects (44%) happened to be more than just a noise variation, and the measurements of factor levels (Table 4-4) confirms that this arose from the time-based deviation of the factor levels from the set values in each experimental run. In fact in product manufacturing situations, this type of shifting of factor levels is more pronounced as the levels of factors involved are subject to variation due to lack of adequate control. Therefore it is evident that the long-term variation during product manufacturing is mostly due to such in time-based variation of factor levels.

However, the fill weight differences, up to 5.5 grams, between consecutive filling-cycles in the same head within a single trial (Figure 6.1) proves the presence of variation which can not be explained solely through deviation of factor levels. The evidence for the existence of unstable filler mechanisms which could significantly affect the variance has been listed (Section 6-2.1.1). It is concluded, therefore, that most of the residual error (52.3%) shown in this analysis was due to unstable filler mechanisms. The evidence presented strongly suggests that the unstable filler mechanisms and deviation of fixed factor combination from set values were responsible for most of the variation of fill weights across filling cycles.

The facility to use heads as blocks provides an opportunity to quantify variation due to head-to-head differences. The percentage contributions to the total variance from head-to-head differences, which was obtained by using heads as blocks in a full matrix, P-high and P-low projection analyses of Var-Ac-Fc, were 3.59%, 10.85 % and 8.92% respectively. The calculations using the ratio of mean range of fill weights across heads to total range across all the trial results (Section 6-3), confirmed that the percentage contributions derived from the blocking of heads were effective in partitioning the variability due to filling heads. Therefore, in conclusion, this analysis is important to quantify the variation of fill weights due to deviation of fixed factor levels in trials, unstable filling mechanisms, and head-to-head differences.

Analysis of Variance across heads

A higher percentage of the variance of fill weights (88.5%) was explained by the factors and their interactions when the analysis variance across filler heads was used. The analysis of variance of fill weights across the filler heads in a single filling cycle represents short-term variation due to factors and their interactions on fill weights and therefore effectively contributes to our understanding of factors and interactions. The effect of filling cycles which were used as blocks was non-significant, and therefore the effect of unsteady filler mechanisms could not have significantly contributed to the variance across filling heads. Hence this analysis could be used effectively to deduce the factor level combinations to minimise the variation of fill weights.

Combinations to minimise variance of fill weights

The loss of significance of temperature and piston stroke on the variation of fill weights both across filler heads and across filling cycles caused the filler speed and concentration to become key factors. Although the effects of both piston stroke and temperature turned out to be nonsignificant, their involvement in the interactions P*T*C, P*C and P*S, dictates the sign of these factors required for the combination (Figure 6-2).

The combination of factors required to minimise the variance of fill weights, was low piston stroke, high speed, low temperature, and high concentration (P+, S+, T-, C+). Both projection design analyses for variance across filling cycles show that the combination of factors required to minimise variation was the same as for their parent design. (S+, T-, C+).

Projection designs for variance of fill weights

The projection designs using variances served as the means of fine tuning for the rest of the factor levels to reduce variation under given stroke adjustment, as the filling operations are carried out at set stroke levels. The analyses of projection designs for Var-Ac-Fc confirm the respective trends in full designs, such as the lesser contribution of factors and their interaction to variance of fill weights.

The high stroke projections of both types of analyses for variance, showed that the factors involved were nonsignificant and contributions to variations were mainly from two-way interactions. The role of unstable filler mechanisms as proposed in section 6-2.1.1 could be the most likely cause for the high residual error associated with the high stroke projections. More importantly, this error is much higher in the P+ projection of variance across filling cycles. Accordingly, it is concluded that high volume operations generate higher contribution from unstable filling mechanisms compared to the total variation of fill weights.

The contribution from heads when used as blocks in projection analyses for Var-Ac-Fc (11% and 9% for P+ and P-, respectively), was higher than that of the full design, while head effects remained nonsignificant. The factorial experiments followed by statistical analysis enabled partitioning the variation of net weights into components, when variance of fill weights was used as responses. The use of mean fill weights as responses were useful in estimating the effect of factors and their interactions on the final fill level. It was also possible to quantify the contribution to total variation of fill weights from each of the major components. The major components identified were factors and their interactions, head-to-head differences, unstable filler mechanisms, and deviation of factor levels from set target values. While only the concentration and the speed contributed significantly to the total variation of fill weights, both across filling cycles and across filling heads, all the four factors identified using brainstorming sessions significantly contributed to the final level of net weight.

8-3 APPLICATIONS

The planned experiments show that different factor combinations produced different levels of variations. The standard manufacturing procedures for a given product dictate the key factor level combination for that product. During operations, changes occur to the key factor combination of the standard product. The changed factor combination causes a shift of the level of variation, explaining why the level of variation changes with time. This explains the high variability of net weights experienced in the long-term (long-term variation), as opposed to the low level of variability experienced in the short-term which is normally due to differences with filling heads.

The DoE as planned and carried out has not been designed to capture this type of long-term variation of trial media. However, the fill weights of each of the heads across filling cycles over a period of time could be used to evaluate the long-term variation of a specific product in addition to unstable filling mechanisms and head-to-head variation.

The limitations of the DoE model applied include: lack of methods to partition variation due filler types other than piston fillers, inability to partition the variability due to particle size, and absence of multi-filling operations. The conflicts between factor combinations required to minimise variation and optimise fill weights at the same time must be tackled prior to applications. The optimising of the fill weights under a reduced status of variation could be considered next, only if this is not conflicting with combinations required for the former process.

The results of analysis may not be applied to products having the same factors but having different operation ranges. The same is true for products having strong interactions with factors not tested in this model of analysis. Another problem is anticipated in trying to apply resolutions of a DoE to a similar product which is filled in a different processing or filling environment that is, a vacuum filler. In vacuum filling situations, collective contribution from heads to the total variance is more practical than estimating the individual differences between heads.

The residual, but considerable, amount of variation caused by filler heads should be tackled in two ways. Firstly, the obvious head-to-head differences as revealed from head analysis graphs (Appendices 1-1 to 1-5) should be resolved using techniques which the author described during the literature survey (3-1.4.5). Secondly the management should engage the expertise of filler mechanisms to find out the causes for the instability of delivered volumes from each of the heads. Once these causes have been eliminated, the filler would be ready for a conformation analysis using designs to monitor and verify improvements. Inability to reproduce a similar pattern of head-head proportions, from trial to trial could adversely affect the analysis using heads as blocks. Therefore it is important to fix random fluctuations of fill volumes due to unstable filling mechanisms. The observed variance of fill weights across filling-cycles rather represents the combined instability of the volumetrics of filling heads and factor levels used for the trial combinations.

8-4 RECOMMENDATIONS

One of the important aspects of DoE is to gain an increased degree of belief in the results before we apply them to optimise processes. It is appropriate, therefore, to conduct conformation trials in areas which are critical to our conclusions. The difficulties encountered in selecting appropriate consecutive filling cycles, as well as the occurrence of a considerable number of outliers may have contributed to the experimental error. It is recommended that photographic methods be used to establish the identity of each can by the head and the inject-coder to establish the run order of the net weights for the selection of stable and consecutive filling cycles in each trial. It is necessary to carefully monitor and make adjustments, if necessary, to set factor levels before releasing the filling medium to filler bowls for trials in order to minimise the residual error attributed to deviation of set factor levels such as temperature, concentration and viscosity and so on. The importance of the role of viscosity during filling operations must be emphasised by incorporation of it as one of the factors wherever necessary, or by establishing its correlation with other key factors such as concentration. Another important contribution to DoE used for analysing the variation of fill weights would be the selection of an appropriate filling medium which is more stable than modified starch under trial conditions, in order to reduce variation caused by the deviation of set factor levels

8-5 AREAS FOR FUTHER RESEARCH

It is proposed to extend the experimental model to cover vacuum filling and pouch filling operations, which are characterised by the absence of variance which is inherently associated with multi-head filling. The DoE carried out provides information only for single shot filling operations and therefore can not be applied to multi-filling situations. In order to complete our understanding of the variability of food processes, it is necessary to cover multi-filling operations as well. The effect of the variation of essential product characteristics such as particle size to the total variation of net weights would help to optimise net weight variation in garnish-based products. This need for research is much felt in operations where particle size plays a key role in one or more fills in a multi-filling situation such as Baked Beans and Sausages. It is also suggested that fractional factorials be used in complex and multiple factor situations to reduce the size of experiments

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References

Aguirre, T. V. & Peres, T. E. (2001). Outliers and the use of the rank transformation to detect active effects in unreplicated 2(f) experiments. *Communications in Statistics*, 637-663.

Arteaga, G., Lichan, E., Vazquezarteaga, M. C. & Nakai, S. (1994). Systematic Experimental-Designs for product formula optimisation. *Trends in Food Science & Technology, 5(8)*, 243-254.

Arvidsson, M.& Gremyr, I. (2003). Deliberate choices of restrictions in complete randomization. *Quality and Reliability Engineering International, 19* (2), 87-99.

Bjerke, F. & Hersleth, M. (2001).Introducing statistical thinking to the food industry – Facilitating and Inhibiting factors. *QMJ*, *8* (3), 49-59.

Bjerke, F., Naes, T. & Ellekjaer, M.R. (2000). Application of projection design in product development. *Chemometrics and Intelligent Laboratory Systems 51*, 23-36.

Bounds, S. (2006). Application of Fluid Dynamics in Can Filling. *[Unpublished Article*], Heinz Wattie's Ltd., Hastings, New Zealand

Carter, J. (2002). Understanding the Average Quantity System. [*Leaflet*], Ministry of Consumer Affairs, New Zealand

Chiao,C. H. & Hamada, M. (2001). *Journal of Quality Technology*. *33*(4). 451-465.

Clark, J. C. & Randal, J. A. (2004). *A First Course in Applied Statistics*

Crow, K. (2002). *Variability Reduction*, 2613, Palos Verdes, CA 90274, DRM Associates

References

Deming, W.E. (1986). Out of the Crisis, Cambridge, MA, Massachusetts Institute of Technology for Advance Engineering Study.

Department of Thermal Process Engineering. *Sterilization Manual* (2005). Heinz Wattie's Ltd., Hastings, New Zealand.

Ellekjaer, M. R., Iiseng, M. A. & Naes, T. (1996). A Case study of the use of experimental design and multivariate analysis in product development. *Food Quality and Preference 79* (1), 29-36.

FMC FoodTech. Food Processing Systems. *[Leaflet]*, (Available from FMC FoodTech, 9100, Sint-Niklaas, Belgium.)

Ghani, J.A., Choudhury, I.A. & Hassan, H.H. (2004). Application of Taguchi method in the optimisation of end milling parameters. *Journal of Materials Processing Technology 145,* 84-92.

Grigg, N. & Graham, I. (2003). The development of process knowledge through experimentation, Palmerston North, Massey University.

Grigg, N. (2005).Case Study: SPC applications in food industry, *[Unpublished manuscript],* Palmerston North, Massey University.

Gonzalez-Miret, M. L., Coello, M. T., Allonso, S. & Heredia, F. J. (2001).Validation of parameters in HACCP verification using univariate and multivariate statistics. *Food Control, 12*, 261-268.

Goos, P. & Vandebroek, M. (2004).Outperforming completely randomized designs. *Journal of Quality Technology 36* (1), 12-26.

References

Heinz Wattie Ltd. (2005) *SPC Data Base*. King St., Hastings, New Zealand

Hines, W.W., Montgomery, D. C., Goldsman, D. M.& Borror, C. .M. *Probability and Statistics in Engineering*, (4^{th} ed.), New York, John Wiley & Sons.

IS department Archives. *Sentinel Process Control Software*. (2000). Version 2.51, Heinz Wattie's Ltd., Hastings, New Zealand.

Ishikawa, K. (1985). *What is total quality control? The Japanese way*. Translated by David J. W. Englewood Cliffs, N.J., Pretice-Hall

Ittzes, A. (2001). Statistical process control with several variance components in dairy. *Food Control*, *12*(2), 119-125.

Juran, J. M. & Gryna, F. M. (1974). *Juran's Quality Control Hand Book*. (4^{th} ed.), Mc Graw-Hill.

Kowalski, S. M. (2002). 24 run split plot experiments for robust parameter design. *Journal of Quality Technology, 34* (4), 399-410.

Lorenzen, T. J. & Anderson, V. L. (1993*). Design of Experiments.*

Minitab Inc. *Minitab for Windows Release 14*, 3081, State College, PA 16801-3008, USA.

Moen, R.D., Nolan, T. W. & Provost, L.P. (1998) *Quality Improvement through Planned Experimentation*. (2nd ed.), Auckland, McGraw-Hill.

Montgomery, D.C. (1991) *Statistical Quality Control,* (2nd ed.), New York, John Wiley & Sons.

References

Montgomery, D. C. (2001). *Design and Analysis of Experiments.* (5th ed.), New York, John Wiley & Sons.

Ott, E.R. (1975). *Process Quality Control.* New York, McGraw-Hill.

Ott, L. & Mendenhall, W. (1990). *Understanding Statistics.* (5th ed.), Boston, PWS-KENT

Ozilgen, M. (1998) Construction of quality control charts with sub-optimal size samples. *Food Control, 9(1)*, 57-60.

Perry, R. H. & Green, D. W. (1997). *Perry's Chemical Engineers' Hand Book.* (7^{Th} ed.), McGraw-Hill.

Santos, J. R. A. & Clegg, M. D. (1999). Factor analysis adds new dimension to Extension Surveys. *Journal of Extension, 37*(5). Retrieved January 15, 2007, from www.joe.org/joe/1999october/rb6.html.

Snee, R. D. (1990). Statistical thinking and its contribution to total quality. *The American Statistician, 44* (2), 116-121.

Srikaeo, K., Furst, J. E. & Ashton, J. (2005). Characterization of the wheat-based biscuit cooking process by statistical process control techniques. *Food Control*, *16*, 309-317.

Taguchi, G. (1978). Offline and On-Line Quality Control Systems. *International Conference on Quality Control*, B4-1 - B4-5, Japanese Union of Scientists and Engineers, Tokyo.

Vithanage, D.S. (2003) Net Weight Performance Progress Report. *[Presentation],* (Available from Department of Quality Services, Heinz Wattie's Ltd, King Street, Hastings, New Zealand)

References

Vithanage, D.S. (1996) DoE Applications. *[Handout]*, (Available from Department of Quality Services, Heinz Wattie's Ltd, King Street, Hastings, New Zealand).

Vithanage, D.S. (1994) Application of Statistical Methods in Net Weight Control. *[Unpublished Diploma thesis in Food Quality Assurance]*, Massey University, Palmerston North, New Zealand.

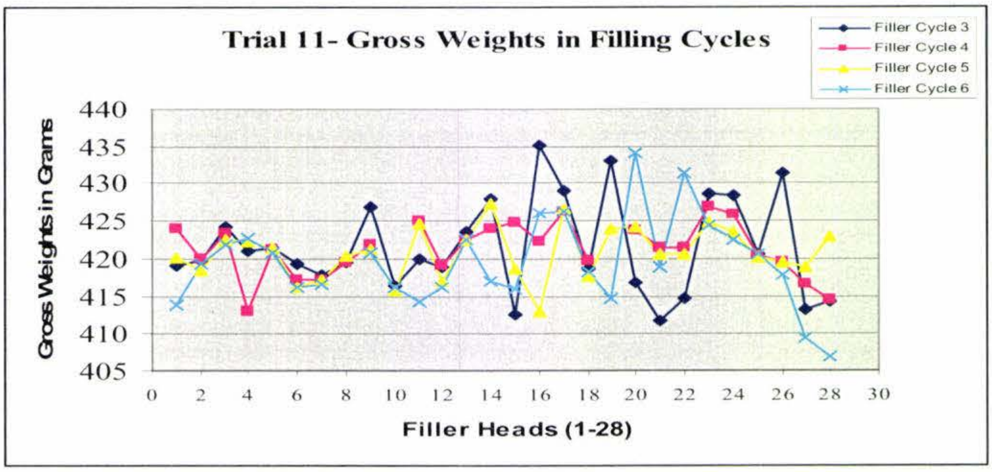
Webb, D. F., Lucas, J. M., & Borkowski, J. J. (2004) Factorial experiments when factor levels are not necessarily reset. *Journal of Quality Technology 36* (1), 1-11.

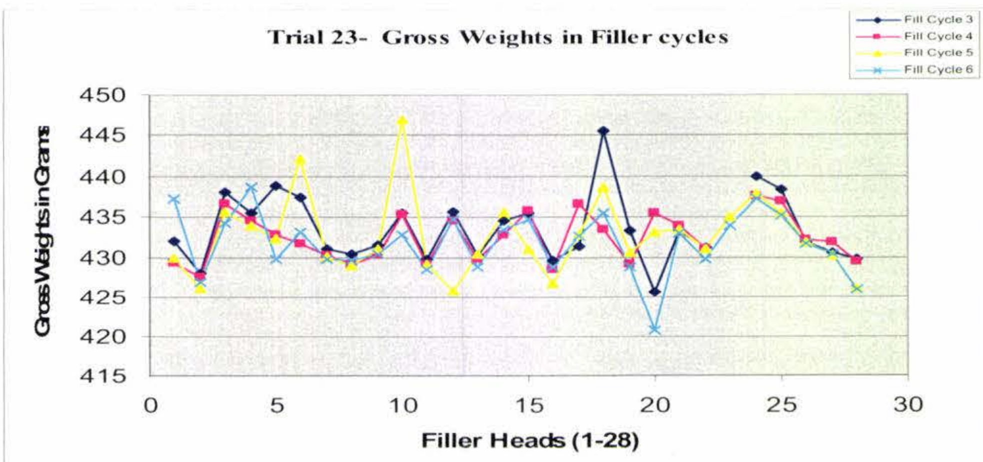
Zacmi Model 0255 Vacuum Filler. *Operating and service manual*. (1999).

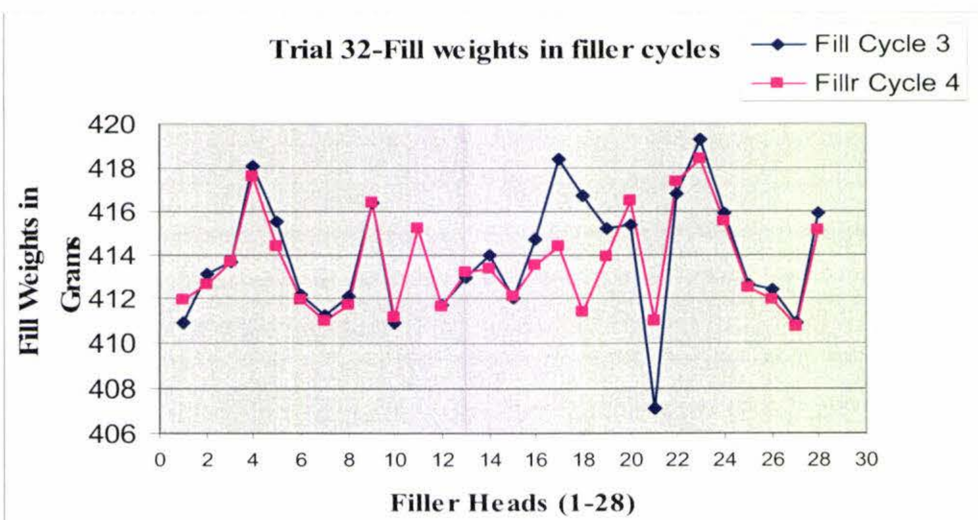
Zacmi Model 0290 Piston Filler. *Operating and service manual*. (2001).

Appendices

Appendix 1-1

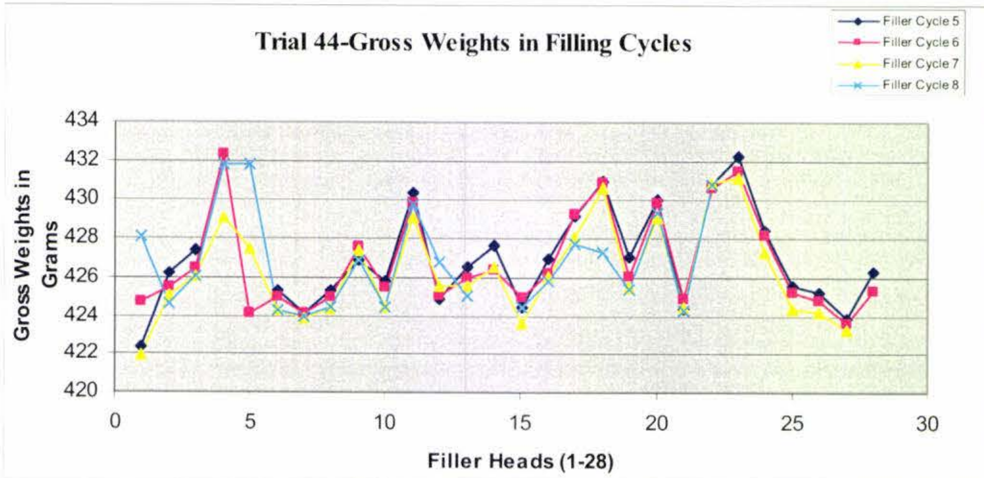


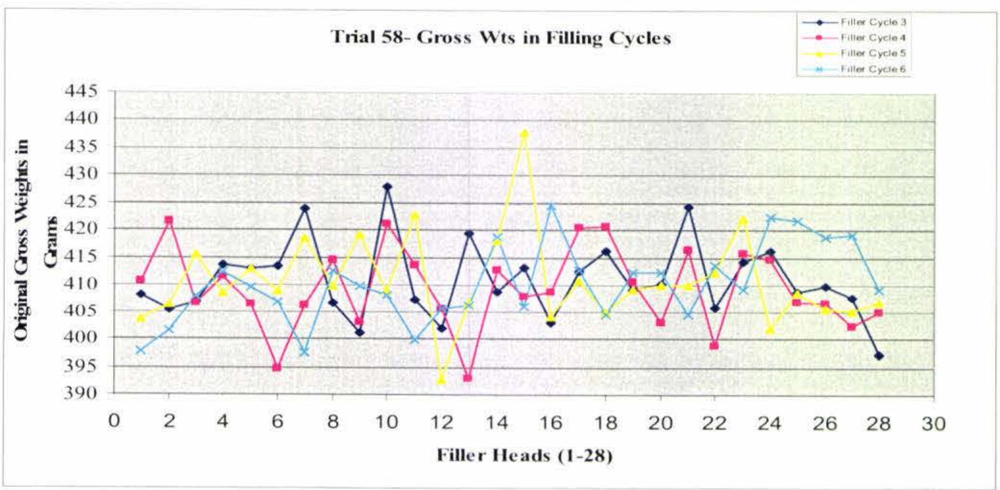


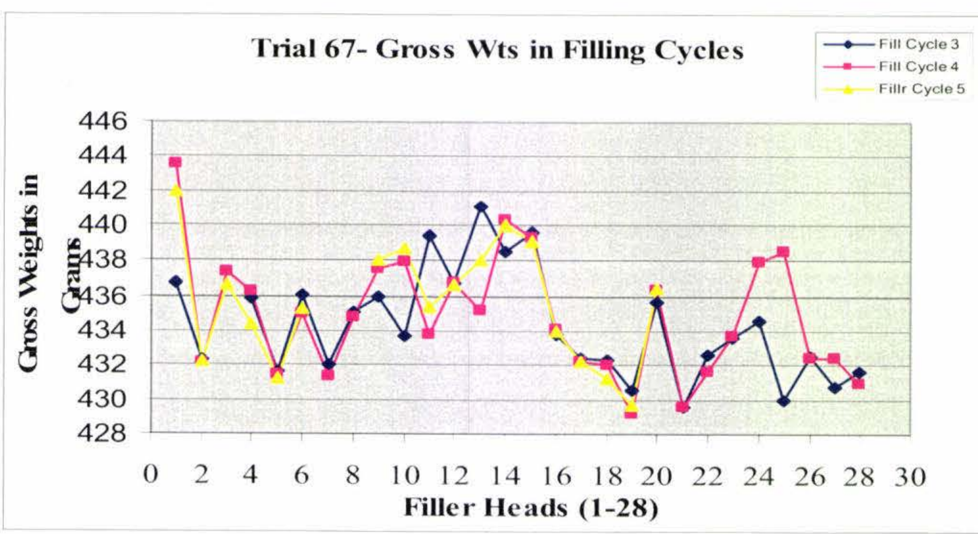


Appendices

Appendix 1-2







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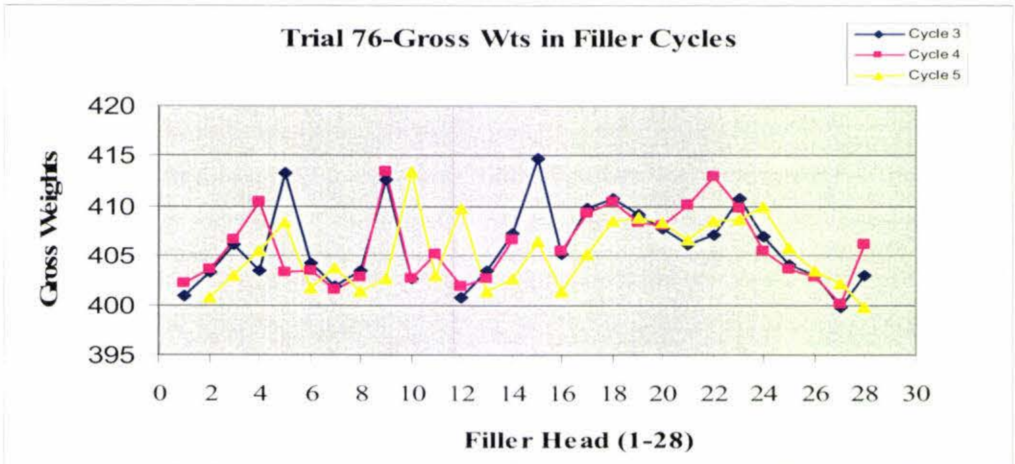
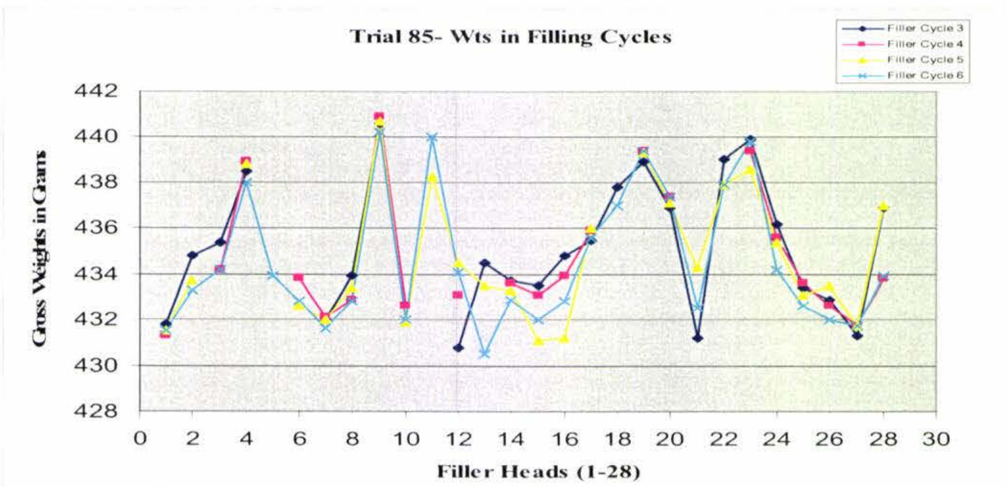
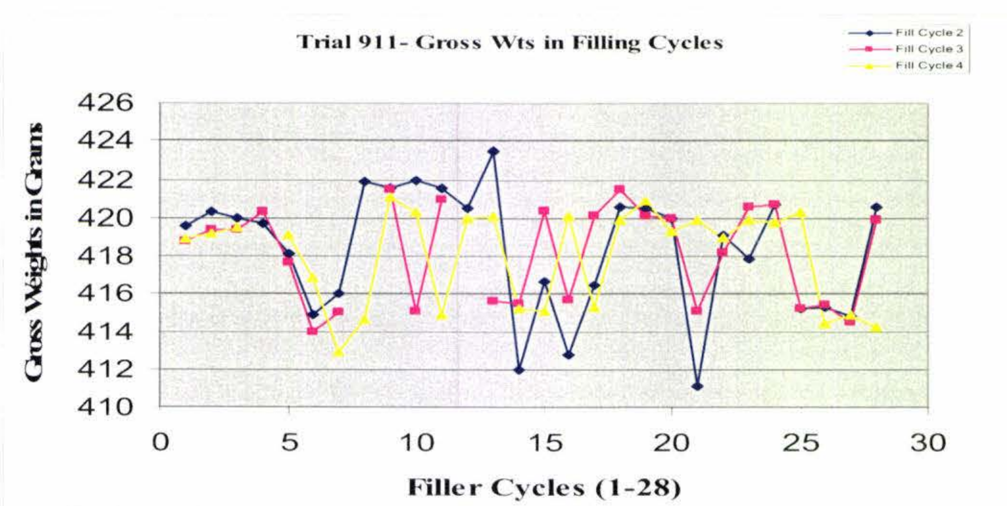
Appendix 1-3







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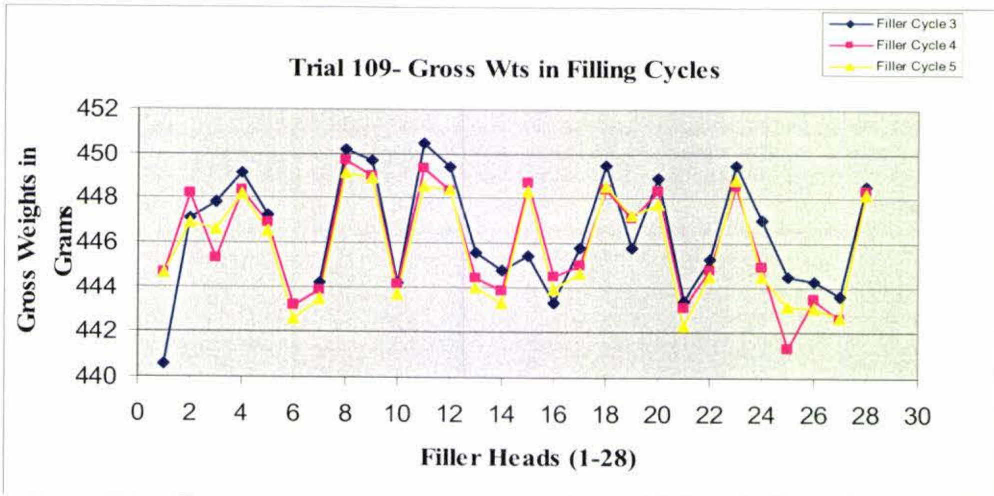
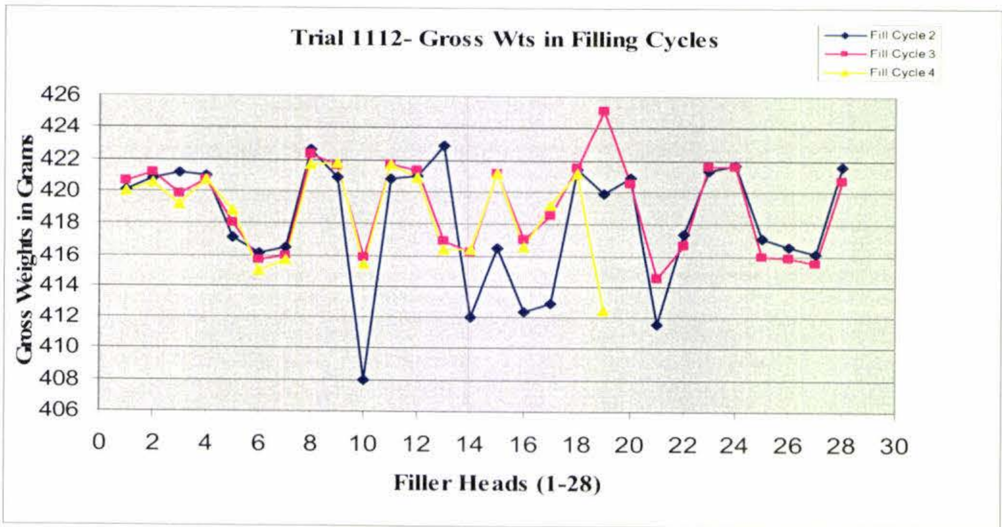
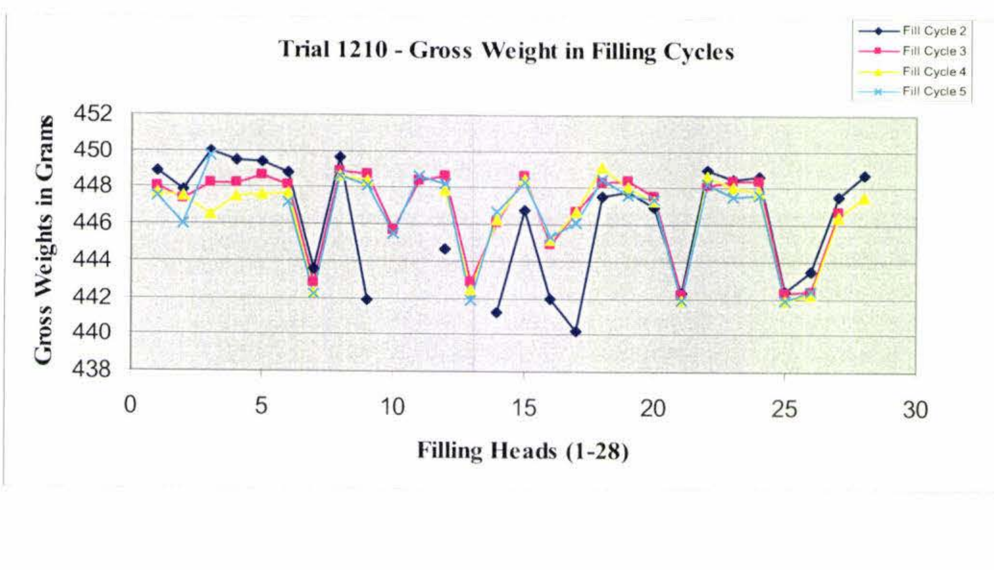
Appendix 1-4







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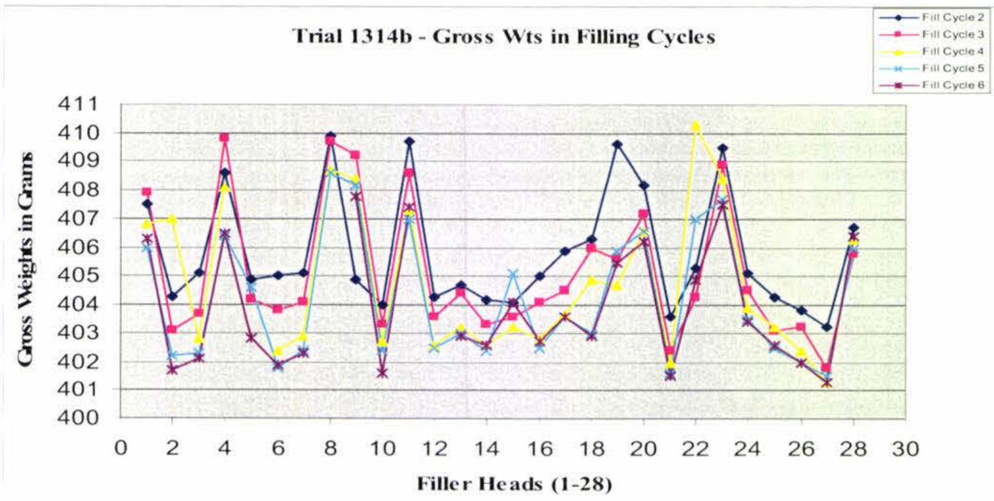
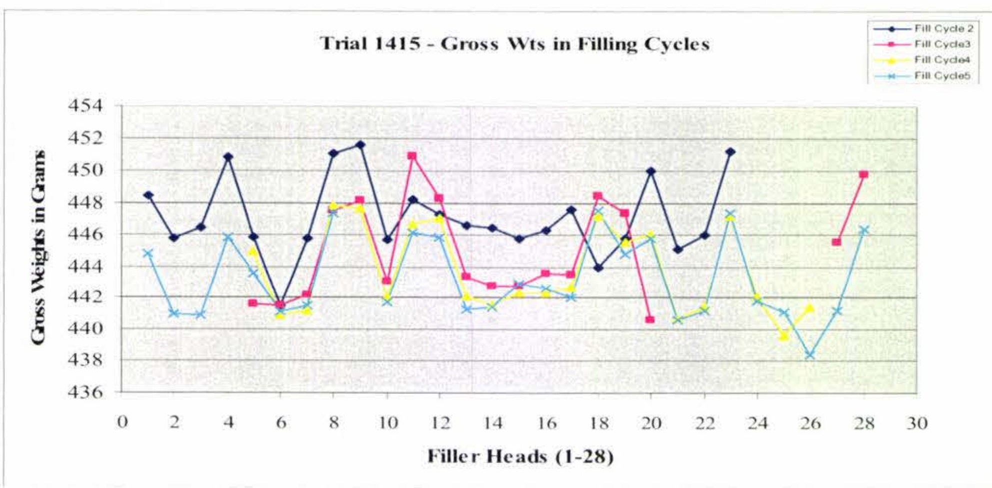
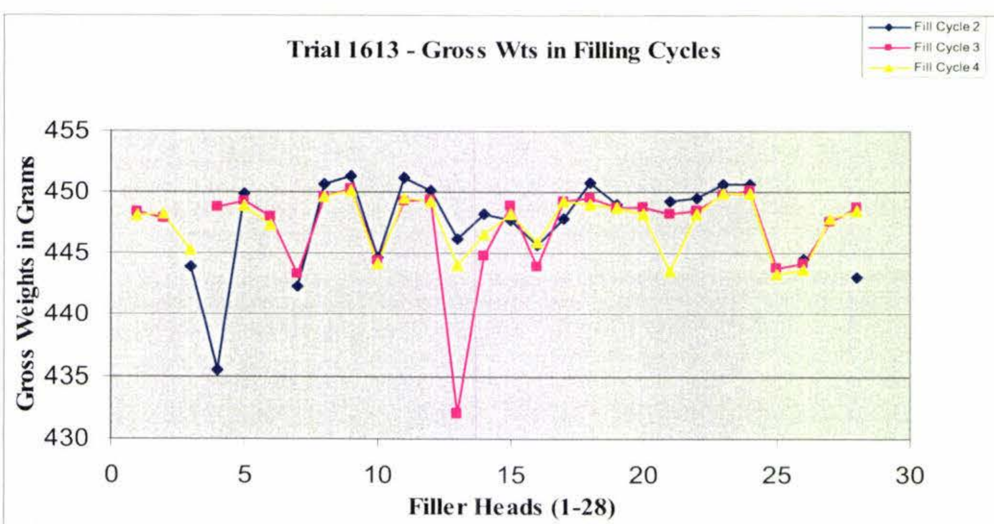
Appendix 1-5







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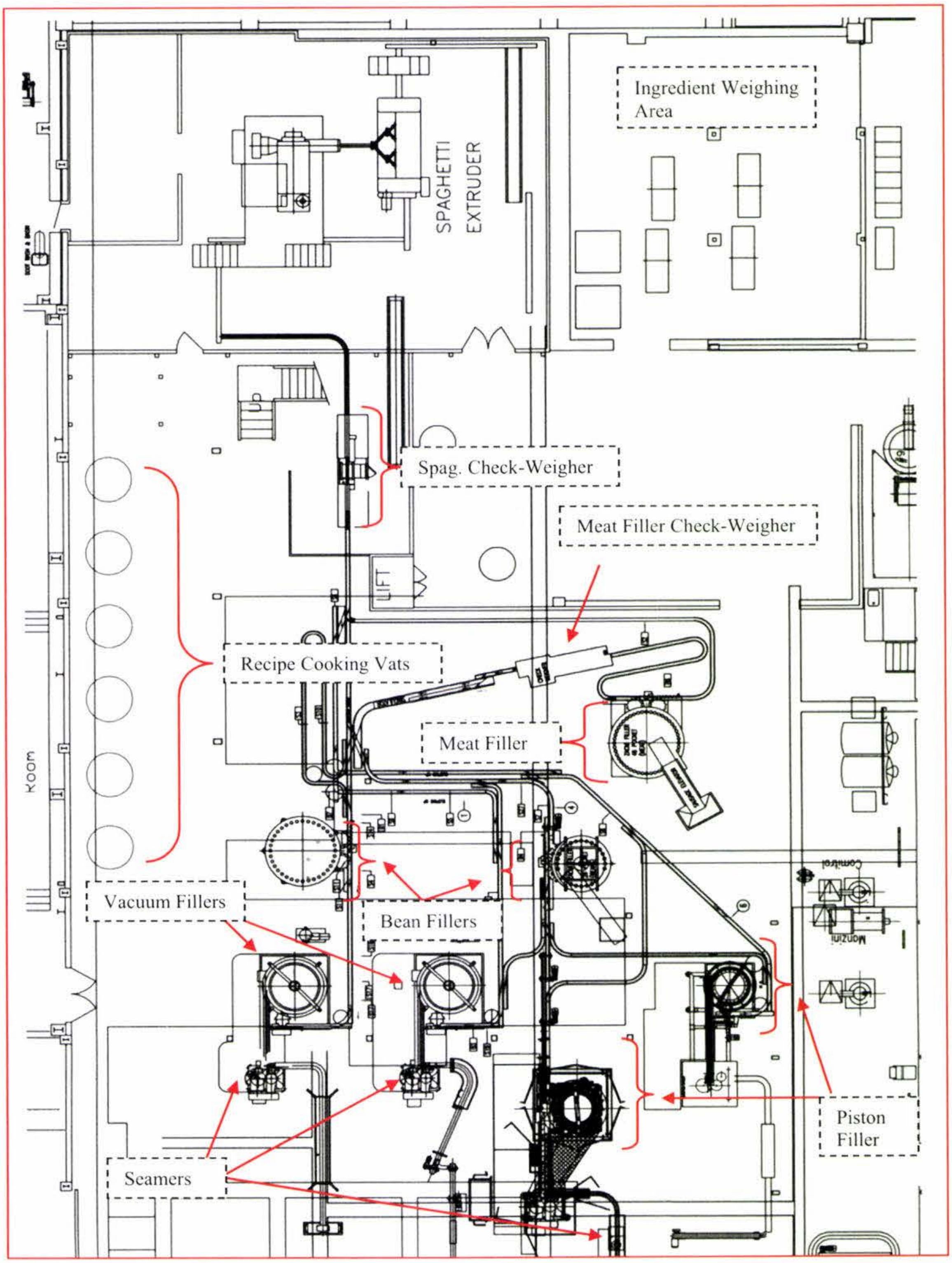
Appendix 2



Recipe floor process flow chart

Appendices

Appendix 3-1

Unit operations in food preparation area

Unit Operation	Processing Equipment	Mode of Action	Product example
Recipe Mixing and preheating	Vat	Vessels are generally taller than Kettles and heated by revolving coils. Rely on boiling action for mixing.	Baked Bean and Spaghetti Sauces
	Kettle	Kettles in Recipe area are fitted with stirrers or scrapers as the case may be for proper mixing and heated by steam jackets.	Most of the product recipes are mixed in them
Size Reduction	Homogenizer	Product is forced through a fine orifice at high pressure (150Bar). May induce viscosity changes as well such as in tomato sauce.	Tomato pulp, White and Gratin sauce
	High Sheer Mixer (Liquivertor)	Basically is a blender, which reduces the size of soft ingredients such as butter and margarine. Baffle attached underneath ensures fast dispersion. Consists of a combination of moderately fast rotating cutting blades.	Slurry base for white, Demiglace and curry sauces
	Commitrol	Achieve size reduction through shear force, applied by set of fast rotating shear blades against a slotted wall.	Demiglace and white sauce
	Manzini	Product is forced from a revolving drum using centrifugal force through a screen of a defined mesh size.	Tomato crushing and seed separation. Corn pulping.
Heat Transfer	Plate Heat transfer units and Steam injector	Plate heat exchangers are used to heat products using steam or water. Product transfer should be carefully controlled to prevent heat damage to product. They are also used to heat retort water. Steam injectors inject high velocity steam into a liquid medium. The condensing steam supplies enough energy to create down steam pumping head and heat up the liquid.	Steam injection to heat up White sauce, Soups and plate heat transfer to heat up Tomato sauce
Filling	Vacuum Piston Pocket Pouch Filler Portion pack filler	Mode of action is discussed in detail in section	All canned products

Appendices

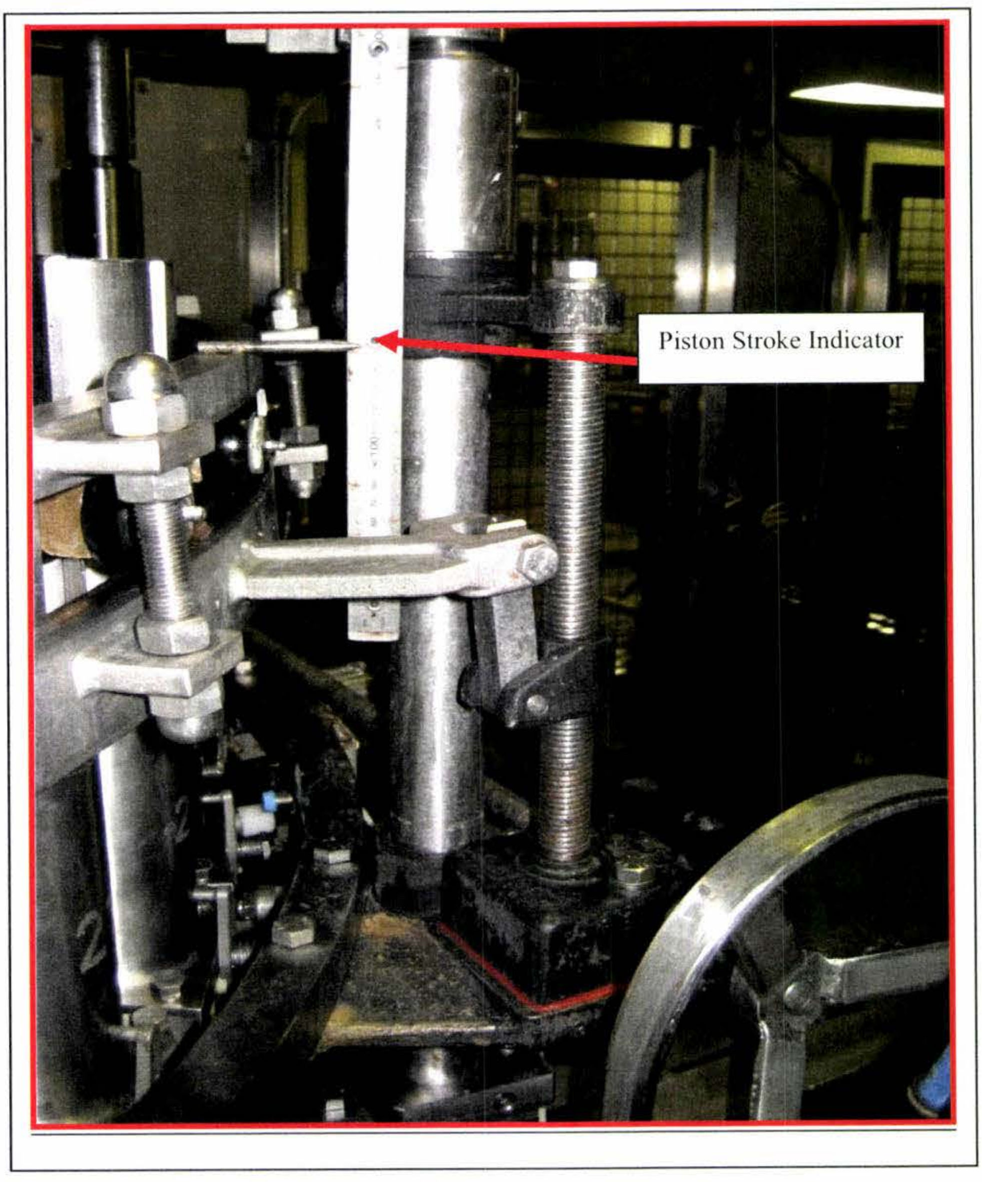
Appendix 3-2 *Unit operations in heat processing area (Department of Thermal Process Engineering, 2005)*

Unit Operation	Processing Equipment	Mode of Action	Product example
Seaming	1,3,4 Seamers - Slow 6,8 -Fast May either work on "Head turn" or "Table turn"	Seamers produce strong and hermetic double seam, incorporating a vacuum. Two rolling operations namely 1st and 2nd joins the ends of can body and lid.	All canned products
Thermal Processing	Batch Still Steam Retorts	Latent heat of steam transferred to cans due to condensation. Cans are still during processing and rely on convection and conductance for heat transfer. Accommodate four crates each holding 720 IT size cans. Typical process has a temperature time regime of 121^0 C at 55 minutes. Speed in terms of CPM range from 92 -400	Used mostly for Export soups and meat sauce, casseroles and vegetable products
	Batch Rotary Steam Retorts	Latent heat of steam transferred to cans due to condensation. Can are agitated by rotating holding crate by the central axis. Accommodate four crates each holding 720 IT size cans. Typical process is made of a temperature time regime of 118 C and 110 minutes for A10 cans. Speed in terms of CPM range from 225 -300. (FMC Food Tech)	Used for A10 baked beans and Spaghetti where agitation is necessary
	Continuous Cookers	Latent heat of steam transferred to cans during condensation. Conduction and convection are the two main mode of heat transfer to product in cans. Combined action of rotation and spinning of cans ensures forced convection inside the can. Speed in terms of CPM range from 88-350 depending on cooker, can size and food. Most of the process is processed within a temperature range of 100 –132 and time range of 16 – 35 minutes. (FMC Food Tech)	Mostly Bean, Spaghetti and Fruits & Vegetables in No 1 Tall cans.
	Hydros	Cans are chain conveyed through water sealed steam doom with no agitation. The speed could vary from 110 – 560 CPM depending on product. Most of the process is processed within a temperature range of 100 –125 and time range of 50 –60 minutes	Mainly 420 & 535g acid recipe products

Appendices

Appendix 4

Piston stroke level indicator



Appendices

Appendix 5

Fill Weight Data Capture system

Appendices

Appendix-6

Variation of tare weights for One-Tall cans

	Gross Wts	Tare Wts	Gross Wts	Tare Wts	Gross Wts	Tare Wts	Gross Wts	Tare Wts
1	416.90	53.47	382.25	52.91	418.56	53.32	407.38	53.21
2	416.90	53.47	382.25	52.91	418.56	53.32	407.38	53.21
3	419.31	53.34	396.61	53.20	418.76	53.73	442.13	53.26
4	419.31	53.34	396.61	53.20	418.76	53.73	442.13	53.26
5	413.69	53.77	439.99	53.28	396.64	53.16	451.72	53.38
6	413.69	53.77	439.99	53.28	396.64	53.16	451.72	53.38
7	417.59	53.24	431.94	53.18	420.68	53.62	443.51	53.15
8	417.59	53.24	431.94	53.18	420.68	53.62	447.63	53.20
9	429.85	53.38	397.99	53.38	454.70	53.71	544.70	53.71
10	429.85	53.38	397.99	53.38	454.70	53.71	444.03	53.47
11	408.90	53.54	412.25	53.41	444.03	53.47	443.04	53.55
12	408.90	53.54	412.25	53.41	444.03	53.47	442.10	53.51
13	427.32	53.12	443.54	53.15	410.49	53.70	442.13	53.26
14	427.32	53.12	443.54	53.15	410.49	53.70	451.72	53.38
15	424.91	52.82	447.63	53.20	404.00	53.51	418.56	53.32
16	424.91	52.82	447.63	53.20	404.00	53.51	418.76	53.73
17	440.59	53.27	443.04	53.55	402.21	53.36	440.59	53.27
18	440.59	53.27	443.04	53.55	402.21	53.36	429.93	53.24
19	429.93	53.24	442.10	53.51	405.10	53.53	397.99	53.38
20	429.93	53.24	442.10	53.51	405.10	53.53	412.25	53.41
21	427.32	53.12	416.90	53.47	407.38	53.21	402.21	53.36
22	413.69	53.77	419.31	53.34	439.99	53.28	429.85	53.38
23	417.59	53.24	396.64	53.16	431.94	53.18	408.90	53.54
24	416.90	53.47	420.68	53.62	410.99	53.70	382.25	53.91
25	419.31	53.34	405.19	53.53	404.00	53.51	396.61	53.20

	Gross Wt.	Tare Wt.		Gross Wt.	Tare Wt.
Average	423.3	53.38	Range	20.3	0.27
Maximum	544.7	53.91	SD	21.7	0.21
Minimum	382.3	52.82	Variance	471.3	0.05

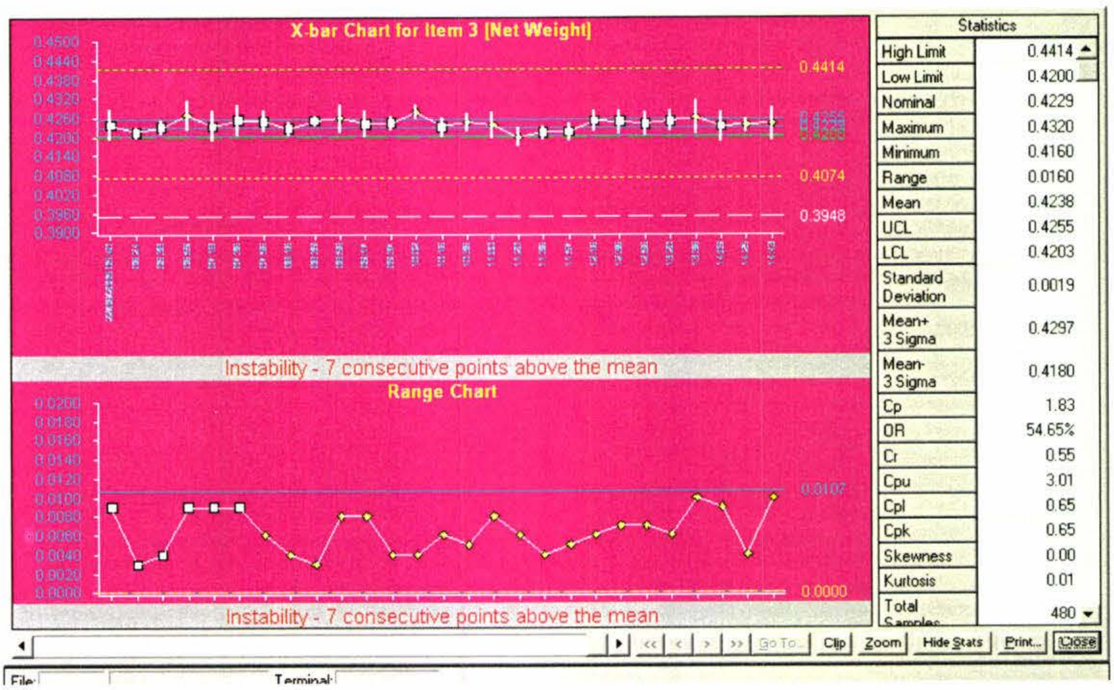
Gross and tare weights of random sample of 100 trial cans

Appendices

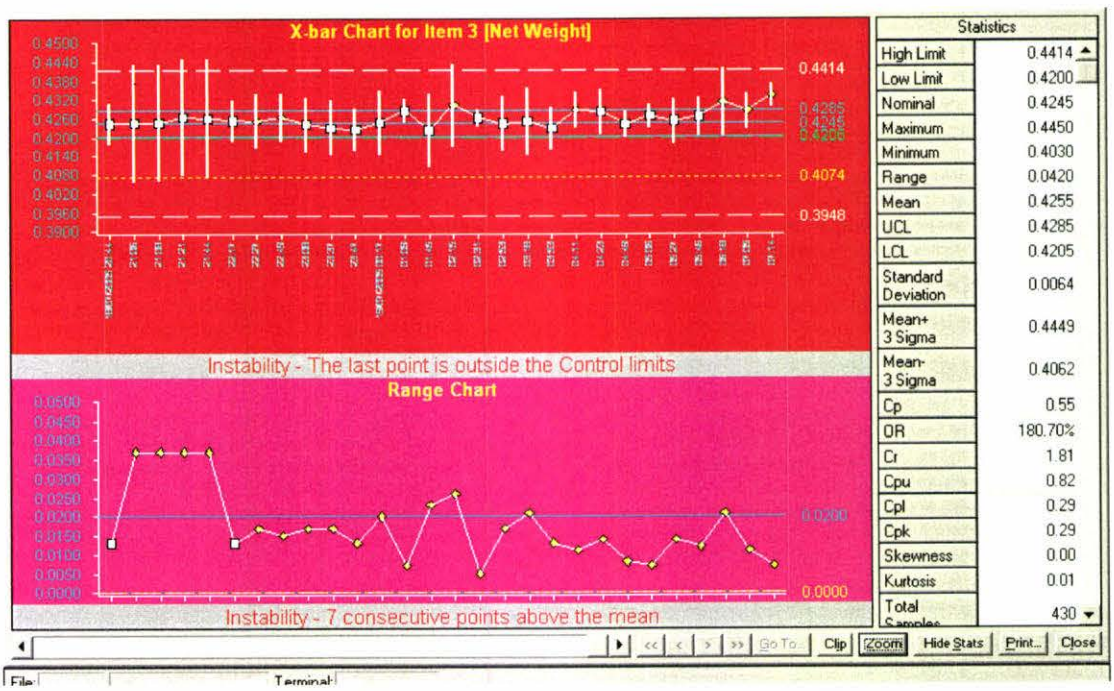
Appendix-7

Differences in variability using different fillers (Wattie Spaghetti 420g)

Using Vaccum Filler on R4 line (Sigma Short Term=1.9g)



Using Piston Filler on H3 line (Sigma Short Term =6.4g)



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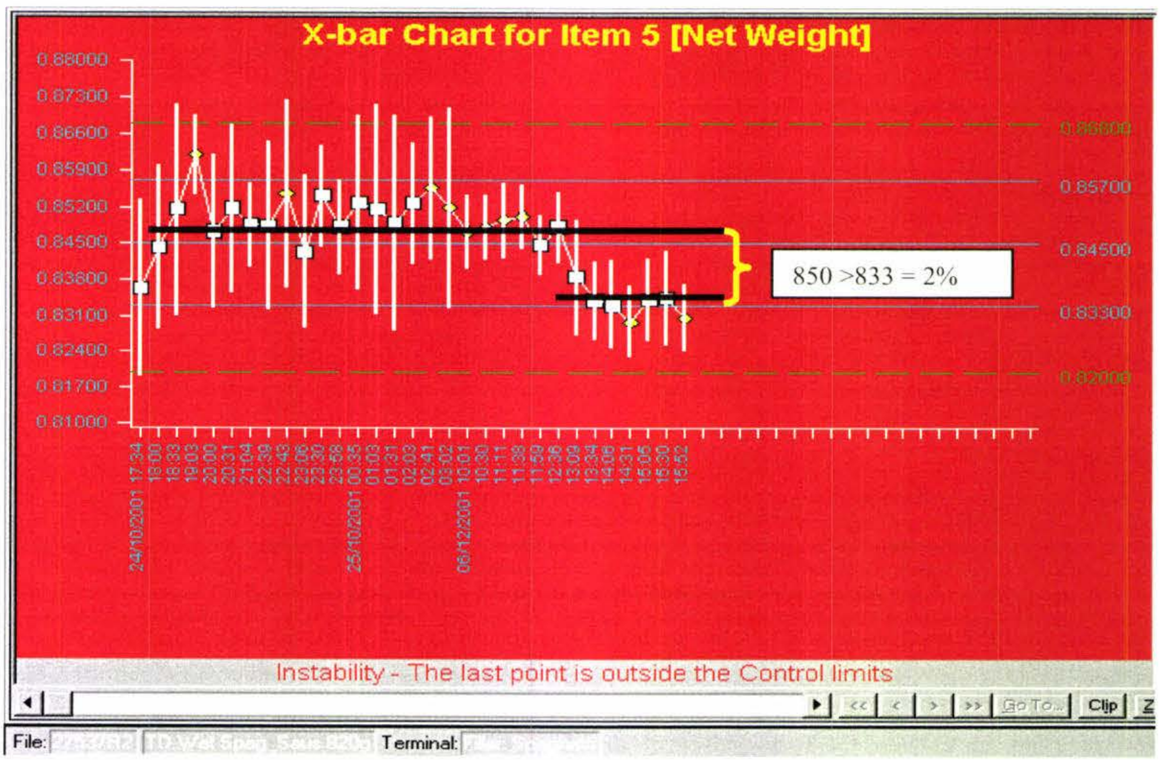
Appendix-8

Saving potential due to Net Weight target reduction

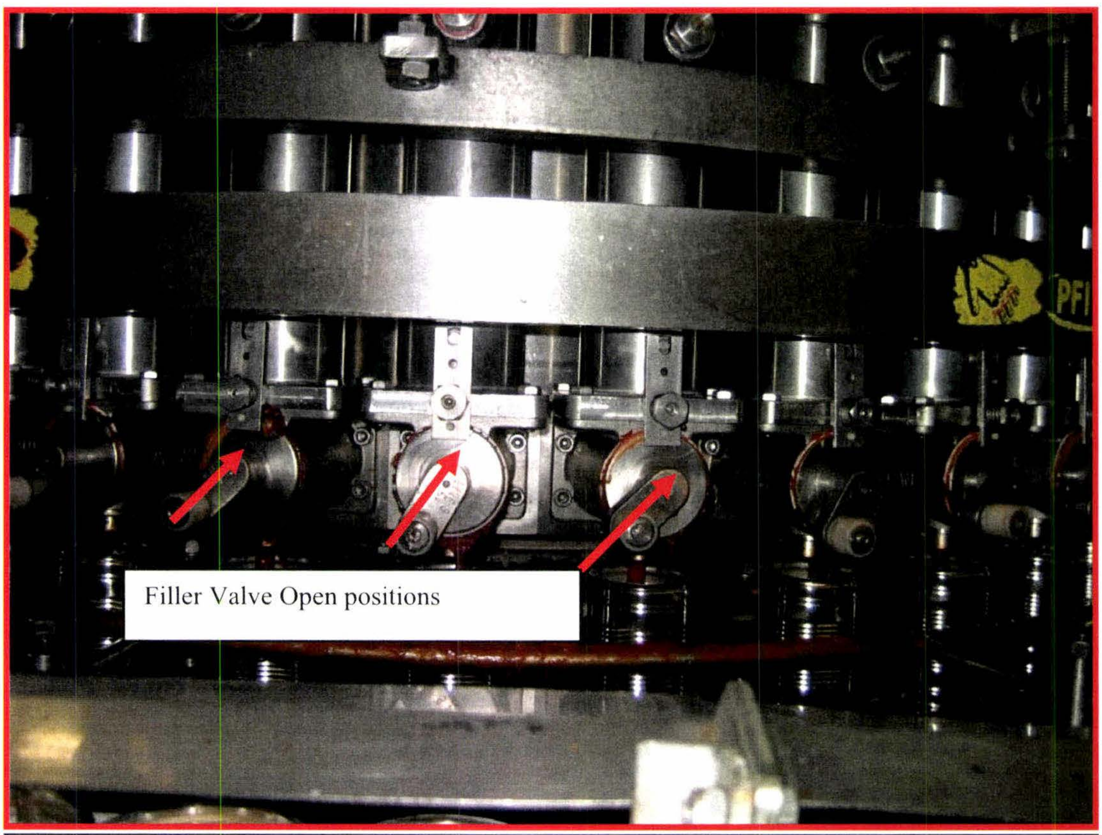


Appendices

Appendix-9

Unstable Filler Mechanisms on H3 Piston Filler

(Note the valve opening directions)



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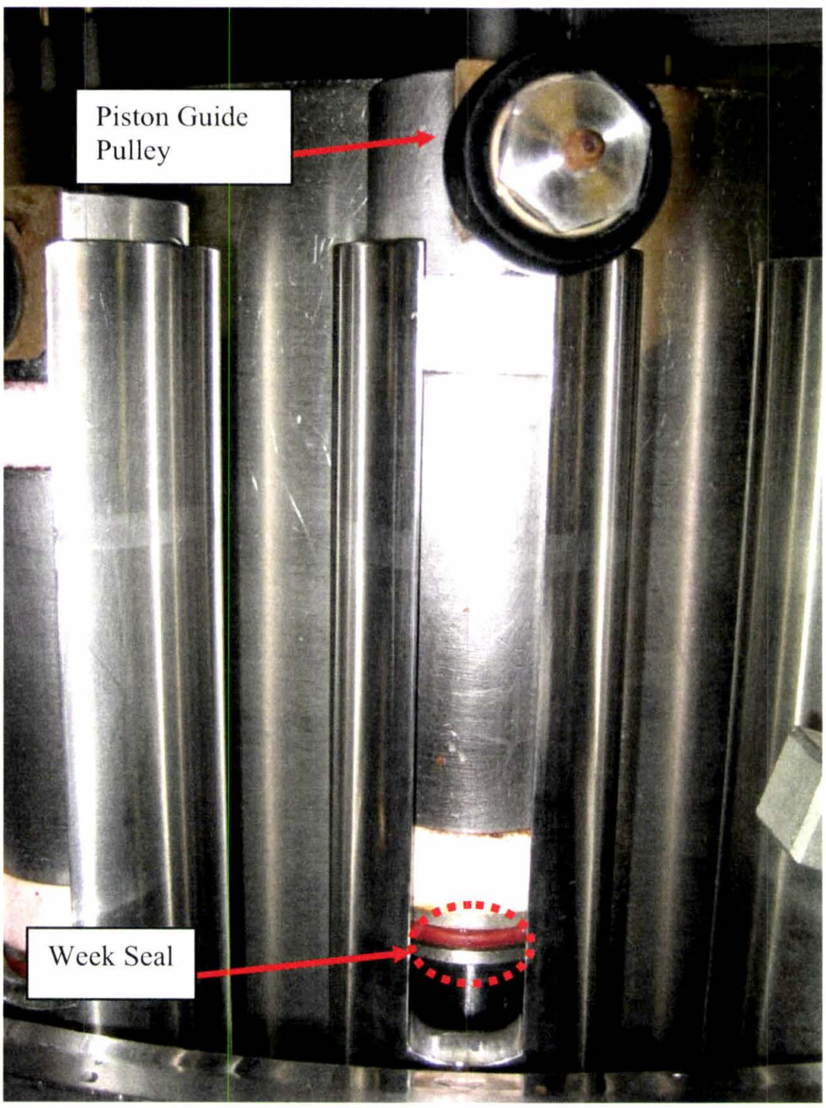
Appendix-10

Unstable Filler Mechanisms on H3 Piston Filler

(Note-Weak Piston Plug Seal)



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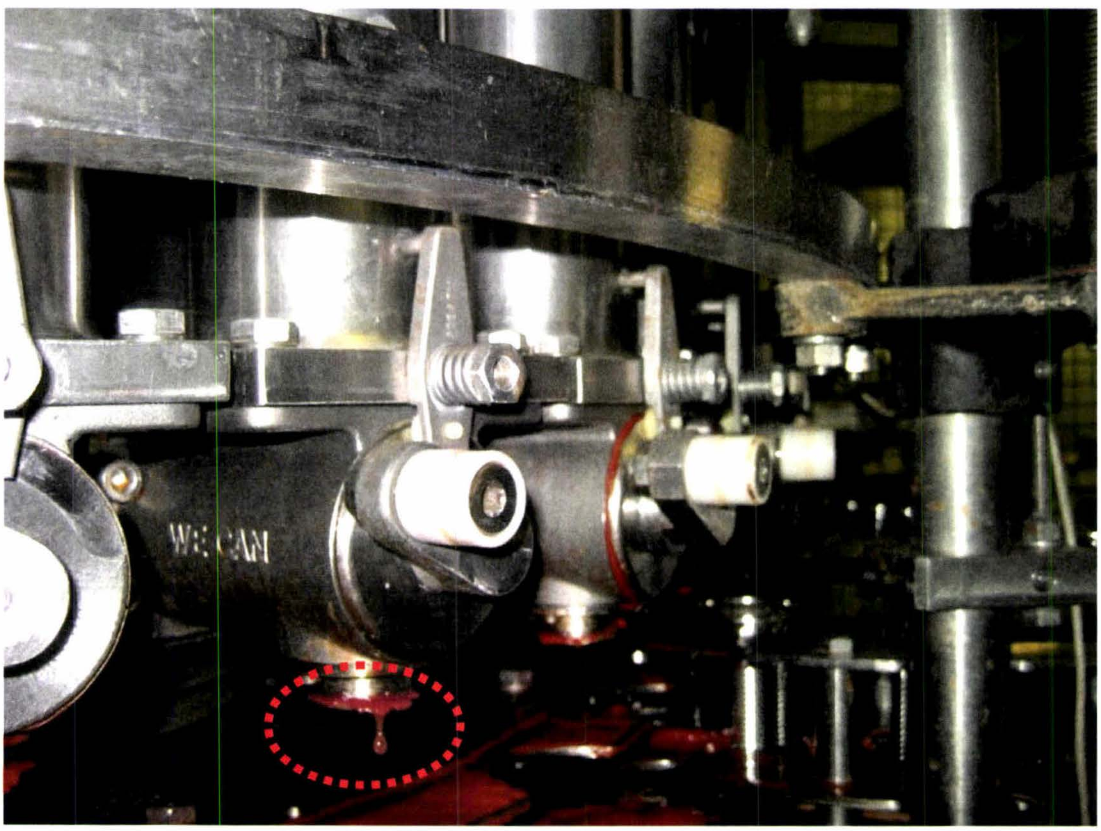
Appendix-11

Unstable Filler Mechanisms on H3 Piston Filler

(Note-After-Drip from the filling nozzle)



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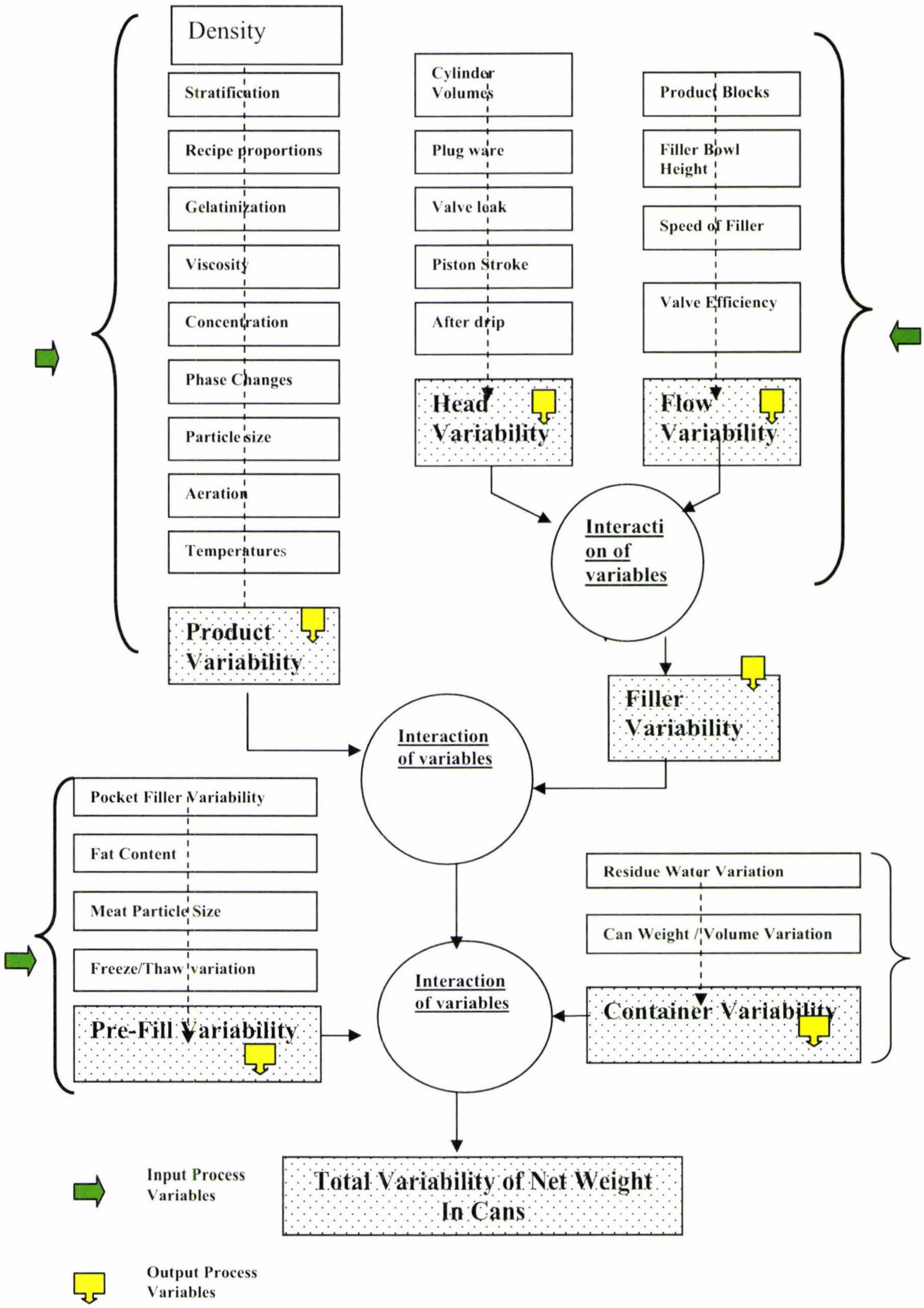
Appendix-12



Process variables involved in the Beef Curry process using a piston filler

Appendices

Appendix-13

Table 5-5 Minitab Analysis for mean -fill weights across filling cycles

Factorial Fit: fill weight versus Block, P, S, T, C

MFw Ac Fc in Fh (Full Matrix with Blocks) 120605

Term	Effect	Coef	SE Coef	T	P
Constant		425.550	0.1574	2703.64	0.000
Block 1		-0.458	0.5973	-0.77	0.444
Block 2		-0.865	0.5973	-1.45	0.148
Block 3		0.435	0.5973	0.73	0.467
Block 4		1.822	0.5973	3.05	0.002
Block 5		0.382	0.5973	0.64	0.523
Block 6		-1.565	0.5973	-2.62	0.009
Block 7		-2.611	0.5973	-4.37	0.000
Block 8		0.575	0.5973	0.96	0.336
Block 9		2.242	0.5973	3.75	0.000
Block 10		-0.765	0.5973	-1.28	0.201
Block 11		1.649	0.5973	2.76	0.006
Block 12		-0.298	0.5973	-0.50	0.618
Block 13		-1.398	0.5973	-2.34	0.020
Block 14		-0.158	0.5973	-0.26	0.791
Block 15		0.695	0.5973	1.16	0.245
Block 16		-1.265	0.5973	-2.12	0.035
Block 17		0.789	0.5973	1.32	0.188
Block 18		1.795	0.5973	3.01	0.003
Block 19		0.895	0.5973	1.50	0.135
Block 20		1.429	0.5973	2.39	0.017
Block 21		-2.105	0.5973	-3.52	0.000
Block 22		0.702	0.5973	1.18	0.241
Block 23		3.175	0.5973	5.32	0.000
Block 24		1.782	0.5973	2.98	0.003
Block 25		-1.425	0.5973	-2.39	0.018
Block 26		-2.105	0.5973	-3.52	0.000
Block 27		-2.651	0.5973	-4.44	0.000
P	27.201	13.600	0.1574	86.41	0.000
S	-1.888	-0.944	0.1574	-6.00	0.000
T	-4.707	-2.354	0.1574	-14.95	0.000
C	6.274	3.137	0.1574	19.93	0.000
P*S	1.246	0.623	0.1574	3.96	0.000
P*T	7.063	3.531	0.1574	22.44	0.000
P*C	7.663	3.832	0.1574	24.34	0.000
S*T	1.113	0.556	0.1574	3.53	0.000
S*C	2.429	1.215	0.1574	7.72	0.000
T*C	-2.621	-1.311	0.1574	-8.33	0.000
P*S*T	0.973	0.487	0.1574	3.09	0.002
P*S*C	-0.229	-0.115	0.1574	-0.73	0.466
P*T*C	-0.116	-0.058	0.1574	-0.37	0.713
S*T*C	-1.029	-0.514	0.1574	-3.27	0.001

S = 2.35573   R-Sq = 97.74%   R-Sq(adj) = 97.49%

Analysis of Variance for fill weight (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%contrib
Blocks	27	983.0	983.0	36.4	6.56	0.000	01.06
Main Effects	4	78392.7	73189.8	18297.5	3297.16	0.000	84.50
2-Way Interactions	6	11126.4	10282.5	1713.8	308.81	0.000	12.00
3-Way Interactions	4	170.5	170.5	42.6	7.68	0.000	00.18
Residual Error	378	2097.7	2097.7	5.5			02.26
Total	**419**	**92770.4**					

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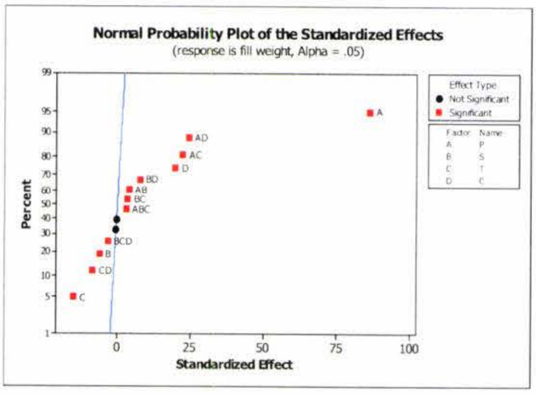
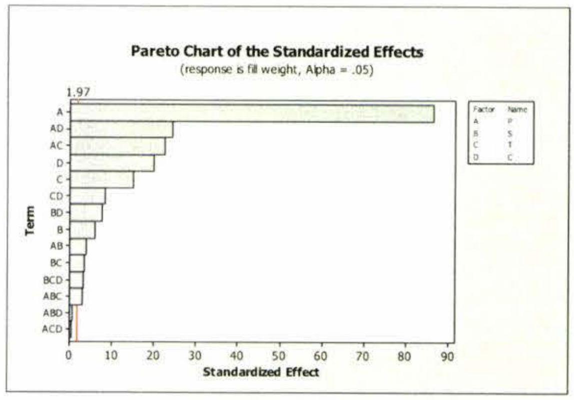
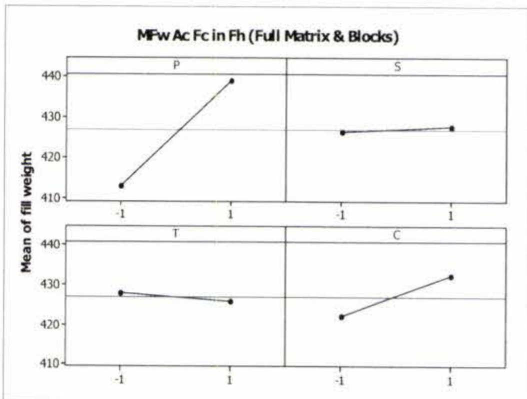
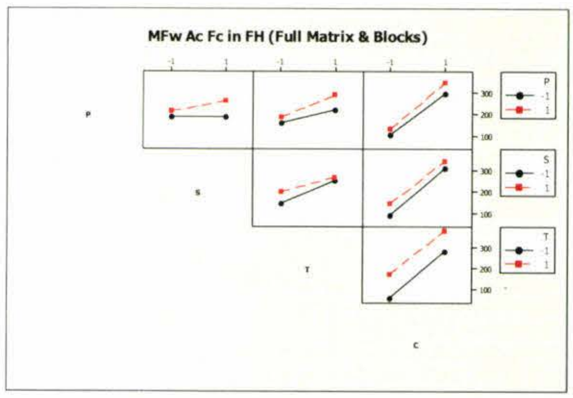
Appendix-14









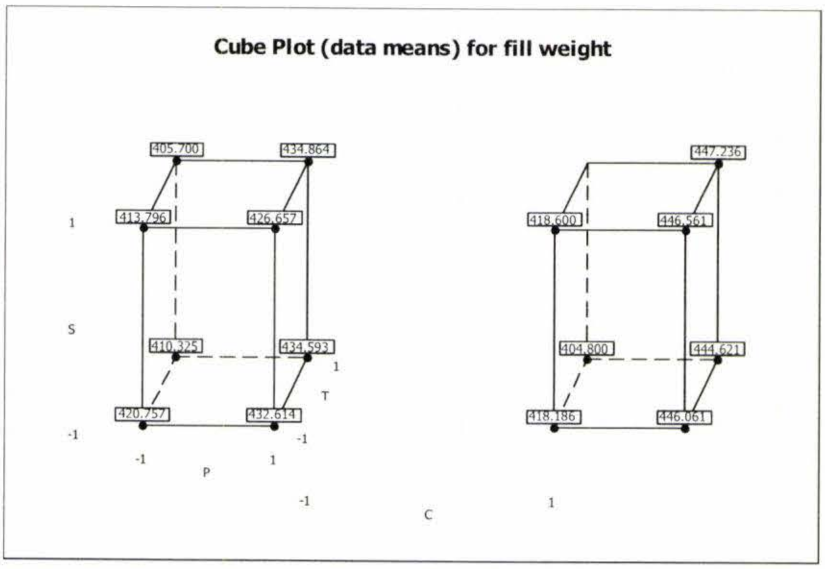


Fig. 5-6 MFw-Ac-Fc (Full Matrix) Minitab graphical out-put

Appendices

Appendix-15

Minitab analysis for mean of fill weights across filling cycles at High-P

Results for: half fraction p high
Factorial Fit: Fill Weight versus Block, S, T, C
MFw Ac Fc in Fh (Half Matrix @ P+)

Estimated Effects and Coefficients for Fill Weight (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		439.151	0.1562	2810.83	0.000
Block 1		0.224	0.8118	0.28	0.783
Block 2		-1.051	0.8118	-1.29	0.197
Block 3		0.574	0.8118	0.71	0.480
Block 4		1.887	0.8118	2.32	0.021
Block 5		0.274	0.8118	0.34	0.736
Block 6		-0.463	0.8118	-0.57	0.569
Block 7		-2.913	0.8118	-3.59	0.000
Block 8		0.812	0.8118	1.00	0.319
Block 9		2.287	0.8118	2.82	0.005
Block 10		-0.538	0.8118	-0.66	0.508
Block 11		2.137	0.8118	2.63	0.009
Block 12		0.987	0.8118	1.22	0.226
Block 13		-1.938	0.8118	-2.39	0.018
Block 14		-0.038	0.8118	-0.05	0.962
Block 15		0.574	0.8118	0.71	0.480
Block 16		-1.751	0.8118	-2.16	0.032
Block 17		-0.038	0.8118	-0.05	0.962
Block 18		2.274	0.8118	2.80	0.006
Block 19		0.224	0.8118	0.28	0.783
Block 20		1.037	0.8118	1.28	0.203
Block 21		-2.363	0.8118	-2.91	0.004
Block 22		0.487	0.8118	0.60	0.550
Block 23		2.524	0.8118	3.11	0.002
Block 24		1.312	0.8118	1.62	0.108
Block 25		-1.863	0.8118	-2.30	0.023
Block 26		-2.626	0.8118	-3.23	0.001
Block 27		-1.813	0.8118	-2.23	0.027
S	-0.643	-0.321	0.1562	-2.06	0.041
T	2.355	1.178	0.1562	7.54	0.000
C	13.937	6.969	0.1562	44.60	0.000
S*T	2.086	1.043	0.1562	6.67	0.000
S*C	2.200	1.100	0.1562	7.04	0.000
T*C	-2.737	-1.369	0.1562	-8.76	0.000
S*T*C	-1.029	-0.514	0.1562	-3.29	0.001

S = 2.33831 R-Sq = 92.50% R-Sq(adj) = 91.15%

Analysis of Variance for Fill Weight (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contrib.
Blocks	27	532.8	532.8	19.73	3.61	0.000	03.87
Main Effects	3	11212.0	11212.0	3737.34	683.53	0.000	81.41
2-Way Interactions	3	934.3	934.3	311.44	56.96	0.000	06.78
3-Way Interactions	1	59.2	59.2	59.25	10.84	0.001	00.43
Residual Error	189	1033.4	1033.4	5.47			07.50
Total	223	13771.8					

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Appendix-16

Minitab analysis for mean of fill weights across filling cycles at Low-P

Factorial Fit: Fill Weight versus Block, S, T, C

MFw Ac Fc in Fh (Half Matrix @ P-)

Estimated Effects and Coefficients for Fill Weight (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		412.464	0.2259	1825.84	0.000
Block 1		-1.238	0.8873	-1.39	0.165
Block 2		-0.652	0.8873	-0.73	0.464
Block 3		0.277	0.8873	0.31	0.756
Block 4		1.748	0.8873	1.97	0.051
Block 5		0.505	0.8873	0.57	0.570
Block 6		-2.823	0.8873	-3.18	0.002
Block 7		-2.266	0.8873	-2.55	0.012
Block 8		0.305	0.8873	0.34	0.731
Block 9		2.191	0.8873	2.47	0.015
Block 10		-1.023	0.8873	-1.15	0.250
Block 11		1.091	0.8873	1.23	0.221
Block 12		-1.766	0.8873	-1.99	0.048
Block 13		-0.781	0.8873	-0.88	0.380
Block 14		-0.295	0.8873	-0.33	0.740
Block 15		0.834	0.8873	0.94	0.349
Block 16		-0.709	0.8873	-0.80	0.425
Block 17		1.734	0.8873	1.95	0.052
Block 18		1.248	0.8873	1.41	0.162
Block 19		1.662	0.8873	1.87	0.063
Block 20		1.877	0.8873	2.11	0.036
Block 21		-1.809	0.8873	-2.04	0.043
Block 22		0.948	0.8873	1.07	0.287
Block 23		3.919	0.8873	4.42	0.000
Block 24		2.319	0.8873	2.61	0.010
Block 25		-0.923	0.8873	-1.04	0.300
Block 26		-1.509	0.8873	-1.70	0.091
Block 27		-3.609	0.8873	-4.07	0.000
S	-2.105	-1.053	0.2259	-4.66	0.000
T	-10.741	-5.371	0.2259	-23.77	0.000
C	-0.361	-0.180	0.2259	-0.80	0.426
S*T	1.168	0.584	0.2259	2.58	0.011
S*C	3.687	1.844	0.2259	8.16	0.000
T*C	-1.477	-0.738	0.2259	-3.27	0.001

S = 2.39074   R-Sq = 89.00%   R-Sq(adj) = 86.76%

Analysis of Variance for Fill Weight (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Blocks	27	588.6	588.6	21.80	3.81	0.000	06.99
Main Effects	3	6103.3	4274.3	1424.75	249.27	0.000	72.50
2-Way Interactions	3	800.2	800.2	266.72	46.67	0.000	09.51
Residual Error	162	925.9	925.9	5.72			11.00
Total	195	8417.9					

Appendices

Appendix-17

Minitab analysis for mean of fill weights across heads

Factorial Fit: Fill Weight_1 versus P, S, T, C

MFw Ac Fh in Fc (Full Matrix without blocks) 130605

Estimated Effects and Coefficients for Fill Weight_1 (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		425.729	0.1258	3385.33	0.000
P	27.208	13.604	0.1258	108.18	0.000
S	-2.058	-1.029	0.1258	-8.18	0.000
T	-4.517	-2.258	0.1258	-17.96	0.000
C	6.375	3.188	0.1258	25.35	0.000
P*S	1.142	0.571	0.1258	4.54	0.000
P*T	7.100	3.550	0.1258	28.23	0.000
P*C	7.608	3.804	0.1258	30.25	0.000
S*T	1.117	0.558	0.1258	4.44	0.000
S*C	2.508	1.254	0.1258	9.97	0.000
T*C	-2.367	-1.183	0.1258	-9.41	0.000
P*S*T	0.850	0.425	0.1258	3.38	0.002
P*S*C	-0.342	-0.171	0.1258	-1.36	0.184
P*T*C	-0.200	-0.100	0.1258	-0.80	0.433
S*T*C	-1.150	-0.575	0.1258	-4.57	0.000

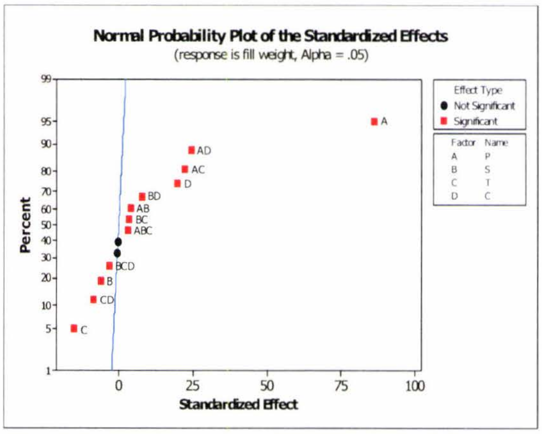
S = 0.616081   R-Sq = 99.88%   R-Sq(adj) = 99.83%

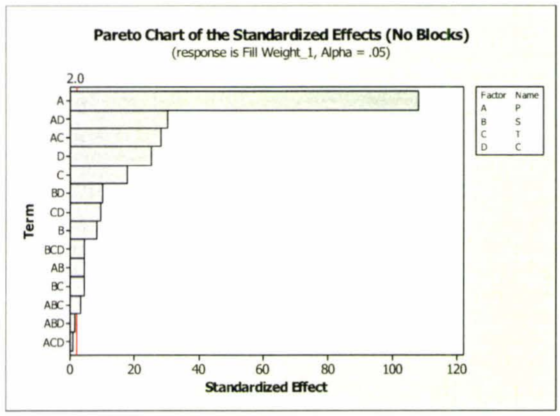
Analysis of Variance for Fill Weight_1 (coded units)

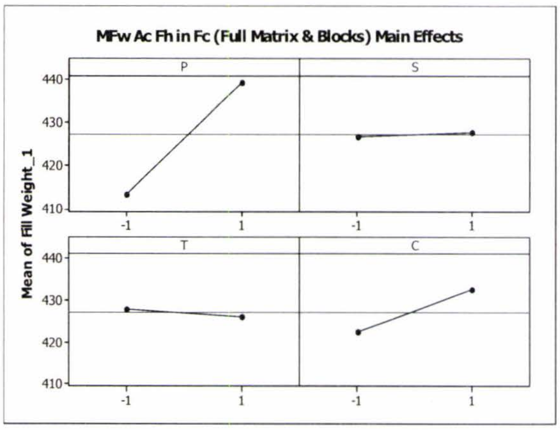
Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Main Effects	4	8436.97	7863.93	1965.98	5179.70	0.000	87.27
2-Way Interactions	6	1196.96	1107.88	184.65	486.48	0.000	12.38
3-Way Interactions	4	21.32	21.32	5.33	14.04	0.000	00.22
Residual Error	30	11.39	11.39	0.38			00.12
Pure Error	30	11.39	11.39	0.38			
Total	44	9666.64					

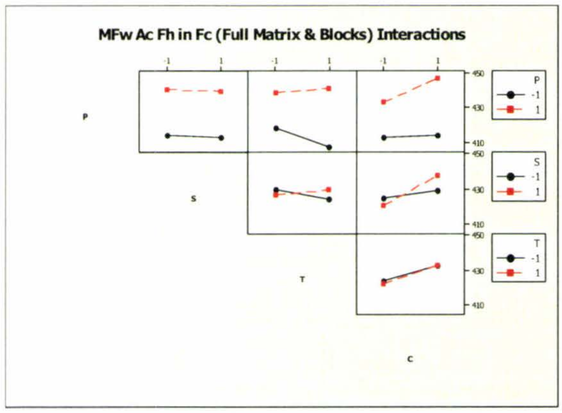
Appendices

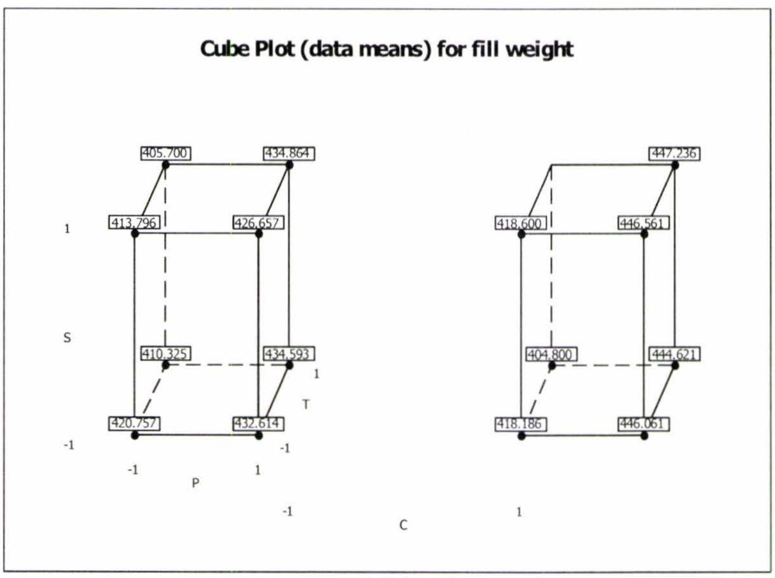
Appendix-18











MFw-Ac-Fh (Full Matrix) Minitab graphical out-put

Appendices

Appendix-19

Minitab analysis for mean of fill weights across heads at High-P

torial Fit: Fill Weight_1 versus S, T, C

MFw Ac Fh in Fc (Half Matrix @ P+) Without Blocks

Estimated Effects and Coefficients for Fill Weight_1 (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		439.333	0.1448	3033.70	0.000
S	-0.917	-0.458	0.1448	-3.16	0.006
T	2.583	1.292	0.1448	8.92	0.000
C	13.983	6.992	0.1448	48.28	0.000
S*T	1.967	0.983	0.1448	6.79	0.000
S*C	2.167	1.083	0.1448	7.48	0.000
T*C	-2.567	-1.283	0.1448	-8.86	0.000
S*T*C	-1.150	-0.575	0.1448	-3.97	0.001

S = 0.709460   R-Sq = 99.39%   R-Sq(adj) = 99.13%

Analysis of Variance for Fill Weight_1 (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Main Effects	3	1218.29	1218.29	406.095	806.81	0.000	91.93
2-Way Interactions	3	90.90	90.90	30.300	60.20	0.000	06.86
3-Way Interactions	1	7.94	7.94	7.935	15.76	0.001	00.60
Residual Error	16	8.05	8.05	0.503			00.61
Pure Error	16	8.05	8.05	0.503			
Total	23	1325.17					

Appendices

Appendix-20

Minitab analysis for mean fill weights across filler heads at Low-P

Factorial Fit: Fill Weight_1 versus S, T, C

MFw Ac Fh in Fc (Half Matrix @ P-) No Blocks

Estimated Effects and Coefficients for Fill Weight_1 (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		412.700	0.1409	2929.88	0.000
S	-2.050	-1.025	0.1409	-7.28	0.000
T	-10.467	-5.233	0.1409	-37.15	0.000
C	-0.083	-0.042	0.1409	-0.30	0.772
S*T	1.417	0.708	0.1409	5.03	0.000
S*C	4.000	2.000	0.1409	14.20	0.000
T*C	-1.017	-0.508	0.1409	-3.61	0.003

S = 0.487950   R-Sq = 99.55%   R-Sq(adj) = 99.36%

Analysis of Variance for Fill Weight_1 (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Main Effects	3	653.969	444.423	148.141	622.19	0.000	88.07
2-Way Interactions	3	85.203	85.203	28.401	119.28	0.000	11.48
Residual Error	14	3.333	3.333	0.238			00.45
Pure Error	14	3.333	3.333	0.238			
Total	20	742.506					

Appendices

Appendix-21

Minitab analyses for Variance of fill weights across filling cycles

Factorial Fit: variance versus Block, P, S, T, C

Estimated Effects and Coefficients for variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		5.555	1.059	5.24	0.000
Block 1		-1.689	4.020	-0.42	0.675
Block 2		-1.593	4.020	-0.40	0.692
Block 3		-4.926	4.020	-1.23	0.221
Block 4		1.671	4.020	0.42	0.678
Block 5		-3.444	4.020	-0.86	0.392
Block 6		-1.805	4.020	-0.45	0.654
Block 7		2.028	4.020	0.50	0.614
Block 8		-5.222	4.020	-1.30	0.195
Block 9		0.569	4.020	0.14	0.888
Block 10		6.155	4.020	1.53	0.127
Block 11		2.067	4.020	0.51	0.607
Block 12		-2.040	4.020	-0.51	0.612
Block 13		6.860	4.020	1.71	0.089
Block 14		-2.674	4.020	-0.67	0.506
Block 15		12.277	4.020	3.05	0.002
Block 16		6.489	4.020	1.61	0.107
Block 17		-3.121	4.020	-0.78	0.438
Block 18		-0.093	4.020	-0.02	0.982
Block 19		0.955	4.020	0.24	0.812
Block 20		0.460	4.020	0.11	0.909
Block 21		1.603	4.020	0.40	0.690
Block 22		-0.305	4.020	-0.08	0.940
Block 23		-5.339	4.020	-1.33	0.185
Block 24		-1.768	4.020	-0.44	0.660
Block 25		-1.464	4.020	-0.36	0.716
Block 26		-2.779	4.020	-0.69	0.490
Block 27		-2.505	4.020	-0.62	0.534
P	-4.293	-2.147	1.059	-2.03	0.043
S	-13.886	-6.943	1.059	-6.55	0.000
T	0.816	0.408	1.059	0.39	0.700
C	-13.615	-6.808	1.059	-6.43	0.000
P*S	12.064	6.032	1.059	5.69	0.000
P*T	0.191	0.096	1.059	0.09	0.928
P*C	13.872	6.936	1.059	6.55	0.000
S*T	-7.680	-3.840	1.059	-3.63	0.000
S*C	4.853	2.427	1.059	2.29	0.023
T*C	-9.218	-4.609	1.059	-4.35	0.000
P*S*T	8.808	4.404	1.059	4.16	0.000
P*S*C	-2.236	-1.118	1.059	-1.06	0.292
P*T*C	12.936	6.468	1.059	6.11	0.000
S*T*C	-1.081	-0.541	1.059	-0.51	0.610

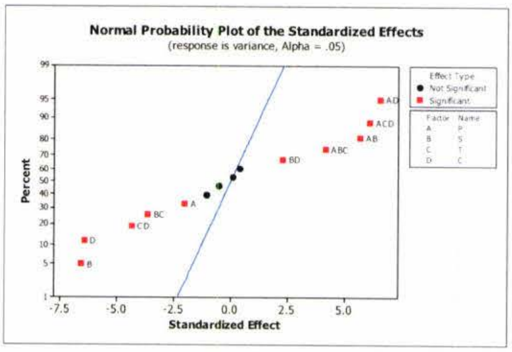
S = 15.8537   R-Sq = 47.68%   R-Sq(adj) = 42.00%

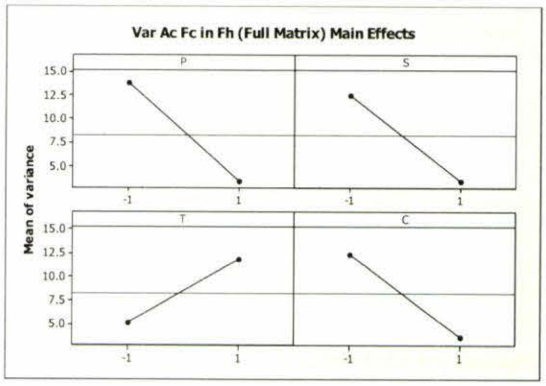
Analysis of Variance for variance (coded units)

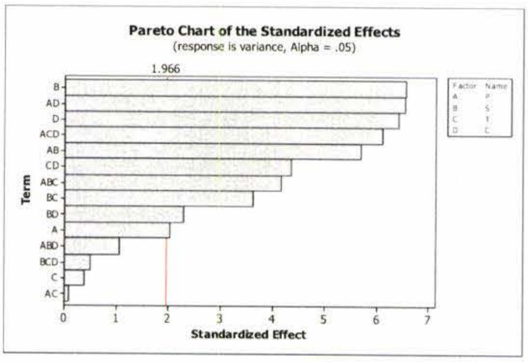
Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contrib.
Blocks	27	6511	6511	241.1	0.96	0.526	03.59
Main Effects	4	30478	33264	8316.1	33.09	0.000	16.79
2-Way Interactions	6	30956	33303	5550.5	22.08	0.000	17.05
3-Way Interactions	4	18624	18624	4656.1	18.53	0.000	10.26
Residual Error	378	95006	95006	251.3			52.32
Total	419	181576					

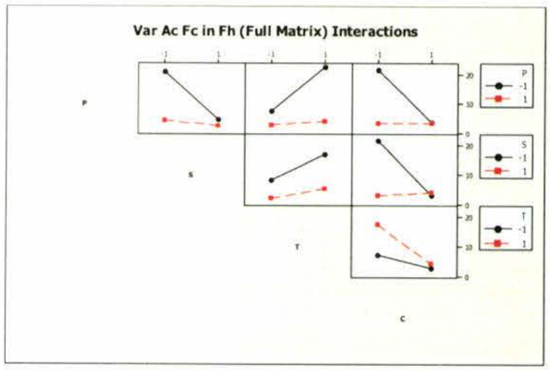
Appendices

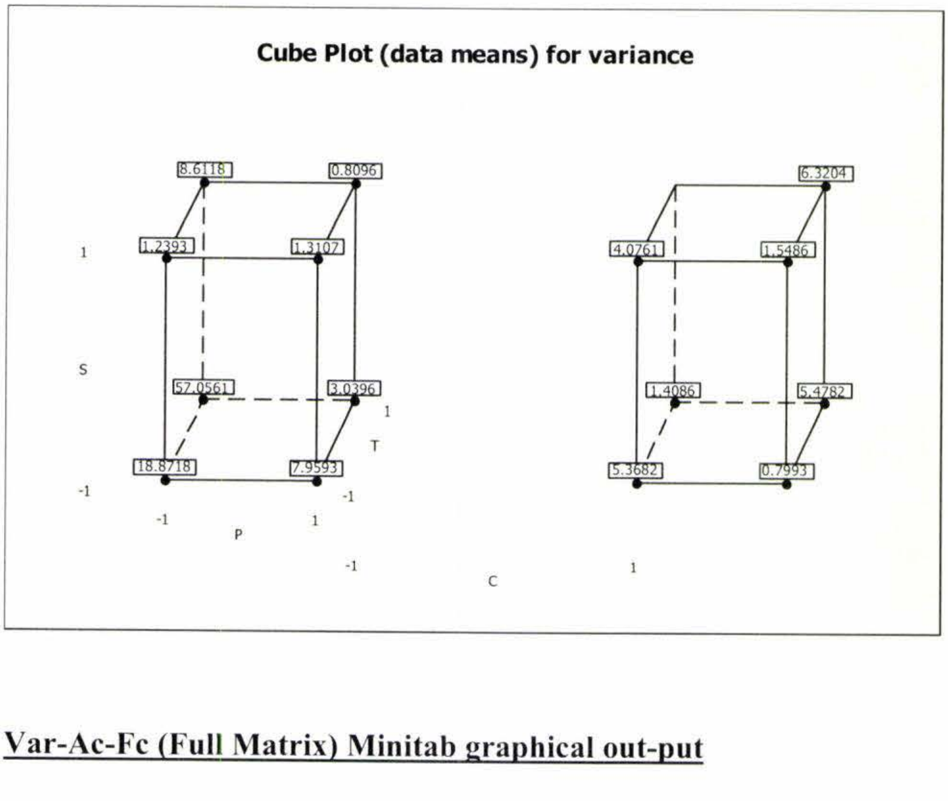
Appendix-22











<u>**Var-Ac-Fc (Full Matrix) Minitab graphical out-put**</u>

Appendices

Appendix-23

Minitab analysis for Variance of fill weights across filling cycles at High-P

Factorial Fit: variance versus Block, S, T, C

Var Ac Fc in Fh (Half Matrix @ P+) with Fhs as Blocks

Estimated Effects and Coefficients for variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		3.408	0.5908	5.77	0.000
Block 1		2.324	3.0698	0.76	0.450
Block 2		-1.584	3.0698	-0.52	0.606
Block 3		-0.341	3.0698	-0.11	0.912
Block 4		10.218	3.0698	3.33	0.001
Block 5		0.909	3.0698	0.30	0.767
Block 6		-0.357	3.0698	-0.12	0.908
Block 7		-2.624	3.0698	-0.85	0.394
Block 8		-2.792	3.0698	-0.91	0.364
Block 9		-1.237	3.0698	-0.40	0.687
Block 10		2.951	3.0698	0.96	0.338
Block 11		-1.293	3.0698	-0.42	0.674
Block 12		0.298	3.0698	0.10	0.923
Block 13		6.438	3.0698	2.10	0.037
Block 14		-1.014	3.0698	-0.33	0.741
Block 15		-1.743	3.0698	-0.57	0.571
Block 16		-1.959	3.0698	-0.64	0.524
Block 17		-0.538	3.0698	-0.18	0.861
Block 18		1.224	3.0698	0.40	0.690
Block 19		-2.502	3.0698	-0.82	0.416
Block 20		4.407	3.0698	1.44	0.153
Block 21		-1.048	3.0698	-0.34	0.733
Block 22		-2.222	3.0698	-0.72	0.470
Block 23		-2.526	3.0698	-0.82	0.412
Block 24		-2.127	3.0698	-0.69	0.489
Block 25		1.933	3.0698	0.63	0.530
Block 26		-2.648	3.0698	-0.86	0.389
Block 27		-1.873	3.0698	-0.61	0.542
S	-1.822	-0.911	0.5908	-1.54	0.125
T	1.008	0.504	0.5908	0.85	0.395
C	0.257	0.128	0.5908	0.22	0.828
S*T	1.128	0.564	0.5908	0.95	0.341
S*C	2.618	1.309	0.5908	2.22	0.028
T*C	3.718	1.859	0.5908	3.15	0.002
S*T*C	-1.081	-0.541	0.5908	-0.92	0.361

S = 8.84195   R-Sq = 19.27%   R-Sq(adj) = 4.74%

Analysis of Variance for variance (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Blocks	27	1985.3	1985.3	73.53	0.94	0.554	10.85
Main Effects	3	246.4	246.4	82.13	1.05	0.371	01.35
2-Way Interactions	3	1229.0	1229.0	409.66	5.24	0.002	06.72
3-Way Interactions	1	65.5	65.5	65.49	0.84	0.361	00.36
Residual Error	189	14776.0	14776.0	78.18			80.73
Total	223	18302.2					

Appendices

Appendix-24

Table 5-13 Minitab analysis for Variance of fill weights across filling cycles at Low-P

Factorial Fit: variance versus Block, S, T, C

Var Ac Fc (Half Matrix @ P-) 190605

Estimated Effects and Coefficients for variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		8.24	1.981	4.16	0.000
Block 1		-6.28	7.781	-0.81	0.421
Block 2		-1.60	7.781	-0.21	0.837
Block 3		-10.17	7.781	-1.31	0.193
Block 4		-8.10	7.781	-1.04	0.300
Block 5		-8.42	7.781	-1.08	0.281
Block 6		-3.46	7.781	-0.44	0.657
Block 7		7.34	7.781	0.94	0.347
Block 8		-8.00	7.781	-1.03	0.305
Block 9		2.63	7.781	0.34	0.736
Block 10		9.82	7.781	1.26	0.209
Block 11		5.91	7.781	0.76	0.449
Block 12		-4.71	7.781	-0.61	0.546
Block 13		7.34	7.781	0.94	0.347
Block 14		-4.57	7.781	-0.59	0.558
Block 15		28.30	7.781	3.64	0.000
Block 16		16.14	7.781	2.07	0.040
Block 17		-6.07	7.781	-0.78	0.436
Block 18		-1.60	7.781	-0.21	0.838
Block 19		4.91	7.781	0.63	0.529
Block 20		-4.05	7.781	-0.52	0.603
Block 21		4.63	7.781	0.60	0.552
Block 22		1.89	7.781	0.24	0.809
Block 23		-8.55	7.781	-1.10	0.273
Block 24		-1.36	7.781	-0.17	0.862
Block 25		-5.35	7.781	-0.69	0.493
Block 26		-2.93	7.781	-0.38	0.707
Block 27		-3.23	7.781	-0.41	0.679
S	-24.87	-12.43	1.981	-6.28	0.000
T	1.71	0.85	1.981	0.43	0.667
C	-26.41	-13.20	1.981	-6.66	0.000
S*T	-15.41	-7.70	1.981	-3.89	0.000
S*C	8.17	4.09	1.981	2.06	0.041
T*C	-21.07	-10.54	1.981	-5.32	0.000

S = 20.9649   R-Sq = 53.15%   R-Sq(adj) = 43.60%

Analysis of Variance for variance (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contrib.
Blocks	27	13553	13553	502.0	1.14	0.299	08.92
Main Effects	3	36543	39444	13148.0	29.91	0.000	24.05
2-Way Interactions	3	30676	30676	10225.4	23.26	0.000	20.18
Residual Error	162	71203	71203	439.5			46.85
Total	195	151976					

Appendices

Appendix-25

Minitab analysis for variance of fill weights across filler heads

Factorial Fit: Variance versus P, S, T, C

Var Ac Fh in Fc (Full Matrix) 03/07/05

Estimated Effects and Coefficients for Variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		10.811	1.169	9.25	0.000
P	-2.886	-1.443	1.169	-1.23	0.227
S	-12.370	-6.185	1.169	-5.29	0.000
T	0.949	0.475	1.169	0.41	0.688
C	-14.317	-7.158	1.169	-6.12	0.000
P*S	10.108	5.054	1.169	4.32	0.000
P*T	-0.410	-0.205	1.169	-0.18	0.862
P*C	11.719	5.860	1.169	5.01	0.000
S*T	-6.759	-3.380	1.169	-2.89	0.007
S*C	5.917	2.958	1.169	2.53	0.017
T*C	-9.306	-4.653	1.169	-3.98	0.000
P*S*T	9.297	4.648	1.169	3.98	0.000
P*S*C	-1.579	-0.790	1.169	-0.68	0.504
P*T*C	11.915	5.957	1.169	5.10	0.000
S*T*C	-1.226	-0.613	1.169	-0.52	0.604

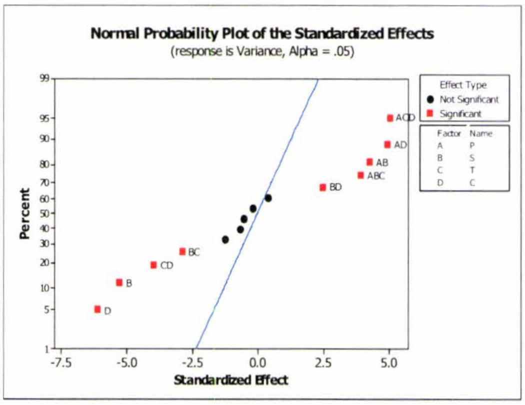
S = 5.72587   R-Sq = 88.47%   R-Sq(adj) = 83.09%

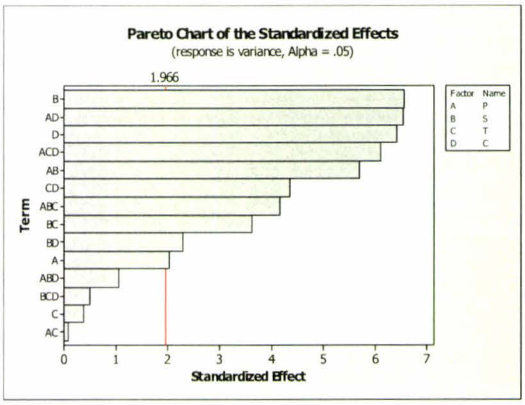
Analysis of Variance for Variance (coded units)

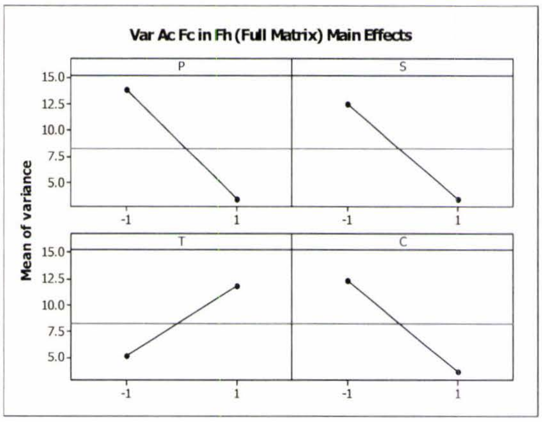
Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contrib.
Main Effects	4	2871.5	3153.3	788.32	24.04	0.000	33.67
2-Way Interactions	6	2929.6	3175.5	529.25	16.14	0.000	34.35
3-Way Interactions	4	1744.5	1744.5	436.13	13.30	0.000	20.45
Residual Error	30	983.6	983.6	32.79			11.53
Pure Error	30	983.6	983.6	32.79			
Total	44	8529.3					

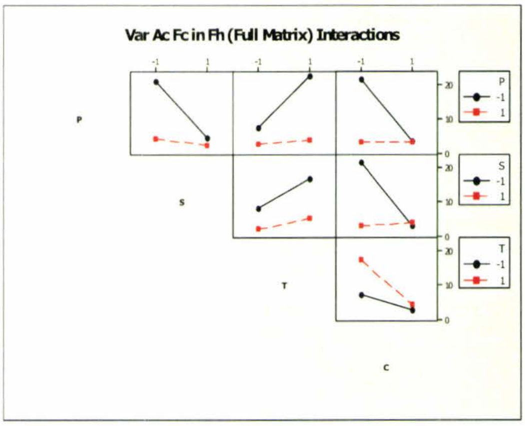
Appendices

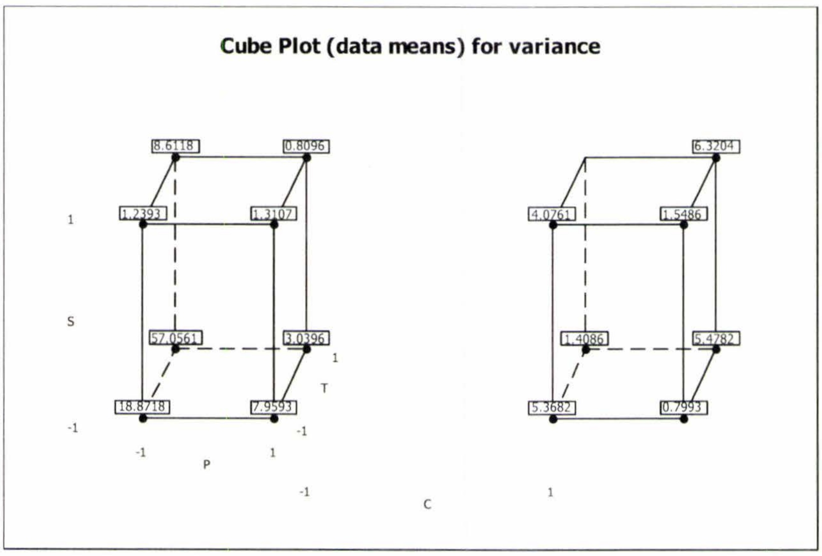
Appendix-26











Var-Ac-Fh (Full Matrix) Minitab graphical out-put

Appendices

Appendix-27

Minitab analysis for variance across filler heads at High-P

Factorial Fit: Variance versus S, T, C

Var Ac Fh in Fc (Half Matrix @ P+) No Blocking

Estimated Effects and Coefficients for Variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		9.368	0.7109	13.18	0.000
S	-2.263	-1.131	0.7109	-1.59	0.131
T	0.539	0.270	0.7109	0.38	0.710
C	-2.598	-1.299	0.7109	-1.83	0.086
S*T	2.537	1.269	0.7109	1.78	0.093
S*C	4.338	2.169	0.7109	3.05	0.008
T*C	2.609	1.305	0.7109	1.84	0.085
S*T*C	-1.226	-0.613	0.7109	-0.86	0.401

S = 3.48266   R-Sq = 58.57%   R-Sq(adj) = 40.44%

Analysis of Variance for Variance (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	% Contrib
Main Effects	3	72.940	72.940	24.313	2.00	0.154	15.57
2-Way Interactions	3	192.363	192.363	64.121	5.29	0.010	41.07
3-Way Interactions	1	9.016	9.016	9.016	0.74	0.401	01.92
Residual Error	16	194.063	194.063	12.129			41.43
Pure Error	16	194.063	194.063	12.129			
Total	23	468.382					

Appendices

Appendix-28

Minitab analysis for variances Across filler heads at Low-P

Factorial Fit: Variance versus S, T, C

Var Ac Fh in Fc (Half Matrix @ P-) using filling cycles with out blocking

Estimated Effects and Coefficients for Variance (coded units)

Term	Effect	Coef	SE Coef	T	P
Constant		12.87	2.168	5.94	0.000
S	-21.25	-10.63	2.168	-4.90	0.000
T	2.59	1.29	2.168	0.60	0.561
C	-24.81	-12.40	2.168	-5.72	0.000
S*T	-14.83	-7.41	2.168	-3.42	0.004
S*C	8.72	4.36	2.168	2.01	0.064
T*C	-19.99	-10.00	2.168	-4.61	0.000

S = 7.50955   R-Sq = 89.12%   R-Sq(adj) = 84.46%

Analysis of Variance for Variance (coded units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P	%Contrib.
Main Effects	3	3315.4	3607.8	1202.59	21.33	0.000	45.68
2-Way Interactions	3	3152.7	3152.7	1050.90	18.64	0.000	43.44
Residual Error	14	789.5	789.5	56.39			10.88
Pure Error	14	789.5	789.5	56.39			
Total	20	7257.6					