A TOOL FOR FUNCTIONAL DATA ANALYSIS AND EXPERIMENTATION

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Abstract

The objective of this research is to demonstrate the necessity of the industry of the use of functional data analysis techniques in order to analyze experiments. The type of experiment analyzed has the peculiarity that the response is measured repeatedly through time or through a specific signal factor. Two case studies are used in order to test the three methods proposed. The first method is a Point-Wise approach in which a classical ANOVA is performed in each level of the signal factor. The second uses a basis to represent the collection of all the response functions in order to relate the coefficients of the basis representation with the factors of the experiment. The third approach is a modification of the second method. The only difference is that regions are predetermined and the basis is applied and analyzed in each region separately. The three methods are proved in order to determine their effectiveness.

Resumen

El objetivo de esta investigación es el demostrar la necesidad de utilizar el análisis de datos funcionales en experimentos industriales. El tipo de experimentos analizados tiene la peculiaridad de que la respuesta se mide repetidamente a lo largo de un factor señal. Dos casos de estudio fueron utilizados para probar los tres métodos propuestos. El primer método se basa en conducir un análisis de varianza en cada nivel del factor señal. El segundo se utiliza una base para representar todas las funciones. Los coeficientes de la base están asociados a los factores del experimento. El tercer método es una modificación del segundo; la única diferencia es que se crean regiones con respecto al factor señal. En cada región se aplica la base y se analizan los coeficientes de la misma. Los tres métodos fueron probados con el propósito de determinar su efectividad.

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Dedicatory

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1 Introduction

1.1 Justification

The technological developments in information processing have made real time process monitoring possible. The result of these developments is the collection of huge amounts of data. For that reason, new techniques are required in order to analyze and take advantage of the data available. Today it is possible to analyze a process or a system considering the input or output variables as functions instead of as discrete points. For this type of analysis some techniques have been developed, for example longitudinal data analysis and the functional data analysis (FDA). These analyses are appropriate when each individual is measured repeatedly through time or through a specific signal factor for example (frequencies, rotating speeds or compression loads [3]). The techniques previously mentioned have been applied successfully in the biological sciences, psychology, and social sciences. Only now are these techniques starting to be applied in engineering problems that affect industry.

In every manufacturing process, it is necessary to establish standards, and monitor the performance of the process in order to ensure the highest quality to the customer. In most of the manufacturing process Statistical Process Control (SPC), the set of tools used to control the process accuracy and precision. However, the implementation of an SPC program is not enough to ensure quality. Sometimes problems occur and it is necessary to have the proper mechanisms to detect the root causes in order to take the necessary corrective actions. One of the most widely used tools to find the root causes of the problems is Design of Experiments (DOE). DOE provides the mechanisms to find the factors that affect directly the process; it can be used as an optimization tool.

For all the reasons mentioned above, it is necessary to develop the proper set of tools to introduce FDA concepts to problems faced by industries. These tools must integrate the analysis of functional data in order to perform successful experiments.

1.2 Objectives

Functional data analysis is very complex; it involves a lot of computational effort and it requires the understanding of topics like, basis functions and Fourier series among others. The main objective of this research is to integrate the capabilities of the functional data analysis to industrial experiments in an efficient manner. Other specific objectives are

- Develop some methods to simplify the experimentation with functional data.
- Analyze and compare the methods proposed
- Develop a series of applications to ease the implementation of the proposed methods in industry

1.3 Organization

Chapter 2 presents the literature review and the background of the most relevant concepts related to the work completed in this research. These concepts include design of experiments (DOE), an introduction to functional data analysis, which is the most important concept, presented in this chapter and some other important topics such as linear regression, and functional analysis of variance. The methodology used to complete the objectives of this thesis is explained in Chapter 3. This chapter includes the discussion of the three methods proposed for this research in detail.

Chapters 4 and 5 present the results for the two case studies selected for this research. The first case is a simulated one; the second is a real world application. Chapter 6 explains the computer applications developed during this research. Chapter 7 presents the conclusions and future work to expand this research.

2 Basic Concepts

Several concepts required for the FDA experimental integration are discussed in this chapter. The concepts are design of experiments, functional data analysis, linear regression, functional analysis of variance, and high dimensional analysis of variance.

2.1 Design of Experiments

2.1.1 General Definition and Objectives

In general terms it is possible to define the concept of design of experiments as the systematic manipulation of certain input variables (factors) to observe their respective impact in an output variable (response variable). The main objectives of the design of experiments are the following

- 1. Obtain the maximum amount of information using the minimum of resources.
- 2. Detect the factors that shift the mean of the response variable.
- 3. Find the factors that affect the dispersion or variability of the response variable.
- 4. Detect the factors that do not have effect any effect in the response variable.
- 5. Construct an empirical model that relates the factors with the response variable.
- 6. Find the proper levels of the main factors to optimize the process.

2.1.2 Factorial Experiments

Factorial experiments are one of the most widely used experimental designs when two or more factors are involved. The basic characteristics of a factorial design are

- 1. All the possible level combinations of every factor are studied.
- 2. It is necessary to investigate the interaction effects among factors.

Among the factorial experiments, the most widely used is the 2^k in which each factor has only two levels. This type of experiment has certain properties desired in experimentation like orthogonality and projection among others.

2.2 Functional Data Analysis

2.2.1 Goals of the Functional Data Analysis

Functional data analysis (FDA) was developed for analyzing functional (or curve) data [2]. In FDA, the data consists of functions not vectors. Samples $y_1, y_2 \dots y_n$ taken at time points t_1, t_2, \dots are converted into functions $\{x(t_j)\}, j = 1, 2, \dots$ as shown on Figure

2-1. The goals of the functional data analysis are

- 1. Represent the data in ways that facilitate further analysis.
- 2. Display the data to highlight various characteristics.
- Explain variation in an outcome or dependent variable by using input or independent variable information.
- Compare two or more sets of data with respect to certain types of variation, where two sets of data can contain different sets of replicates of the same functions, or different functions for a common set of replicates

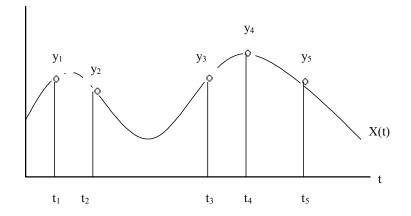


Figure 2-1 Graphical Representation of the Functional Data Problem

2.2.2 Main Steps in an Functional Data Analysis

Assuming that a functional datum for replication *i* arrives as a set of discrete measured values, $y_{i1}, y_{i2} \dots y_{in}$, the tasks required to perform the functional data analysis are [2]

1. The raw data is collected, cleaned and organized.

- Data are converted to functional form. That is, the raw data for observation *i* are used to define a function x_i that can be evaluated at all values of t over some interval.
- 3. Summary statistics and plots can be generated in order to ease the analysis.
- 4. The functions may be registered or aligned in some way; so important features found in each curve occur at roughly the same argument values.
- 5. Exploratory analyses can be carried out on the registered data, for example principal components analysis.
- 6. Models can be constructed to establish the relationship between a dependent variable with respect one or more independent variable.

2.2.3 Representing the Functional Data as a Smooth Function

The simplest way to convert the raw data into a functional object is using interpolation [2], [4]. This technique can be applied in cases when the measures do not have too much observational noise. When the raw data have, considerable noise is necessary to apply a smoother to reduce the effect of the noise in calculations and analysis. There are several types of smoothers that can be applied to functional data for example linear smoothing and smoothing based in basis-function methods. Those two types are explained with more details in the following sections.

2.2.3.1 Linear Smoothing

A linear smoother estimates the function value x(t) by a linear combination of discrete observations

$$\hat{x}(t) = \sum_{j=1}^{n} S_{j}(t) y_{j} \, . \qquad t \in T$$
(2.1)

The behavior of the smoother at t is determined by the weights $S_j(t)$. Linear smoothers can be represented in a matrix form. Suppose that the sequence $s_1 < s_2 < ... < s_m$ of evaluation points in T at which the function x is to be estimated, is on hand. Notice that the evaluation points do not need to be the same as the observation values t_j . Let \hat{x} be the m-vector of values $x(s_i)$ and y for the vector of observed data y_j . Is possible to write

$$\hat{x} = Sy \tag{2.2}$$

where $S_{ij}=S_j(s_i)$.

Many widely used smoothers are linear. The linearity of a smoother is a desirable feature for various reasons: The linearity property

$$S(ay + bz) = aSy + bSy$$

is important for obtaining various properties of the smooth representation. Simplicity of the smoother implies relatively fast computation. The concept of linear smoothing it is shown in Figure 2-2

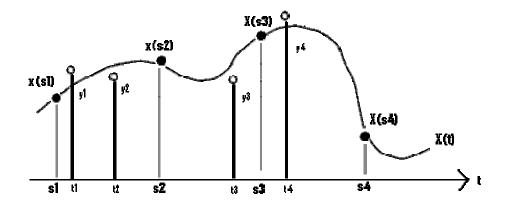


Figure 2-2 Graphical Explanation of the Linear Smoothing approach

From Figure 2-2 it is possible to observe the observed points y_i , i = 1,2,3,..., at times t_i , i = 1,2,3,..., and the predetermined evaluation points are S_i, i = 1,2,3,...

2.2.3.2 Smoothing Based in Basis Function Methods

The function x_i can be represented by a basis function expansion, which is defined by a set of basis functions, $\phi_k, k = 1, ..., K$ [2]. In this approach, a functional observation x_i is expressed as

$$x_{i}(t) = \sum_{k}^{K} c_{ik} \phi_{k}(t)$$
 (2.3)

When these basis functions ϕ_k are specified, then the conversion of the data into a functional data object involves computing and storing the coefficients of the expansion, c_{ik} , into a coefficient matrix.

There are many bases possible, and many considerations to take into account. The following list provides a number of the more common bases:

- 1. Fourier Basis, typically used for periodic data.
- 2. B-Spline Basis, typically used for nonperiodic data.
- 3. Polygonal Basis, defining a function made up of straight-line segments.
- 4. Monomial Basis, consisting of the power of t: 1, t, t^2 , t^3 ...
- 5. Exponential basis, a set of exponential functions, $e^{\alpha_k t}$ each with a different rate parameter α_k .

Of these basis functions, the first two are by far the most important [2]. The Fourier and the Polygonal basis are used when the data does not present many local features in extremely stable functions.

2.2.4 Summary Statistics for Functional Data

The classical summary statistics apply equally for functional data [2]. The mean, variance, covariance and correlation are shown in this section.

1. Mean

$$\bar{x}(t) = N^{-1} \sum_{i=1}^{N} x_i(t)$$
(2.4)

2. Variance

$$\operatorname{var}_{x}(t) = (N-1)^{-1} \sum_{i=1}^{N} \left[x_{i}(t) - \overline{x}(t) \right]^{2}$$
(2.5)

3. Covariance

$$\operatorname{cov}_{x}(t_{1},t_{2}) = (N-1)^{-1} \sum_{i=1}^{N} \left\{ x_{i}(t_{1}) - \overline{x}(t_{1}) \right\} \left\{ x_{i}(t_{2}) - \overline{x}(t_{2}) \right\}$$
(2.6)

4. Correlation

$$corr_{x}(t_{1},t_{2}) = \frac{cov_{x}(t_{1},t_{2})}{\sqrt{Var_{x}(t_{1})Var_{x}(t_{2})}}$$
 (2.7)

2.2.5 Functional Linear Regression

Sometimes it is necessary to establish the relationship between one response variable and two or more independent variables. There are a few possible situations in which the functional linear regression applies [2], and these are

- 1. Functional response with non-functional independent variables.
- 2. Non-functional response with functional independent variables.
- 3. Functional response and functional independent variables.

In this thesis, the situation under study is the first one. This is because in the design of experiments, the set of independent variables (factors) is fixed. The design matrix (in a 2^k factorial design) contains ones and minus ones representing the two levels (low and high) of each factor. To complete the linear regression, which is the fundament of the analysis conducted in every design of experiment, is necessary to understand the linear regression when the data is not functional.

2.2.5.1 Linear Regression

Linear regression analysis is probably the most widely used technique to establish the relationship between a response variable and one or more decision (independent) variables in the form of

$$y = X\beta + \varepsilon \tag{2.8}$$

where X is a matrix n x p, β is a vector p x 1 of the regression coefficients that has to be estimated by $\hat{\beta}$, and ε is the random error that are assumed to be independent are normally distributed with constant variance.

The essence of the linear regression is obtain a model which minimizes the sum of squared errors that are defined as

sum of square errors (SSE) =
$$\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$
. (2.9)

It can be proved that the coefficients that minimize the sum of the square errors can be obtained using the formula

$$\hat{\beta} = (X^T X)^{-1} (X^T y).$$
(2.10)

A serious problem that may dramatically affect the usefulness of a regression model is multicollinearity, or near linear dependence among the regression variables [5]. Regression models fit to data by the method of least of squares when strong muticollinearity is present are notoriously poor prediction equations, and the values of the coefficients are often very sensitive to the data in the particular sample collected [5]. Another effect of the multicollinearity problem is the physical interpretation of the coefficients of the model obtained. The model can fit the data, but the coefficients that are used to determine which factors are more relevant in the experiment can be seriously affected not only in magnitude, the sign of the coefficient can affected. In order to detect the multicollinearity problem the variance inflation factors (VIF) are used. Variance inflation factors greater than 10 imply a serious multicollinearity problem.

In linear regression, not all the regression variables are relevant to the model all the times. Sometimes it is necessary to eliminate some variables from the model. One of the most widely used techniques for variable selection is the backward elimination stepwise procedure. The procedure begins with all **K** candidate regressors. Then a partial F-statistic is computed for each regressor as if it were the last variable to enter the model. The smallest of these partial F-statistics is compared with a pre-selected value F_{out} (or F-to-remove), for example, and if the smallest partial F value is less than F_{out} , the regressor is removed from the model. Now a regression with **K**-1 regressors is fit, the partial F-statistics for this new model calculated, and the procedure repeated. The backward elimination algorithm terminates when the smallest partial F value is no less than the preselected cutoff value F_{out} [5]. The stepwise procedure can be used to improve models that have the multicollinearity problem; due the elimination of the variables that are correlated, the model can be improved dramatically.

2.2.5.2 Functional Analysis of Variance (FANOVA)

The concepts of linear regression can be applied in a Point-Wise manner [2], [3] to functional data following these steps

1. Convert the response variable into a functional form; this implies the execution of most of the steps mentioned previously for example smoothing, registration, etc.

- For each selected level of the signal factor, the coefficients of the model have to be calculated.
- 3. Each coefficient is converted into a function of the signal factor.

In other words the result of this procedure is a group of coefficients that are functions of the signal factor in the same manner that the response variable. In addition, of the functional linear regression a functional analysis of variance can be used to analyze the effects of some variables over the response. FANOVA considers the problem as a univariate ANOVA problem for each specific level of the signal factor. A crucial drawback to this approach is that an enormous number of hypothesis (the number of data points per curve can be hundreds or thousands) has to be tested simultaneously that causes a serious multiplicity problem [9].

2.2.5.3 High-Dimensional Analysis of Variance (HANOVA)

It is a powerful overall test for functional hypothesis testing based on the decomposition of the original functional data into Fourier or wavelet series, and applied the adaptive Neyman and wavelet thresholding procedures to the resulting empirical Fourier and wavelet coefficients respectively. The underlying idea based on the sparcity of the underlying signal's representation in the Fourier or wavelet domains that allows a significant reduction of dimensionality [6], [9]. This procedure is not used in the methods proposed, but it is a good example of how complex the methods developed for curves comparison are.

2.2.5.3.1 Testing Differences among Multiple Groups of Curves

Consider the observed curves from *I* different groups:

$$\{X_{ij}(t), i = 1, 2, \dots, I, j = 1, \dots, n_i, t = 1, \dots, T\}$$

It is possible to assume that

$$X_{ii}(t) = f_i(t) + \varepsilon_{ii}(t) \tag{2.11}$$

where $\{e_{ij}(t), t = 1,..., T\}$ are stationary time series with mean 0. One is interested in testing hypothesis:

$$Ho: f_i(t) = f(t)$$

 $H_1: f_i(t) \neq f(t)$ for i = 1,..., I and t = 1,..., T

Let $\{X_{ij}^*(t)\}$ be the direct Fourier transform of the vector $\{X_{ij}(t)\}$. Then $\{X_{ij}^*(t)\}$ satisfied the ideal model

$$X_{ij}^{*}(t) = f_{i}^{*}(t) + \varepsilon_{ij}^{*}(t)$$
(2.12)

Then the previous hypothesis is equivalent to the following problem $Ho: f_i^*(k) = f^*(k)$ for i = 1,...,I and k = 1,...,T then it is possible to apply the Adaptive Analysis of Variance [6].

2.2.5.3.2 Adaptive Analysis of Variance

For simplicity of notation, it is possible to state the HANOVA as follows: let $X_{ij} \sim N(\mu_{ij}, \sigma_{ij}^2)$ be independent and random variables [6]. One wants to test

Ho :
$$\mu_{ij} = \mu_j$$
 for i = 1,..., I and j = 1,..., n

where n is large. It is assumed that $\{\sigma_{ij}^2\}$ are known. Suppose that prior knowledge indicates that useful information is concentrated on the first *m* cells. Then the following sub-problem is considered

Ho :
$$\mu_{ij} = \mu_j$$
 for j = 1,..., m

The maximum likelihood ratio statistic for the sub-problem is

$$X^{2} = \sum_{j=1}^{m} \sum_{i=1}^{I} \sigma_{ij}^{-2} \left(X_{ij} - \overline{X}_{.j} \right)^{2}$$
(2.13)

with

$$\overline{X}_{.j} = \frac{\sum_{i=1}^{I} \sigma_{ij}^{-2} X_{ij}}{\sum_{i=1}^{I} \sigma_{ij}^{-2}}$$
(2.14)

Thus a level- α test is to reject Ho when

$$F_{m} = \frac{1}{\sqrt{2(I-1)m}} \left\{ \sum_{j=1}^{m} \sum_{i=1}^{I} \sigma_{ij}^{-2} (X_{ij} - \overline{X}_{.j})^{2} - (I-1)m \right\}$$

$$\geq \frac{1}{\sqrt{2(I-1)m}} \left\{ X_{(I-1)m}^{2} (1-\alpha) - (I-1)m \right\}$$
(2.15)

Note that when the degrees of freedom (I-1)m are large, F_m is normally distributed with

mean
$$\delta_m^{*2} = \frac{\delta_m^2}{\sqrt{2(I-1)m}}$$
 and variance 1. Where $\delta_m^2 = \sum_{j=1}^m \sum_{i=1}^I \sigma_{ij}^{-2} (\mu_{ij} - \overline{\mu}_{j})^2$ with

$$\overline{\mu}_{j} = \frac{\sum_{i=1}^{I} \sigma_{ij}^{-2} \mu_{ij}}{\sum_{i=1}^{I} \sigma_{ij}^{-2}}.$$
 In practice, *m* must be determined as $\hat{m} = \underset{1 \le m \le n}{\operatorname{arg\,max}} F_{\mathrm{m}}$ leading to the

adaptive testing statistic, which defines the HANOVA

$$F_{\hat{m}} = \max_{1 \le m \le n} \frac{1}{\sqrt{2(I-1)m}} \left\{ \sum_{j=1}^{m} \sum_{i=1}^{I} \sigma_{ij}^{-2} (X_{ij} - \overline{X}_{j})^2 - (I-1)m \right\}$$
(2.16)

Specifically when I=2, the test statistic reduces to

$$F_{\hat{m}} = \max_{1 \le m \le n} \frac{1}{\sqrt{2m}} \left\{ \sum_{j=1}^{m} \frac{\left(X_{1j} - X_{2j}\right)^2}{\sigma_{1j}^2 + \sigma_{2j}^2} - m \right\}$$
(2.17)

From the previous sections, it is possible to observe the amount of concepts that will be integrated and simplified on this work. As mentioned on the first chapter, the intention of this research is to make feasible the use of these tools in industry. The next chapter presents the details of the methodology that will be used during this work. Three methods were proposed based on the concepts presented on this chapter.

3 Methodology

3.1 **Point-Wise method**

The Point-Wise method is based on the ideas of the functional data analysis (FDA) proposed by Ramsay and Silverman [2] in their book and papers in specific in the functional analysis of variance (FANOVA) mentioned in the previous chapter. A linear regression model is generated at each level of the signal factor. Then curves of coefficients are obtained. In other words, dynamic models are generated. The main difference of this method with respect the FDA is that no smoothing techniques have been used. In the type of industrial experiments considered there is no interest with respect the derivatives of the response variable; this is the justification for not using the smoothers; also simplification is highly desired in a technique that will be applied in the industry. In addition to the coefficients, the respective statistical tests to validate the regression are performed at each level of the signal factor. To be more specific, an F-test to verify the significance of the regression and a T-test to verify the contribution of each factor are performed at each level of the signal factor resulting in curves for the F and T tests. In addition, the residuals and the coefficients of determination are calculated at each level of the signal factor.

3.1.1 Model Validation and Inference

As mentioned previously, an F test is applied to validate the significance of the regression at each level of the signal factor. The F test is used to complete the following hypothesis test

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$
$$H_1: \beta_j \neq 0 \text{ for at least one j.}$$

The statistical test is given by

$$F_0 = \frac{MSR}{MSE} \tag{3.1}$$

where the MSE is the mean squared error and the MSR is the mean squared regression. The hypothesis is rejected if $F_0 > F_{\alpha,p-1,n-p}$.

The coefficients are verified in order to know which ones are making a real contribution to the model. This is very important because the coefficients of the regression are associated with a factor or combinations of factors in the experiment. The hypothesis for the coefficients is given by

$$H_0: \beta_j = 0$$
$$H_1: \beta_j \neq 0$$

The statistical test t used is given by

$$t_0 = \frac{\hat{\beta}_j}{\sqrt{\hat{\sigma}^2 C_{jj}}} \tag{3.2}$$

where C_{jj} is the diagonal element of $(\mathbf{X}^{*}\mathbf{X})^{-1}$ corresponding to $\hat{\beta}_{j}$. The null hypothesis is rejected if $|t_{o}| > t_{\alpha/2,n-k-1}$ [1].

An important measure of performance for the linear regression models is the determination coefficient R^2 that is a measure of the total variability of the data explained by the model. The formula for this coefficient is

$$R^2 = \frac{SSR}{SSE}$$
(3.3)

Because R^2 always increases as more terms enter to the model [1]. It is preferred to use the adjusted R^2 defined as

$$R_{adj}^{2} = 1 - \left(\frac{n-1}{n-p}\right) (1-R^{2})$$
(3.4)

In addition to the previous measures of performance, the Matlab® applications created generate the plots for the residuals in order to validate the stochastic assumptions for the linear regression. The model validation procedure is also part of the other two methods that are going to be presented in this chapter.

3.2 Basis Representation Model

The focus of this method is to represent the response functions as a sum of basis functions. However, in this representation the coefficients of the basis functions are going to be dependent on the factors of the experiment. The purpose of this representation is to provide a direct way to capture the factors that have more relevance in the experiment. In the FDA, the basis representation is used to estimate the response curves. In this method, the idea is to relate directly the response to the factors. Several bases can be applied. The basis selection is going to depend on the behavior of the responses. In the Matlab, applications developed in this work three type of basis are considered: Monomial basis, Fourier basis and a Cubic Spline basis. These bases have been widely used. To illustrate this method, an example is presented in the next section.

3.2.1 An Example for the Basis Representation Method

Suppose that an experiment with two factors $(x_1 \text{ and } x_2)$ and a functional response is being analyzed. The analyst considers important the interaction between the factors and considers that a Fourier basis will be appropriate for the data due the periodical behavior of the response. The general form for a Fourier basis expansion is the following:

$$y(t) = c_0 + c_1 \sin(\omega t) + c_2 \cos(\omega t) + c_3 \sin(2\omega t) + c_4 \cos(2\omega t) + \dots$$
(3.5)

where $\omega = \frac{2\pi}{T}$ and T is the highest level of the signal factor [2]. Since the interaction is going to be considered, the first term of the expansion will be $c_0 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2$ and the general basis representation model for this example will be

$$y(t) = (\beta_{00} + \beta_{10} x_{10} + \beta_{20} x_2 + \beta_{30} x_1 x_2) + (\beta_{01} + \beta_{11} x_1 + \beta_{21} x_2 + \beta_{31} x_1 x_2) \sin(\omega t) + (\beta_{02} + \beta_{12} x_1 + \beta_{22} x_2 + \beta_{32} x_1 x_2) \cos(\omega t) + (\beta_{03} + \beta_{13} x_1 + \beta_{23} x_2 + \beta_{33} x_1 x_2) \sin(2\omega t) + (\beta_{04} + \beta_{41} x_1 + \beta_{24} x_2 + \beta_{34} x_1 x_2) \cos(2\omega t) + \dots$$
(3.6)

The dependence of the coefficients of the basis representation on the factors of the experiment can be observed directly. The measures of performance discussed previously

(Section 3.1.1) can be applied in order to determine the effectiveness of the model. If the design matrix \mathbf{X} have coded variables then the magnitudes of the resulting coefficients can be used to determine which factors are the most important in the experiment. The same procedure can be applied to the other bases; the key element is to pick the right basis and the best number of terms for the basis expansion.

3.3 Piece-wise Method

In all the previously designed methods, the dimensionality is an issue. As the number of levels of the signal factor increases so does the complexity of the analysis. It is necessary to develop an approach able to deal with the dimensionality problem and detect which factors are more relevant in the experiment. A Piece-Wise approach has been proposed the idea of this method is the following:

- Divide the range of the signal factor in a series of regions
- Use a common basis representation in each region.
- Perform a stepwise procedure in order to simplify the model and eliminate the non-relevant terms in the regressions.
- Verify the coefficients of the regression in order to determine which factors are more relevant in the experiment per region.

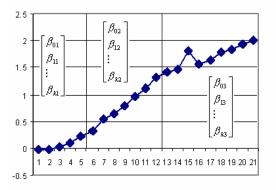


Figure 3-1 Illustration of the Piece-Wise method. In each region, there is a set of coefficients for one experimental condition

This procedure is a modification to the basis representation method. The only difference between both procedures is the division of the levels of the signal factor. This

procedure is used when one desires to know which factors are affecting the response in some specific regions of the signal factor.

A challenge behind this method is to find an optimal method to obtain the knots that are used to divide the levels of the signal factor in regions. For a predetermined number of knots k that divides the levels of the signal factor in k+1 region, it is necessary to determine the optimal position of those knots. Let *knots* be the vector of positions for the different levels of the signal factor, that are equally spaced. Let SSE_i be the Sum Squared of Error for the region i. The optimization problem is stated as follows

$$\min z = \sum_{i} SSE_{i}$$
(3.7)

Subject to

$$knots(j+1) - knots(j) \ge B \quad \forall j, j = 1, 2, \dots k$$
 (3.8)

$$length(knots) \le floor\left(\frac{length(t)}{B}\right) - 1$$
 (3.9)

$$knots(1) \ge B \tag{3.10}$$

$$knots(k) \le length(t) - B$$
 (3.11)

$$B \ge 0 \tag{3.12}$$

where length(t) is the number of levels of the signal factor *t*, and B is a parameter that sets the minimum distance between knots in order to ensure the feasibility of the regressions.

The first constraint forces the knots to keep a distance of B levels in order to make the regression estimation possible. The second restriction delimits the number of knots to be used. This number cannot be more than the total levels of the signal factor divided by the constant B minus one; this constraint guarantees that there are enough points for the last region. The third constraint forces the first knot to be at the B position or higher in the levels of the signal factor, as the previous restriction this forces the regions to have enough points to estimate the regressions required at each region. The value for the constant B was selected to be equal to three. That value was selected in order to limit the maximum number of knots to be less than a third part of the signal factor levels. Equation 3.11 ensures enough points for the regressions in the last region. The last restriction is for the values of B that must be positive. All the values of the vector *knots* have to be integer due the definition of the variable. This is a limitation in terms of the software that is been used because the optimizations tools of Matlab do not deal with integer variables.

There is another constraint that has to be considered, the continuity of the functions at the knots. In order to force the models to obey this restriction the following final procedure was used.

- 1. Divide the response matrix into regions delimited by the knots
- 2. Obtain the models for each region using the ordinary least of squares
- 3. Find the average of the estimated responses per experimental condition at the last signal factor level of the first (previous) region
- Use the averages previously calculated as constraints for the indicator variables of the next region. The number of indicator variables to use will be the number of experimental conditions minus one.
- 5. Calculate the coefficients of the regression using the restricted least of squares procedure based on the following formula

$$\mathbf{b}_{r} = \mathbf{b} + (\mathbf{X}^{T}\mathbf{X})^{-1}\mathbf{R}^{T}[\mathbf{R}(\mathbf{X}^{T}\mathbf{X})^{-1}\mathbf{R}^{T}]^{-1}(\mathbf{r} - \mathbf{R}\mathbf{b})$$
(3.13)

where b_r is the vector of the restricted coefficients obtained from Equation 3.13, b is the vector of coefficients obtained by the ordinary least of squares regression, R and r are the restrictions expressed in the following form $\mathbf{R}\beta = \mathbf{r}$. The number of rows of the matrix R will be equal to the number of the experimental conditions minus one. The number of columns of the R matrix it is going to be equal to the number of terms of the basis expansion plus the number of indicator variables.

6. Repeat steps 3 to 5 on the other regions

A procedure was developed in order to find the optimal set of knots given a desired number of knots. This method is not efficient but it is effective. The main idea is to evaluate all the possible combinations of knots for a pre-selected quantity; and select the combination that minimizes the total sum of squared errors. The computational effort increases as the number of knots increases. The optimal knots are used to delimit the regions and perform the rest of the procedure.

In each region a basis, it is going to be used in order to model the behavior of the responses. The bases that are going to be used are the monomial basis and a Fourier basis, the cubic spline is not going to be considered. Since this basis in the previous method was used to incorporate some delimitation of regions in the estimates. In this method is not necessary because the signal factor has been divided before completing the basis expansions. The following section presents a detailed example for this method.

3.3.1 An Example for the Piece-wise Method

Suppose that an experiment was conducted considering two factors $(x_1 \text{ and } x_2)$, with functional response. The analyst wants to study two regions; this means that only one knot is required. Assume that the optimal knot location is known and the initial models were obtained, considering a monomial basis. The Figure 3-2 illustrates the separation of the response curves of the two regions at the knot for two experimental conditions with two replicates.

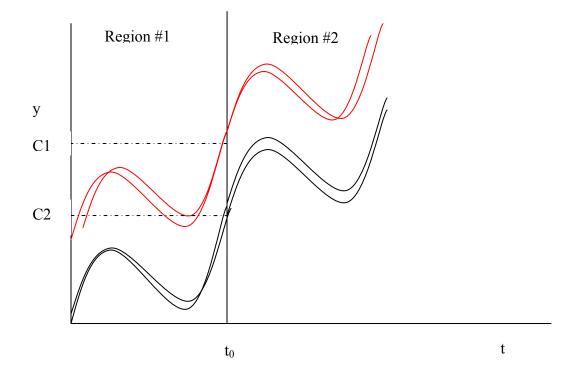


Figure 3-2 Illustration of the separation of two adjacent curves at the knot t₀

The point C1 and C2 represents the averages of the estimated responses at the last level of the first region for two of the experimental conditions. The functions on represents the functions obtained in each region without the continuity constraint. The next step of this procedure is to set C1 or C2 (one of the experimental conditions must be used as a base for the indicator variables) as the constraint for the indicator variable for the next region model; let us take C2 for this example. Suppose that a monomial basis is used, then the expansion for the second region is in the form of the Equation 3.14

$$y(t) = (b_{00} + b_{10}x_1 + b_{20}x_2 + b_{30}x_1x_2) + (b_{01} + b_{11}x_1 + b_{21}x_2 + b_{31}x_1x_2)(t - t_0) + (b_{02} + b_{12}x_1 + b_{22}x_2 + b_{32}x_1x_2)(t - t_0)^2$$
(3.14)

From Equation 3.14 it is possible to observe that the terms related to the signal factor the knot is subtracted. The reason for this is in order to let the indicators variables to take all the effect of the imposed restrictions. The restrictions matrix (R) and right hand side (r) have the following form

$$R = (1,0,\dots,0,1)$$
 and $r = (C_2)$ (3.15)

After imposing the restriction, the restricted least of squares procedure is completed for the second region. The coefficients of all the regions except for the first one are obtained using the restricted least of squares.

3.4 Metric of comparison for the all methods

In order to compare all the methods it is necessary to establish a metric or a measure of performance. The metric considers some important quantities such as the number of parameters estimated, the sum of all the squared sums of error and the total number of data points used. The name given to this metric is "pseudo-MSE" and the following equation defines it.

Pseudo MSE =
$$\frac{\text{Total SSE}}{\text{N} - \text{total number of parameters}}$$
 (3.16)

where *Total SSE* is the total sum of all the SSE. In the basis representation method, this is a single number but in the Point-Wise approach, there is an SSE at every level of the signal factor. The variable N represents the total number of data points used, and the variable *total number of parameters* is the total number of parameters (coefficients) estimated in the procedure. For the basis representation method this is the total number of coefficients of the basis expansion, for the Point-Wise and the Piece-Wise methods is the total number of coefficients calculated for the whole procedure. It is important to mention that Equation 3.16 must include the indicator variables used for the continuity constraint, which implies an additional lost of degrees of freedom. In general, the method with the lowest pseudo-MSE will be preferred.

The next chapter presents the results obtained using the methods presented on a theoretical case study that was developed in order to challenge the proposed methods and verify their efficacy. Also was intended to compare the procedures as mentioned earlier in order to determine which procedure is better than the others.

4 Theoretical Case Study

4.1 Introduction

Two case studies are used to compare and validate the proposed methods. The first case is presented in detail in this chapter. This chapter begins with a description of the experiment. Then the results obtained using each method is going to be presented and discussed.

4.2 **Experiment Description**

A macro was created in MS Excel® to generate the functions that correspond to each treatment in the experiment. It is important to mention that the function used to create the macro and the nature of the errors was unknown to the author until the end of the study. Appendix #1 shows some details with respect to the function used. The experiment has two factors each one with two levels (a classical 2^2 experiment) and 21 measures of the response variable were generated in each treatment. In addition, a central treatment was performed in each run. A sample of a single run of this experiment is shown in Figure 4-1.

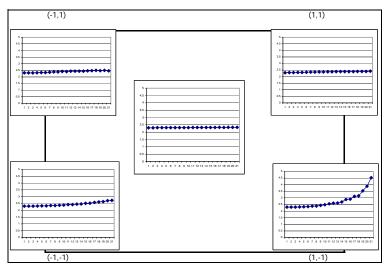


Figure 4-1 A graphical representation of a full run of the theoretical case study

From Figure 4.1 shows that the response function changes at each combination of factors. Five runs of the experiment were used to test the methods. The figures and the

tables for all the runs are presented in the Appendix #1. The general model used as a base for all the methods is given by

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \hat{\beta}_3 x_1 x_2 \tag{4.1}$$

where x_1 and x_2 are the factors of interest in the experiment. For the Point-Wise method, the coefficients of Equation 4.1 are calculated at each level of the signal factor. For the other two methods, the Equation 4.1 is inside each term in the expansions. In the same way as presented in the example on section 3.2.1. The results for the application of each method are presented next.

4.3 **Results for Theoretical Case**

4.3.1 Point-Wise Method

A variable transformation $y = \ln(y+10)$ was necessary to scale all the functions. The transformation was selected because adding the ten eliminated the possibility of having negatives inside the logarithm and this mathematical function was used due the shape of the original functions. This transformation is used for all the methods. From Figure 4-2 one can observe the need of the variable transformation in order to put all the runs of the experiment in a more suitable scale. A Matlab® program was created in order to ease the analysis of the data. The results of the Point-Wise analysis of variance and the measure of performance for the method are shown in the next pages.

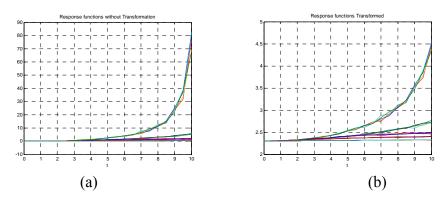


Figure 4-2 Plot of all the functions for the five runs of the theoretical experiment. (a) Responses without Transformation, (b) Responses Transformed.

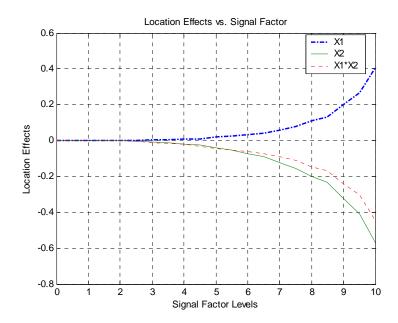


Figure 4-3 Location effects for theoretical case study using the Point-Wise method

The model generated in each level of the signal factor corresponds to Equation 4.1 as mentioned previously and the coefficients at each level are included in Table 4-1. It is possible to observe from Figure 4-3 that both factors are relevant in this experiment. In the first levels of the signal factor, the values for of the effects are very close to zero. The effects that correspond to x_1 have larger magnitudes with respect x_2 and their interaction on the first levels of the signal fact (0 to 2); then x_2 becomes more relevant than x_1 but the interaction effects have the larger magnitudes on the higher levels of the signal factor (2.5 to 10).

t	\hat{eta}_0	$\hat{oldsymbol{eta}}_1$	\hat{eta}_2	\hat{eta}_3
0	2.3016	0.001875	-5.50E-05	3.50E-05
0.5	2.3035	0.00183	-8.00E-05	0.00137
1	2.3078	0.001705	-0.00018	0.001605
1.5	2.3139	0.00178	-0.00079	0.00018
2	2.322	0.00172	-0.00172	-0.0011
2.5	2.3315	0.00207	-0.00402	-0.00549
3	2.3432	0.00302	-0.00616	-0.01015
3.5	2.3545	0.00539	-0.01182	-0.01548
4	2.3681	0.008675	-0.01905	-0.02124
4.5	2.3871	0.010345	-0.02607	-0.0322
5	2.4057	0.01938	-0.0421	-0.04274
5.5	2.4241	0.024105	-0.05247	-0.05179
6	2.4448	0.03193	-0.07309	-0.06225
6.5	2.4643	0.04327	-0.09145	-0.07266
7	2.493	0.05878	-0.12118	-0.09134
7.5	2.5238	0.078595	-0.15351	-0.11118
8	2.5666	0.11049	-0.20129	-0.14681
8.5	2.5963	0.12966	-0.23407	-0.16937
9	2.6718	0.20146	-0.32303	-0.24241
9.5	2.7434	0.2648	-0.40945	-0.30374
10	2.877	0.40942	-0.57222	-0.44798

Table 4-1 Coefficients Table

The residuals plot is next. The importance of this plot is to validate the stochastic assumptions with respect to the behavior of the regression errors. Residuals are shown in Figure 4-4.

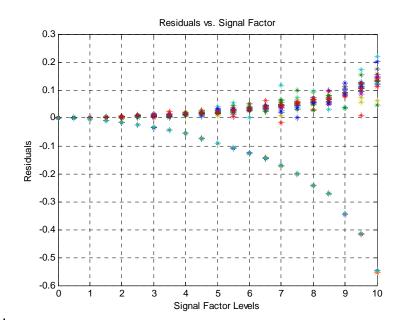


Figure 4-4 Residuals plot for the theoretical case using the Point-Wise method

This graph can be used to verify if the variance of the models is constant. The obtained models variances are not constant. The problem corresponds to a specific experimental condition $(x_1 = 1, x_2 = -1)$. A dramatic change in the response occurs in that experimental condition. This change can be seen in Figure 4-1 and in Figure 4-2. The models underestimation of the response at the mentioned experimental condition increases with the signal factor. For the rest of the experimental conditions the residuals look approximately constant. The next three figures provide different measures of performance in order to verify the model adequacy. These measures of performance include the F ratio tests, the determination coefficient and the T test discussed previously.

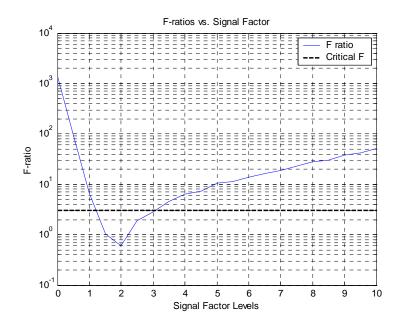


Figure 4-5 F ratio test for the theoretical case using the Point-Wise method

Figure 4-5 show that all the regressions conducted by the Point-Wise procedure for this experiment were significant. The critical F distribution value for all cases is 3.0725.

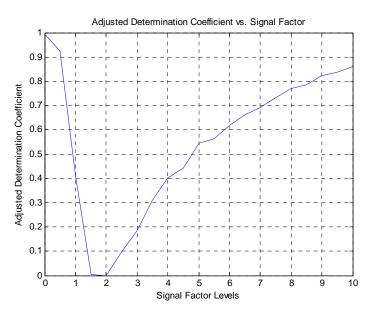


Figure 4-6 Adjusted R² for the theoretical case study using the Point-Wise method

Figure 4-6 shows the adjusted determination coefficient for all the regressions executed. It is possible to deduce that most of the regressions are reasonable because the adjusted R^2 is over 0.60, which might be acceptable in practice. For the signal factor levels from 0.5 to 5, the regressions are not very effective and the adjusted R^2 's are very low.

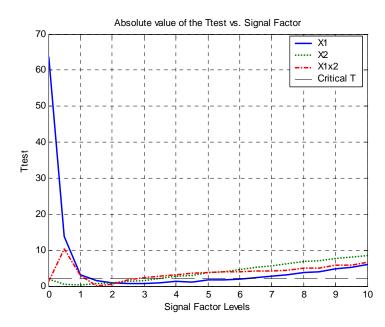


Figure 4-7 Absolute value of the T test for the theoretical case using the Point-Wise method

The T test plot in Figure 4-7 shows that the coefficients were significant for most of the regressions. In the signal factor, levels from 0.5 to 5 most of the coefficients are considered non-relevant.

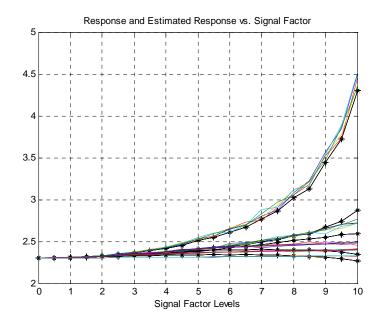


Figure 4-8 Response and Estimated Response Plot for the theoretical case using the Point-Wise method. The asterisks represent the estimated response.

Figure 4-8 shows the response and the estimated response on the same set of axes. The asterisks on the plot represent the estimated response. Form this figure can be observed that the obtained models estimate the response function in a reasonable manner. The next Figure 4-9 shows the lack of fit F ratio test for the Point-Wise analysis of variance realized. This graph potentially indicates a curvature component that has not been considered by the individual analyses of variance. This can be the reason of the low values of the adjusted determination coefficients in this procedure. In addition, it could be the explanation for the behavior of the residuals.

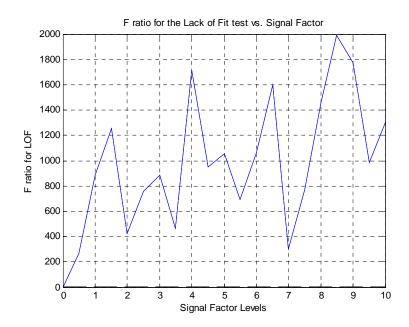


Figure 4-9 F ratio test for the lack of fit for the theoretical case study

The pseudo-MSE for this procedure is summarized in the next table.

Total SSE	Total Number of	Total Number of	Pseudo MSE
	Parameters	Data Points	
5.48682	84	525	0.0124

Table 4-2 Pseudo-MSE for the theoretical case using the Point-Wise method

In general, this method worked is adequate for this experiment, with the transformed data. An important fact is that the results obtained using the Point-Wise method are exactly the same results obtained using the functions prepared by Ramsay to perform the Functional Analysis of Variance (FANOVA) with exception of the smoothing of the curves, the shape and the inferences obtained with both methods are the same (see Appendix #2). In the next section, the results for the basis representation method are presented.

4.3.2 Basis Representation Method

4.3.2.1 Monomial Basis

The selected monomial basis has the following general form

$$y(t) = c_0 + c_1 t + c_2 t^2 + c_3 t^3 + \dots + c_k t^k$$
(4.2)

Inserting the general model used in the experiment provides the following a basis representation with k = 2:

$$y(t) = (b_{00} + b_{10}x_1 + b_{20}x_2 + b_{30}x_1x_2) + (b_{01} + b_{11}x_1 + b_{21}x_2 + b_{31}x_1x_2)t + (b_{02} + b_{12}x_1 + b_{22}x_2 + b_{32}x_1x_2)t^2$$
(4.3)

The k =2 was selected because a higher number in this case will produce a serious multicollinearity problem. The results obtained for this model are shown in the next pages. The calculations were performed using an application created in Matlab. The first column of the Matlab output labeled as "Terms" indicates with a number which term of the basis corresponds to each coefficient. The Table 4-3 summarizes the relationship between the column "Term" and the coefficient of the basis that is being represented.

Table 4-3 Relation between the Matlab's output column "Term" and the coefficients of Equation 4.3

Terms	Coefficient Represented	Related Factor	Basis Term
0	b ₀₀	1	1
1	b ₁₀	X1	1
2	b ₂₀	X2	1
3	b ₃₀	X1*X2	1
4	b ₀₁	1	t
5	b ₁₁	X1	t
6	b ₂₁	X2	t
7	b ₃₁	X1*X2	t
8	b ₀₂	1	t^2
9	b ₁₂	X1	t^2
10	b ₂₂	X2	t^2
11	b ₃₂	X1*X2	t^2

The following is the initial output generated by the application.

Table 4-4 Initial Matlab Output for the Theoretical Case Study Using the Basis Representation Model with a Monomial Basis (K =2)

```
The model is not a good one due a multicollinearity problem
§_____§
Results for the Analysis of Variance for the Basis Representation Model
&_____%
Type of Basis: monomial
Number of basis functions or knots if the basis is a Cubic Spline:
ş_____ş
                 Coefficients and Variance Inflation Factors
&_____&
Term Intercept SE Coef T-test P-value
      2.3266 0.014077 165.2737 0
  0
 Term Coefficients SE Coef T-test P-value
                                            VIF
  1.00000.04020.01572.55340.01102.0000-0.04350.0157-2.76350.0059
                                            7.4822
                                             7.4822
  3.0000 -0.0312 0.0157 -1.9827 0.0479 7.4822
  4.0000 -0.0210 0.0065 -3.2125 0.0014 14.7300
  5.0000 -0.0411 0.0073 -5.6316 0.0000 54.9026
 5.0000-0.04110.0073-5.63160.000054.90266.00000.04890.00736.70460.000054.90267.00000.03410.00734.68060.000054.90268.00000.00680.000610.8124014.73009.00000.00680.00079.6571032.214910.0000-0.00910.0007-12.9937032.214911.0000-0.00660.0007-9.4092032.2149
<u>&_____&</u>
            R^2 and Adjusted R^2
ş_____$
 R^2, R^2(adj)
0.85255 0.84939
۶_____۶
           Analysis of Variance
%_____
                                                    _____%

        Source
        DF
        SS
        MS
        F
        P

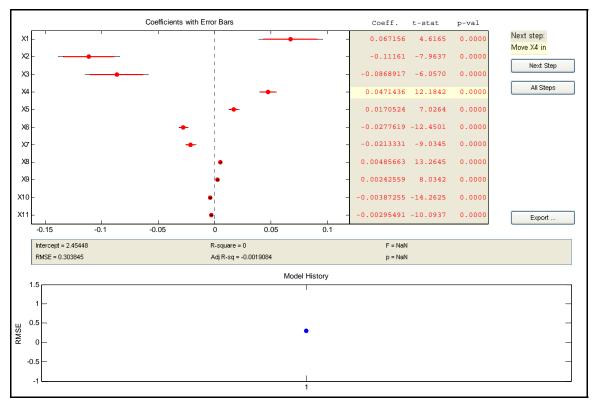
        Regression
        11
        41.2436
        3.7494
        269.6507
        0

        Residual Error
        513
        7.1331
        0.013905
        7

        Total
        524
        48.3767
        48.3767
        48.3767

<u>%</u>_____%
```

By inspecting the VIF in Table 4-4 one can conclude that the model has a multicollinearity problem. In addition to that problem, some of the terms must be eliminated in order to improve the adequacy of the basis representation model. To complete that task the stepwise command of Matlab is used. This command generates a graphical use interface (GUI) in which the user can select the terms to eliminate. For each term selected, the root mean squared, the determination coefficient R^2 , the F ratio and the corresponding p-value are calculated. The Figure 4-10 shows the GUI that corresponds to



the stepwise command with all the terms in the model. When a term is eliminated, the text and graphs that correspond to that term change the font color.

Figure 4-10 Outputs of the Matlab stepwise command.

After the elimination of some terms, the final results using the monomial basis representation model are obtained. The final results are shown in Table 4-5 and in Figure 4-11.

 Table 4-5 Final Matlab Output for the Theoretical Case Study Using the Basis Representation Model with a Monomial Basis (K =2)

5							
5			nts and Var				
Cerm Intero							
0 2.32	266	0.015659	148.5765	0			
Term Coe	efficient	s SE Coe	f T-test	P-value	VIF		
2.0000			4.7834				
4.0000	-0.0210	0.0073	-2.8879	0.0040	14.7300		
8.0000	0.0068	0.0007	9.7201	0	14.7300		
			17.5755	0	1.0000		
10.0000	-0.0046	0.0002	-22.4980	0	2.1870		
11.0000				0	1.0000		
	1	R^2 and A	 djusted R^2				
R^2, R^2							
0.81577 0.83	L364						
			of Variance				
Source	DF	SS	MS		F	P	
Regression	б	39.4642	6.577	4 382	.2813	0	
Residual Error	c 518	8.9125	0.017	206			
Total	524	48.3767					

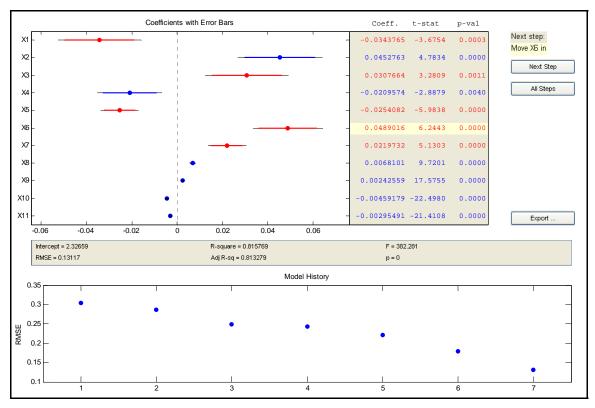


Figure 4-11 Final results for the Monomial basis representation model.

After the elimination of some terms, the multicollinearity problem was almost eliminated. Considering the problem presented by the model, some observations can be realized. The terms 2, 4, 8, 9, 10, and 11 are the coefficients relevant in the model. The Table 4-6 summarizes the results previously mentioned and shows the factors that correspond to each of the coefficients that stayed in the model.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
2	b ₂₀	0.0453	X2	1
4	b ₀₁	-0.0210	1	t
8	b ₀₂	0.0068	1	t ²
9	b ₁₂	0.0024	X1	t^2
10	b ₂₂	-0.0046	X2	t^2
11	b ₃₂	-0.0030	X1*X2	t^2

Table 4-6 Results summary for Monomial basis representation for the theoretical case

Using the results presented in the Table 4-6 some inferences can be done. The more relevant terms corresponds to both factors and their interaction. These results are acceptable because most of the multicollinearity problem was solved using the stepwise procedure. The first model had a maximum Variance Inflation Factor (VIF) over 50 and the final model has a maximum VIF of 15. In addition, the adjusted determination coefficient is over 80%, which is an acceptable number for that adequacy measure. The graphs for the estimated responses and residuals are shown in the next two figures.

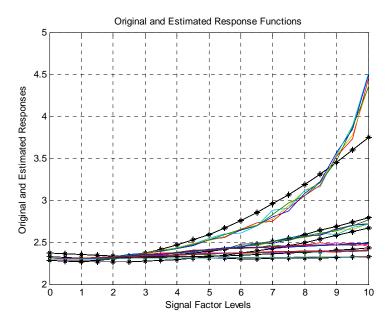


Figure 4-12 Responses and estimated responses for the Basis Representation Final Model with a Monomial Basis for the Theoretical Case Study. The asterisks correspond to the estimated functions.

From Figure 4-12 one can observe that estimated responses are adequate for most of the experimental conditions. The residuals plot presented in Figure 4-13, shows that the model does not obey the stochastic assumption for the regression model of constant variance.

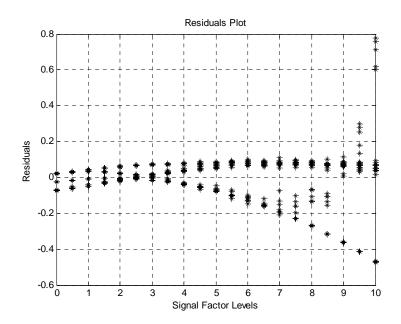


Figure 4-13 Residuals for the Basis Representation Final Model with a Monomial Basis for the Theoretical Case Study

The Table 4-7 presents the pseudo-MSE that is going to be used to compare this procedure with the other methods.

Table 4-7 Pseudo-MSE for the theoretical case using the basis representation method with a
Monomial basis

Total SSE	Total Number of Parameters	Total Number of Data Points	Pseudo MSE
8.9124	7	525	0.0172

The next section have the results obtained using a Fourier Basis Representation

4.3.2.2 Fourier Basis

The general Fourier series representation has the following form

$$y(t) = c_0 + c_1 \sin(\omega t) + c_2 \cos(\omega t) + c_3 \sin(2\omega t) + c_4 \cos(2\omega t) + \dots$$
(4.4)

where $\omega = \frac{2\pi}{T}$ and T is the highest level of the signal factor. The model used for the experiment was the following

$$y(t) = (b_{00} + b_{10}x_1 + b_{20}x_2 + b_{30}x_1x_2) + (b_{01} + b_{11}x_1 + b_{21}x_2 + b_{31}x_1x_2)\sin(wt) + (b_{02} + b_{12}x_1 + b_{22}x_2 + b_{32}x_1x_2)\cos(wt) + (b_{03} + b_{13}x_1 + b_{23}x_2 + b_{33}x_1x_2)\sin(2wt) + (4.5) (b_{04} + b_{14}x_1 + b_{24}x_2 + b_{34}x_1x_2)\cos(2wt)$$

This type of basis is widely used when the data shows a periodical behavior. In this case, there is no periodical behavior but the basis was used just to illustrate the procedure. As done in the previous section the following table summarizes the terms of the model with the Matlab output and factors related with each term.

Terms	Coefficient Represented	Related Factor	Basis Term
0	b ₀₀	1	1
1	b ₁₀	X1	1
2	b ₂₀	X2	1
3	b ₃₀	X1*X2	1
4	b ₀₁	1	sin(wt)
5	b ₁₁	X1	sin(wt)
6	b ₂₁	X2	sin(wt)
7	b ₃₁	X1*X2	sin(wt)
8	b ₀₂	1	cos(wt)
9	b ₁₂	X1	cos(wt)
10	b ₂₂	X2	cos(wt)
11	b ₃₂	X1*X2	cos(wt)
12	b ₀₃	1	sin(2wt)
13	b ₁₃	X1	sin(2wt)
14	b ₂₃	X2	sin(2wt)
15	b ₃₃	X1*X2	sin(2wt)
16	b ₀₄	1	cos(2wt)
17	b ₁₄	X1	cos(2wt)
18	b ₂₄	X2	cos(2wt)
19	B ₃₄	X1*X2	cos(2wt)

Table 4-8 Relation between the Matlab's output column "Term" and the coefficients of Equation 4.5

The Matlab application created for the Basis Representation Model was used setting the basis to be a Fourier one. The initial output produced by the application is shown next.

Table 4-9 Initial Matlab Output for the Theoretical Case Study Using the Basis Representation Model with a Fourier Basis (K =2)

0,							0,
Pequite	for the Ar	nalysis of V					
&							
Type of Bas							v
		ions or kno	ts if the	basis is	a Cubic Spl	ine:	2
8							
-		Coefficien	ts and Var	iance Inf	Elation Fact	ors	-
8							%
		SE Coef T					
0 2	2.4499	0.008836	277.2606	0			
		nts SE Coef					
1.0000		0.0099					
2.0000			-10.6832	0	1.0080		
3.0000	-0.0824 -0.1291	0.0099	-8.3365		1.0080		
4.0000			-10.1228	0	1.0000		
5.0000	-0.0584 0.1058		-4.0934 7.4202		1.0000 1.0000		
7.0000	0.1058			$0.0000 \\ 0.0000$	1.0000		
8.0000	0.0655			0.0000	1.0076		
9.0000	0.0650		5.3570 4 7495	0.0000	1.0120		
10.0000	-0.0900			0.0000	1.0120		
11.0000	-0.0625		-4.5666	0.0000	1.0120		
12.0000	-0.0730			0.0000	1.0000		
13.0000	-0.0431		-3.0232	0.0026	1.0000		
14.0000	0.0677		4.7450	0.0000	1.0000		
15.0000	0.0506	0.0143	3.5464	0.0004	1.0000		
16.0000	0.0310	0.0122	2.5359	0.0115	1.0076		
17.0000		0.0137	2.2929				
18.0000	-0.0375	0.0137 0.0137	-2.7437	0.0063	1.0120		
19.0000	-0.0328	0.0137	-2.3975	0.0169	1.0120		
8							%
		R ² and Ad	justed R^2				
l°							%
R^2, 0.57551 C	R^2(adj)						
).55954						0
8							0
e		Analysis o					o
Source	DF			MS	 F	р	
Regression		27.8412		4653	-	-	
	ror 505	20.5355	0.04	0664	20.0310	5	
Total	524	20.5355 48.3767	0.01				
8							%
L							-

From Table 4-9 one can observe that this model does not have the multicollinearity problem. In addition, the regression model is significant and has an adjusted determination coefficient close to a 56%, which is not acceptable in many applications. In this case, the stepwise procedure was not necessary because all the terms were relevant in the model and the multicollinearity problem was not present.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
0	b ₀₀	2.4498	1	1
1	b ₁₀	0.0626	X1	1
2	b ₂₀	-0.1055	X2	1
3	b ₃₀	-0.0824	X1*X2	1
4	b ₀₁	-0.1291	1	sin(wt)
5	b ₁₁	-0.0584	X1	sin(wt)
6	b ₂₁	0.1058	X2	sin(wt)
7	b ₃₁	0.0773	X1*X2	sin(wt)
8	b ₀₂	0.0655	1	cos(wt)
9	b ₁₂	0.065	X1	cos(wt)
10	b ₂₂	-0.09	X2	cos(wt)
11	b ₃₂	-0.0625	X1*X2	cos(wt)
12	b ₀₃	-0.073	1	sin(2wt)
13	b ₁₃	-0.0431	X1	sin(2wt)
14	b ₂₃	0.0677	X2	sin(2wt)
15	b ₃₃	0.0506	X1*X2	sin(2wt)
16	b ₀₄	0.031	1	cos(2wt)
17	b ₁₄	0.0314	X1	cos(2wt)
18	b ₂₄	-0.0375	X2	cos(2wt)
19	b ₃₄	-0.0328	X1*X2	cos(2wt)

Table 4-10 Results Summary for Fourier basis representation for the theoretical case

The model with the Fourier expansion indicates that both factors and the interaction are relevant in the model. However, this model is not very reliable because can explain only the 50% of the variability of the data. The next plots correspond to the estimated responses and the residuals.

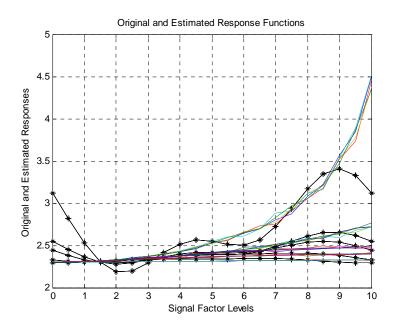


Figure 4-14 Responses and estimated responses for the Basis Representation Final Model with a Fourier Basis for the Theoretical Case Study. The asterisks correspond to the estimated functions.

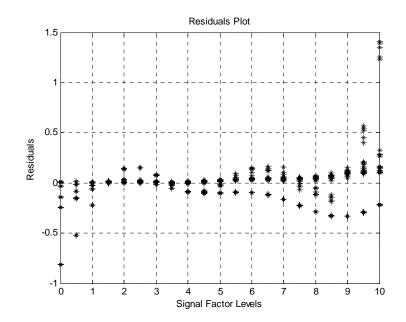


Figure 4-15 Residuals for the Basis Representation Final Model with a Fourier Basis for the Theoretical Case Study

From Figure 4-14, one can observe the lack of fit of the obtained model. The residuals plot shows the non-constant variance presented by the model. Table 4-11 presents the estimated pseudo-MSE.

Total SSE	Total Number of Parameters	Total Number of Data Points	Pseudo MSE
20.5355	20	525	0.0406

 Table 4-11 Pseudo-MSE for the theoretical case basis using the representation Method with a Fourier basis

The next section shows the last type of basis selected which is a Cubic Spline.

4.3.2.3 Cubic Spline Basis

The general cubic spline basis follows the form

$$y(t) = c_{00} + c_{01}t + c_{02}t^{2} + c_{03}t^{3} + c_{1}(t - \tau_{1})_{+}^{3} + c_{2}(t - \tau_{2})_{+}^{3} \dots c_{k}(t - \tau_{k})_{+}^{3}$$
(4.6)

where k is the number of basis functions and $(t - \tau_i)^3_+$ is defined if $t - \tau_i > 0$ otherwise is zero; τ represents the knots selected for the spline.

The model selected for the experiment was the following

$$y(t) = (b_{00} + b_{10}x_1 + b_{20}x_2 + b_{30}x_1x_2) + (b_{01} + b_{11}x_1 + b_{21}x_2 + b_{31}x_1x_2)t + (b_{02} + b_{12}x_1 + b_{22}x_2 + b_{32}x_1x_2)t^2 + (b_{03} + b_{13}x_1 + b_{23}x_2 + b_{33}x_1x_2)t^3 + (b_{04} + b_{14}x_1 + b_{24}x_2 + b_{34}x_1x_2)(t - \tau_1)_+^3 + (b_{05} + b_{15}x_1 + b_{25}x_2 + b_{35}x_1x_2)(t - \tau_2)_+^3 + (b_{06} + b_{16}x_1 + b_{26}x_2 + b_{36}x_1x_2)(t - \tau_3)_+^3$$

$$(4.7)$$

The selected knots for this model are shown in Table 4-12. The values presented were selected looking for levels of the signal factor where the response started to change dramatically. This selection could have a great impact in the performance of the models.

Table 4-12 Knots Location for Cubic Spline Basis τ_1 2

$ au_1$	2
τ_2	6
τ_3	8

The relation between the terms and the Equation 4.7 are shown in Table 4-13.

Terms	Coefficient Represented	Related Factor	Basis Term
0	b ₀₀	1	1
1	b ₁₀	X1	1
2	b ₂₀	X2	1
3	b ₃₀	X1*X2	1
4	b ₀₁	1	t
5	b ₁₁	X1	t
6	b ₂₁	X2	t
7	b ₃₁	X1*X2	t
8	b ₀₂	1	t^2
9	b ₁₂	X1	t^2
10	b ₂₂	X2	t ²
11	b ₃₂	X1*X2	t^2
12	b ₀₃	1	t ³
13	b ₁₃	X1	t ³
14	b ₂₃	X2	t ³
15	b ₃₃	X1*X2	t ³
16	b ₀₄	1	$(t-2)^3$
17	b ₁₄	X1	$(t-2)^3$
18	b ₂₄	X2	$(t-2)^3$
19	b ₃₄	X1*X2	$(t-2)^3$
20	b ₀₅	1	$(t-6)^3$
21	b ₁₅	X1	$(t-6)^3$
22	b ₂₅	X2	$(t-6)^3$
23	b ₃₅	X1*X2	$(t-6)^3$
24	b ₀₆	1	$(t-8)^3$
25	b ₁₆	X1	$(t-8)^3$
26	b ₂₆	X2	$(t-8)^3$
27	b ₃₆	X1*X2	$(t-8)^3$

Table 4-13 Relation between the Matlab's output column "Term" and the coefficients of Equation 4.7

The initial output for the cubic spline it is shown in Table 4-14.

Table 4-14 Initial Matlab Output for the Theoretical Case Study Using the Basis Representation Model with a Cubic Spline Basis

Results	for the A	a good one due Analysis of Var	iance for the H	 Basis Repres	entation Mode	
pe of i	Basis: (Cubic_spline Inctions or kno				
Term 0	Intercept 2.3017		T-test 114.1847			
Term	Coefficie	ents SE Coef	T-test	P-value	VIF	
	0.0021043		0.09337		19.223	
	0.00020305		-0.0090096	0.99282	19.223	
3 –	0.00016942	0.022537 0.022537 0.022537	-0.0075177	0.994	19.223	
		0.055133	0.013216	0.98946	1318.2	
	-0.0022255	5 0.06164	-0.036105	0.97121	4913.3	
	0.0013893	3 0.06164	0.022539	0.98203	4913.3	
	0.0058583		0.09504	0.92432	4913.3	
8	0.0056588	0.03855	0.14679	0.88336		
	0.00177	7 0.0431	0.04123		1.5121e+005	
	-0.0011363		-0.026359		1.5121e+005	
	-0.004196		-0.097355		1.5121e+005	
	0.00046446	5 0.0075006	-0.061924 -0.037334		2.4526e+005	
	0.00031308 .3964e-005		-0.037334	0.97023	4.2866e+005 4.2866e+005	
	.3964e-00: 0.00039213		0.04676	0.99867		
	0.00054622		0.064774	0.94838		
	0.00074768		0.079303		1.183e+005	
	0.0005651		-0.059943	0.95223	1.183e+005	
	0.00048651		-0.051603	0.95887		
	0.001296		0.3039	0.76133	235.11	
	0.00067352		0.14121	0.88776	286.36	
	0.00041589		-0.087193	0.93055	286.36	
23	-0.0017558	0.0047698	-0.36812	0.71294	286.36	
	0.01276		0.98838	0.32345	25.925	
25	0.017029	9 0.014442	1.1791	0.2389	28.722	
		5 0.014442	-1.2149	0.22499	28.722	
27	-0.014239	0.014442	-0.98593	0.32465	28.722	
		R^2 and Ad	justed R^2			
		 : \				
R^2,).88599	R^2(ad) 0.8798	J <i>\</i>				
	·	Analysis o	f Variance	_	-	
ource		DF SS	MS	 F	P	
gressi	on	27 42.8614			0	
sidual	Error 4	497 5.5153		110.001	u u u u u u u u u u u u u u u u u u u	
tal		524 48.3767				
						%

Table 4-14 has a warning indicating that there is multicollinearity problems present in the model, as the Variance Inflation Factors (VIF) are extremely high. Performing the same, procedure for variables elimination, a new and more reduce model is obtained. The Figure 4-16 shows the results. The following is the Table that corresponds to the final model.

Table 4-15 Final Matlab Output for the Theoretical Case Study Using the Basis Representation
Model with a Cubic Spline Basis

& Resul		-		iance for the	-		% Model
8	MODEL WI		IN VALIADI				%
		Coe	efficients	and Variance	e Inflation	Factors	
%							%
Term I 0	-		loef T-te 1060996 3	est P-val 880.5503 0	ue		
Term	Coeffic	ients	SE Coef	T-test	P-value	VIF	
12	0.000	508	1.52E-05	33.407	0	1	
13	0.000	136	2.76E-05	4.929	1.11E-06	4.594	
14	-0.00	031	2.76E-05	-11.421	0	4.594	
15	-0.00	023	2.76E-05	-8.5119	2.22E-16	4.594	
21	0.003	977	0.000606	6.5598	1.31E-10	4.594	
22	-0.00	373	0.000606	-6.1512	1.54E-09	4.594	
23	-0.00	296	0.000606	-4.879	1.42E-06	4.594	
%		R^2	and Adjus				Ũ
8							%
	R^2(adj 0.87895						9
° %		Ana	lysis of V	Variance			0
Source	1	OF	SS	MS	F	P	-
5				6.0856	544.5379	0	
Residual Total	Error 53	L'/ D/ /	5.7778 8.3767	0.011176			
*	.c.	4 					%
L							

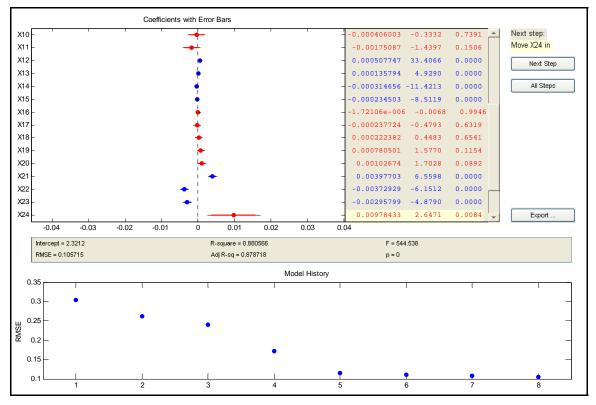


Figure 4-16 Final results for the Cubic Spline basis representation model.

The next figures correspond to the estimated responses and the residuals for the final model obtained.

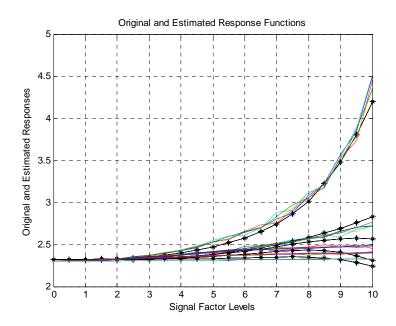


Figure 4-17 Responses and estimated responses for the Basis Representation Final Model with a Cubic Spline Basis for the Theoretical Case Study. The asterisks correspond to the estimated functions

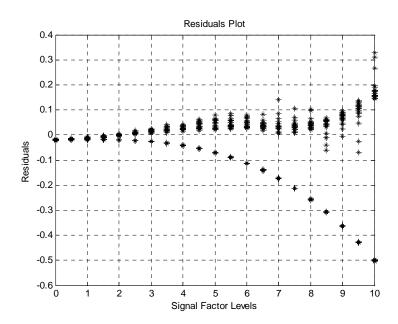


Figure 4-18 Residuals for the Basis Representation Final Model with a Cubic Spline Basis for the Theoretical Case Study

From Figure 4-17 it is possible to observe the fit of the estimated functions. The estimation using the Cubic Spline looks better in comparison with the two previous bases. Table 4-16 shows the terms that were considered relevant and the factors that are related to those terms.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
12	b ₀₃	0.000508	1	t ³
13	b ₁₃	0.000136	X1	t ³
14	b ₂₃	-0.00031	X2	t ³
15	b ₃₃	-0.00023	X1*X2	t ³
21	b ₁₅	0.003977	X1	$(t-6)^3$
22	b ₂₅	-0.00373	X2	$(t-6)^3$
23	b ₃₅	-0.00296	X1*X2	$(t-6)^3$

Table 4-16 Results Summary for Cubic Spline basis representation for the theoretical case

These terms confirm once again that factors x_1 and x_2 , and their interaction are relevant in the experiment. This model only has 8 terms and a good adjusted determination coefficient, over 87%. Table 4-17 presents the pseudo MSE as in the previous sections.

 Table 4-17 Pseudo-MSE for the theoretical case basis using the representation method with a Cubic

 Spline basis

Total SSE	Total Number of	Total Number of	Pseudo MSE
	Parameters	Data Points	
5.7778	8	525	0.0111

The total SSE of this model is almost equal to the total SSE of the Point-Wise method, but the difference in the number of terms is dramatic. In the next section, the Piece-Wise method is applied to this Theoretical case study and their results and discussion are shown.

4.3.3 Piece-Wise Method without the Continuity Constraint

4.3.3.1 Monomial Basis

The models that are going to be used in each region are identical to the Equation 4.3. In order to complete, this procedure it is necessary to find the combination of knots that provides the minimal sum of squares of error for all the regions. The objective function and the restrictions considered for optimization were presented on Chapter 3. The equation that corresponds to the objective function is the Equation 3.7, and the restrictions are represented by equations 3.8 to 3.12. The Table 4-18 shows the results obtained for this case.

Monomial Basis	K=2					
Number of knots	Objective function	ve function optimal knots				
5	5.4869	5	9	12	15	18
4	5.4872	9	12	15	18	*
3	5.4879	10	15	18	*	*
2	5.4929	10	18	*	*	*
1	5.5294	16	*	*	*	*

Table 4-18 Summary of the Knots Search for the Theoretical Case Study using a monomial basis Monomial Basis K-2

Due the small difference that exists among the objective functions for the models with 3, 4, and 5 knots the one with the smaller number of knots was selected. In other words, the knots selected for the procedure were 10, 15, and 18. The plots that correspond to each region are shown in Figure 4-19. This figure shows the different behaviors of the response functions in each region.

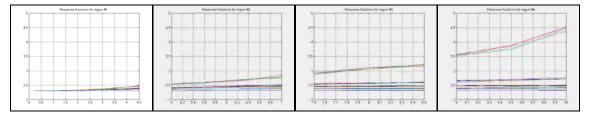


Figure 4-19 Plots for all the regions delimited before using the Piece-Wise procedure for the theoretical case study with a monomial basis

The results for this procedure are shown in the next pages. The results are presented region by region. At the beginning of each section, the tables that correspond to the initial outputs of Matlab are shown. Then the stepwise plots and final model details are shown. To conclude, the results are discussed and the relevant factors for each region are presented.

4.3.3.1.1 Results for Region #1

Table 4-19 is the initial Matlab output for the procedure in this region

8						%
Results region #		lysis of Variand	ce for the Ba	sis Represent	ation Model d	for the
%						%
Type of	Basis: mon	nomial				
Number o	f basis fund	ctions or knots	if the basis	is a Cubic S	pline: 2	
8						%
0		Coefficients	and Variance	Inflation Fa	ictors	0
*	Coefficie	ents SE Coef	T-test	P-value	VIF	%
Terms O	2.3013		795.25		VIF 0	
1	0.0024691		0.76314	0.44614	-	
2	-0.0012226		-0.37788	0.70586	6.1818	
3	-0.0001135				6.1818	
4		0.002995	1.0918	0.27601	13.656	
5	-0.0021578		-0.64442			
6	0.0041098	0.0033485	1.2274	0.2209	47.176	
7	0.0041849	0.0033485	1.2498	0.21261	47.176	
8	0.0034566	0.00064071	5.3948	1.6537e-007	13.656	
9	0.00087436	0.00071634	1.2206	0.22345	29.04	
10	-0.0021076	0.00071634	-2.9421	0.0035816	29.04	
11	-0.0024629	0.00071634	-3.4381	0.00069138	29.04	
%						%
<u>۹</u>		R^2 and Adju				9
° ₽^2	R^2(adj)					0
	0.75182					9
•		Analysis of V	Variance			Ű
% Source		 F SS	 MS	 F	 Р	%
source Regressi			MS 0.023563		P 0	
	Error 23	8 0.080605	0.00033867		0	
Total	24		3.00033007			
8						%

Table 4-19 Initial Output for the Piece-Wise Method using a Monomial basis for region #1

The model has a serious multicollinearity problem. In order to solve this problem and reduce the model a stepwise procedure was performed. The following figure shows the stepwise procedure conducted.

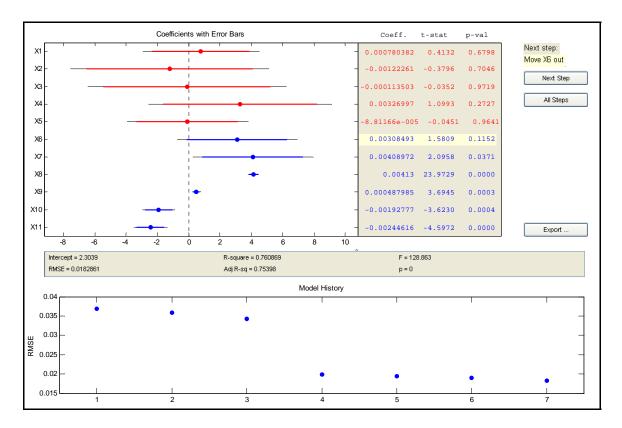


Figure 4-20 Final results for the Piece-Wise method using a monomial basis for region #1.

Table 4-20 correspond to the final model after the completion of the stepwise procedure

Results for	the Anal		ariance for				n Model
	(Coefficient		ance Infl	lation Fa	ctors	
erm Interce		Coef T-	-test P-	value			
0 2.303	9 (0.0016865	1366.0952	2 0			
Term Coef	ficients	s SE Coef	T-test	P-value	VIF		
6.0000 0	.0031	0.0020	1.5809	0.1152	16.2281		
7.0000 0	.0041	0.0020	2.0958	0.0371	16.2281		
8.0000 0	.0041	0.0002	23.9729	0	1.0000		
9.0000 0	.0005	0.0001	3.6945	0.0003	1.0000		
10.0000 -0	.0019	0.0005	-3.6230	0.0004	16.2281		
11.0000 -0	.0024	0.0005	-4.5972	0.0000	16.2281		
	1 	R^2 and Ad	justed R^2				
R ² , R ² (5,						
	1	Analysis of					
ource	DF	SS			 F	P	
egression	б	0.25854	0.04309) 128.	.8631	0	
esidual Error			0.00033				
otal	249	0.33979					

Table 4-20 Final Output for the Piece-Wise Method using a Monomial basis for region #1

The model still having the multicollinearity problem but is not as serious as the initial one. Table 4-21 shows the most relevant terms and the factors that are associated with the coefficients.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
6	b ₂₁	0.0031	X2	t
7	b ₃₁	0.0041	X1*X2	t
8	b ₀₂	0.0041	1	t^2
9	b ₁₂	0.0005	X1	t ²
10	b ₂₂	-0.00019	X2	t ²
11	b ₃₂	-0.0024	X1*X2	t ²

Table 4-21 Results summary for Region #1

The main factors and their interaction are relevant in the experiment. The following pages show the results for the second region. The next figures correspond to the estimated responses and the residuals. Figure 4-21 shows the estimated responses that look adequate for this region and Figure 4-22, shows the non-constant variance problem presented by this model.

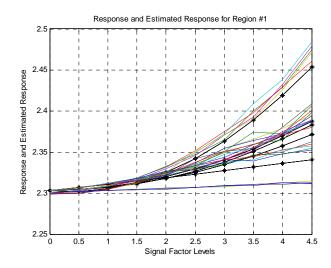


Figure 4-21 Response and estimated response for the region #1. The asterisks correspond to the estimated functions.

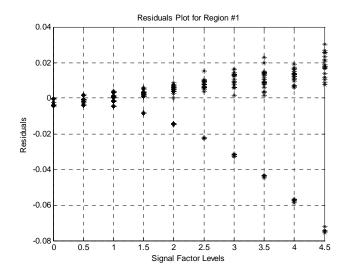


Figure 4-22 Residuals plot for region #1

4.3.3.1.2 Results for Region #2

In the same way as done with the previous region, region #2 was also analyzed in detail. The initial Matlab output it is shown in Table 4-22.

Table 4-22 Initial Output for the Piece-Wise Method using a Monomial basis for region #2

§						%
Results	ion #2			Basis Represen		for •
0	Basis: mono					8
			if the bas	is is a Cubic	Spline: 2	
8						%
		Coefficients		ce Inflation F		
š						%
Terms		s SE Coef	T-test		VIF	
0 1	2.3847	0.53493		1.9605e-005		
1 2	0.17257 -0.20932	0.59807 0.59807	0.28855 -0.34999	0.77345 0.727	7274.4 7274.4	
∠ 3	-0.20932	0.59807	-0.34999 -0.19608	•••=	7274.4	
4	-0.023315	0.18013	-0.19808 -0.12944	0.8449	412.43	
5	-0.066486	0.20139	-0.33013	0.89724 0.74191	30107	
6	0.085584	0.20139	0.42497	0.67167	30107	
7	0.042236	0.20139	0.20972	0.83426	30107	
8	0.005523	0.014993	0.36838	0.71328	412.43	
9	0.0071735	0.016762	0.42796	0.6695	8025.3	
10	-0.010418	0.016762	-0.62149	0.53553	8025.3	
11	-0.0054877	0.016762	-0.32738	0.74398	8025.3	
5		R^2 and Adjus				0
\$						%
	R^2(adj) 7 0.68173					
*		Analysis of V				%
≴						%
Source Regressi		SS 1.3601		F 25.1465	P 0	
	l Error 113		0.12365 0.004917	23.1405	U	
rotal	124 124		0.00491/			-

The problem of multicollinearity is present in this model. In this region the problem is even higher than in the previous one. The stepwise procedure was completed in order to improve the obtained model. In Figure 4-23, the plots for this procedure are presented.

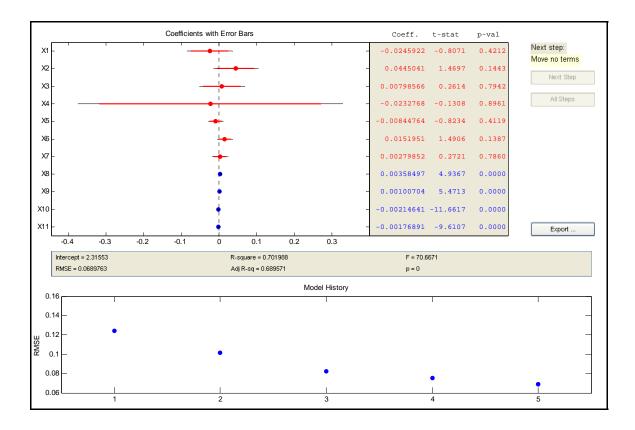


Figure 4-23 Final results for the Piece-Wise method using a monomial basis for region #2 The output for the final model it is shown in Table 4-23.

2______ Results for the Analysis of Variance for the Basis Representation Model ______ Coefficients and Variance Inflation Factors ______ Term Intercept SE Coef T-test P-value 2.3155 0.027215 85.0822 0 0 TermCoefficientsSE CoefT-testP-valueVIF80.00358480.000726214.93632.5973e-006190.0010070.000184065.4712.4845e-007110-0.00214630.00018406-11.6610111-0.00176890.00018406-9.61052.2204e-0161 _____ R^2 and Adjusted R^2 ______ R^2, R^2(adj) 0.70196 0.69203 _____ Analysis of Variance _____
 Source
 DF
 SS
 MS
 F
 P

 Regression
 4
 1.3448
 0.33619
 70.6577
 0

 Residual Error
 120
 0.57096
 0.004758
 0

 Total
 124
 1.9157
 0
 0
 §_____8

Table 4-23 Final Output for the Piece-Wise Method using a Monomial basis for region #2

The results summary it is presented in Table 4-24

Terms	Coefficient	Value	Related	Basis Term
	Represented		Factor	
8	b ₀₂	0.0041	1	t^2
9	b ₁₂	0.0005	X1	t^2
10	b ₂₂	-0.00019	X2	t^2
11	b ₃₂	-0.0024	X1*X2	t^2

Table 4-24 Results summary for Region #2

In this case, the design matrix for this model it is orthogonal and this eases dramatically the analysis. Both factors are relevant, but the cross-term is the most relevant in this case. The following plots correspond to the estimated response and residuals. From Figure 4-24 one can observe that this model is not as good as the model of obtained for the first region. The residuals plot shows a better behavior in terms of the model variance if is compared to the first region model.

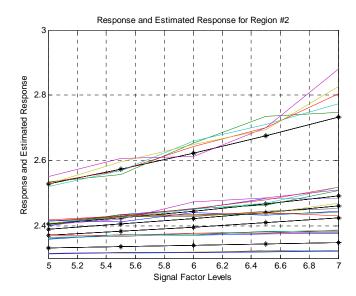
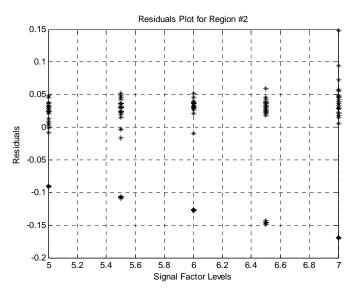


Figure 4-24 Response and estimated response for the region #2. The asterisks correspond to the estimated functions.





The next section presents the results for the region #3.

4.3.3.1.3 Results for Region #3

The Matlab initial output for this region is presented in Table 4-25

```
Table 4-25 Initial Output for the Piece-Wise Method using a Monomial basis for region #3
```

```
_____
Results for the Analysis of Variance for the Basis Representation Model for
the region #3
Type of Basis: monomial
Number of basis functions or knots if the basis is a Cubic Spline:
                                                                 2
§_____§
                    Coefficients and Variance Inflation Factors
  ______§
        CoefficientsSE CoefT-testP-valueVIF0.30018.2460.0363940.971080-1.92379.2193-0.208660.835392.9376e+0052.36259.21930.256260.798592.9376e+0051.99399.21930.216270.829472.9376e+0050.494112.06590.239180.8117430730.457472.30970.198060.843631.1831e+006-0.560412.3097-0.242630.809081.1831e+006-0.476992.3097-0.206520.837051.1831e+006-0.026350.1291-0.204110.838923073-0.02540.14433-0.175980.860872.9952e+0050.0261750.144330.181350.856672.9952e+005
  Terms Coefficients SE Coef
                                 T-test P-value VIF
   0
   1
   2
   3
   4
   5
   б
   7
   8
   9
  10
  11
  R^2 and Adjusted R^2
  R^2, R^2(adj)
0.80091 0.76615
  Analysis of Variance
<u>%</u>_____%

        Source
        DF
        SS
        MS
        F
        P

        Regression
        11
        4.3998
        0.39998
        23.0405
        0

        Residual Error
        63
        1.0937
        0.01736

        Total
        74
        5.4935

        ______
```

Once again, the initial model is not a good one due a serious multicollinearity problem. Figure 4-26 shows the plots that correspond to the stepwise procedure for this region.

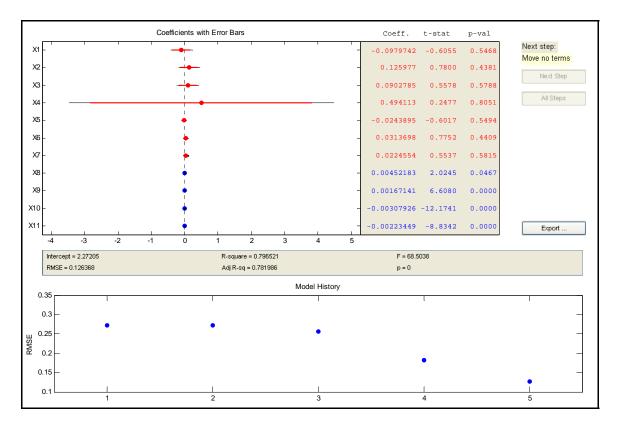


Figure 4-26 Final results for the Piece-Wise method using a monomial basis for region #3.

Table 4-26 corresponds to the final model obtained.

Table 4-26 Final Output for the Piece-Wise Method using a Monomial basis for region #3

```
_____8
   Results for the Analysis of Variance for the Basis Representation Model
   _____8
                    Coefficients and Variance Inflation Factors
     ______

        Term
        Intercept
        SE Coef
        T-test
        P-value

        0
        2.272
        0.14406
        15.7717
        0

  TermCoefficientsSE CoefT-testP-valueVIF80.00452180.00223352.02450.046732190.00167140.000252946.6086.4236e-009110-0.00307930.00025294-12.1740111-0.00223450.00025294-8.83425.3269e-0131
  ______
            R^2 and Adjusted R^2
  -----
  R^2, R^2(adj)
0.79652 0.78489
    _____8
              Analysis of Variance
 ______

        Source
        DF
        SS
        MS
        F
        P

        Regression
        4
        4.3757
        1.0939
        68.5038
        0

        Residual Error
        70
        1.1178
        0.015969
        0

        Total
        74
        5.4935
        0

          _____
```

In this model, the terms considered in the previous region were also considered. Once again, the final design matrix is orthogonal and the coefficients can be compared easily. Table 4-27 is a summary for these results.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
8	b ₀₂	0.0045218	1	t ²
9	b ₁₂	0.0016714	X1	t ²
10	b ₂₂	-0.0030793	X2	t ²
11	b ₃₂	-0.0022345	X1*X2	t ²

Table 4-27 Results summary for Region #3

The factors and their interaction are relevant in this region. The term that has the most influence in the model corresponds to the factor x_2 . The estimated response plot (Figure 4-27) shows a better fit for the responses compared to the previous two regions.

The residuals plot presents a better behavior in terms of the models variance with respect the models of the previous regions.

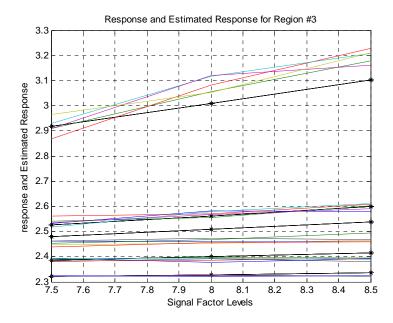
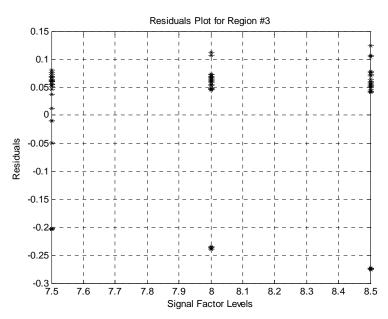


Figure 4-27 Response and estimated response for the region #3. The asterisks correspond to the estimated functions.





The results for the fourth and last region are shown in the next section.

4.3.3.1.4 Results for Region #4

Table 4-28 corresponds to the initial model obtained for this region.

```
Table 4-28 Initial Output for the Piece-Wise Method using a Monomial basis for region #4
```

```
9
Results for the Analysis of Variance for the Basis Representation Model for
the region #4
Type of Basis: monomial
Number of basis functions or knots if the basis is a Cubic Spline:
                                                                        2
§_____§
                      Coefficients and Variance Inflation Factors
  Terms CoefficientsSE CoefT-testP-valueVIF012.00121.5670.556460.579870112.95424.1130.537250.592995.8482e+0052-11.81624.113-0.490050.62585.8482e+0053-13.31724.113-0.552280.582715.8482e+0054-2.15424.5472-0.473740.6373243335-2.87945.0839-0.566380.573152.3507e+00662.65065.08390.521370.603932.3507e+00672.94525.08390.579310.564452.3507e+00680.124180.23930.518930.60563433390.16250.267540.607360.54585.9295e+00510-0.152620.26754-0.570450.57045.9295e+00511-0.165830.26754-0.619810.537625.9295e+005
  ______§
   ______
                    R^2 and Adjusted R^2
   _____§
 R^2, R^2(adj)
 0.86992 0.84721
  Analysis of Variance
8------8

        Source
        DF
        SS
        MS
        F
        P

        Regression
        11
        25.1315
        2.2847
        38.3014
        0

        Residual Error
        63
        3.758
        0.05965
        0.05965

        Total
        74
        28.8895
        0.05965
        0.05965

         _____
```

As in the previous regions, the model has a serious multicollinearity problem. The next page shows the plots for the stepwise procedure.

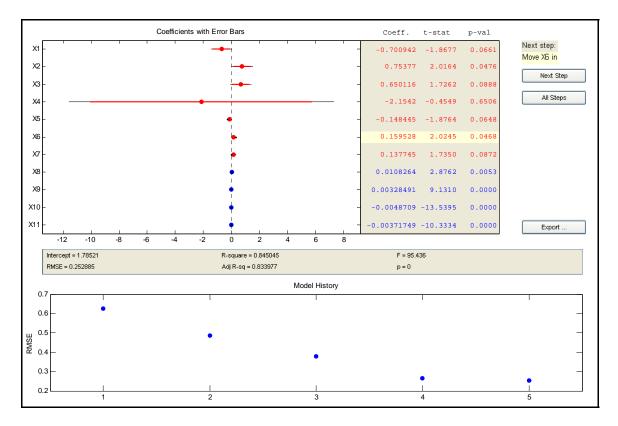


Figure 4-29 Final results for the Piece-Wise method using a monomial basis for region #4.

Table 4-29 output shows the final results for this region.

Table 4-29 Final Output for the Piece-Wise Method using a Monomial basis for region #4

```
------
   Results for the Analysis of Variance for the Basis Representation Model
             ______
                Coefficients and Variance Inflation Factors
           ______
Term Intercept SE Coef T-test P-value
0 1.7852 0.34159 5.2262 1.7057e-006
  Term Coefficients SE Coef T-test P-value VIF
   8.0000 0.0108 0.0038 2.8762 0.0053 1.0000
  9.0000 0.0033 0.0004 9.1310 0.0000 1.0000
  10.0000 -0.0049 0.0004 -13.5395 0 1.0000
  11.0000 -0.0037 0.0004 -10.3334 0.0000 1.0000
  -----
             R^2 and Adjusted R^2
                  -----%
  R^2, R^2(adj)
0.84504 0.83619
<u>8</u>______8
               Analysis of Variance
 _____
                                           ----%

        Source
        DF
        SS
        MS
        F
        P

        Regression
        4
        24.4129
        6.1032
        95.436
        0

        Residual Error
        70
        4.4766
        0.063951
        0

        Total
        74
        28.8895
        0
        0

<u>%</u>_____%
```

The same terms obtained for the previous two regions were selected again by the stepwise procedure. Table 4-30 summarizes the results.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
8	b ₀₂	0.0108	1	t^2
9	b ₁₂	0.0033	X1	t ²
10	b ₂₂	-0.0049	X2	t^2
11	b ₃₂	-0.0037	X1*X2	t^2

Table 4-30 Results summary for Region #4

This model has the peculiarity that has an adjusted determination coefficient over 80%. The most relevant terms in this model correspond to the factor x_2 and the cross-term. The following plots correspond to the estimated responses and residuals for this region. Figure 4-30 shows the estimated responses for this region. This looks to be the

region with the best fit. The residuals plot shows a behavior very close to a model with constant variance, this is presented in Figure 4-31

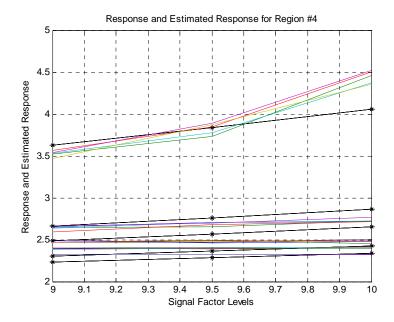


Figure 4-30 Response and estimated response for the region #4. The asterisks correspond to the estimated functions.

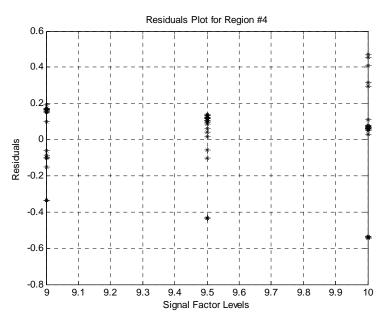


Figure 4-31 Residuals plot for region #4

The next plots correspond to the estimated responses and the residuals for all the regions combined.

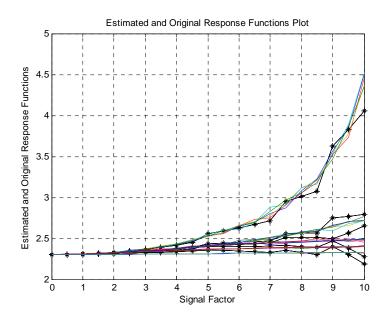


Figure 4-32 Estimated and Original Functions for the Piece-Wise Method for all the regions Combined

The models fit relatively well the response functions. The problems occur on the last region due to the dramatic change on the curves behavior. The next plot is the residuals plot for the combined model.

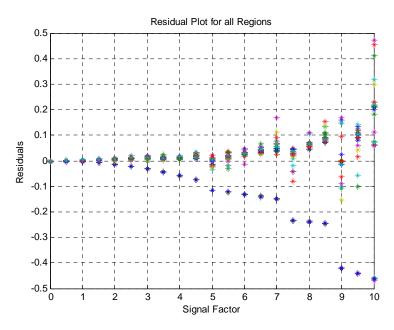


Figure 4-33 Residuals Plot for all the Regions

Figure 4-33 shows that the residuals present the same behavior than the obtained with the basis representation method. In the next pages, the results for the same procedure using a Fourier Basis are shown.

4.3.3.2 Fourier Basis

In order to begin with the procedure the knots location was completed. Table 4-31 presents the results of the knots search.

Table 4-31 Summary of the Knots Search for the Theoretical Case Study using a Fourier basis

 Fourier

 Basis
 K=2

 Number of
 Objective

 knots
 function

Number of	Objective					
knots	function		op	otimal kno	ots	
5	7.5641	3	6	9	12	16
4	5.5241	3	7	11	16	*
3	5.4986	6	11	16	*	*
2	5.6749	11	16	*	*	*
1	6.7496	16	*	*	*	*

The selected quantity of knots is 3 and the selected knots are 6, 11, and 16. Due the use of a Fourier Basis, the models in each region are going to equal to the Equation 4.5. The Figure 4-34 presents the plots for each of the four regions delimited by the knots.

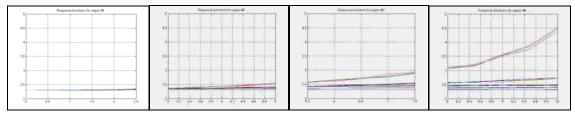


Figure 4-34 Plots for all the regions delimited before using the Piece-Wise procedure for the theoretical case study with a Fourier basis

The next sections show the results obtained in each region in detail.

4.3.3.2.1 Results for Region #1

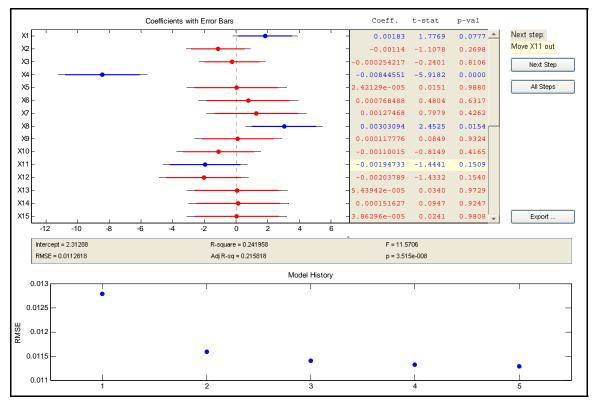
5

As done with the previous basis, the initial Matlab output is presented in order to show the results obtained for this region.

Table 4-32 Initial Output for the Piece-Wise Method using a Fourier basis for region #1

%							%
	rion #1		rsis of Variance				
8							%
Type of	Basis:						
			ions or knots i	if the basi	s is a Cubic S	pline: 2	
							%
0			Coefficients a	nd Varianc	e Inflation Fa	ators	0
۹							2
Terr			ents SE Coef				0
0			0.00099084	2334.1	o o o o o o o o o o o o o o o o o o o	0	
1		8039			-	1.08	
				1.0284	0.10587		
2	-0.0009		0.0011078	-0.86757	0.38723	1.08	
3	-0.0001		0.0011078	-0.12153	0.90346	1.08	
4	-0.008			-5.7187		1	
5	2.415e			0.014624	0.98835	1	
б	0.000		0.0016514	0.46579		1	
7	0.001	2705	0.0016514	0.76932	0.4431	1	
8	0.002	7616	0.0013211	2.0903	0.038536	1.0667	
9	9.657e	-005	0.0014771	0.06538		1.12	
10	-0.000	7232	0.0014771	-0.48962	0.62523	1.12	
11	-0.001	6348	0.0014771	-1.1068	0.27044	1.12	
12	-0.002	0372	0.0014771	-1.3792	0.1702	1	
13	5.1963e		0.0016514	0.031466	0.97495	1	
14	0.0001		0.0016514	0.09092	0.9277	1	
15	3.9023e		0.0016514	0.02363	0.98118	1	
16		1068	0.0013211	0 80841	0.42033	1.0667	
10	7.6214e		0.0014771		0.95893	1.12	
18	-0.0003		0.0014771	0.051596	0.80996	1.12 1.12	
_			0.0014771	-0.24096 -0.64703	0.00990		
19	-0.000	955/	0.0014771	-0.64/03	0.51875	1.12	
8							%
			R^2 and Adjust	ced R^2			
8							%
R^2	, R^2(adj)					
	0.165						
8							%
			Analysis of Va	ariance			
8							%
Source		DF		MS	F	P	
Regress	sion	19	0.0066259	0.00034	873 2.5575	0.000981	76
-	al Error						
Total		149	0.024352	0.00010			
\$							%
Ŭ							0

This model does not have the multicollinearity problem presented by the monomial basis, but it has a series of non-relevant terms that can be eliminated. This in



order to improve and simplify the model the stepwise procedure was completed. Figure 4-35 correspond to this procedure.

Figure 4-35 Final results for the Piece-Wise method using a Fourier basis for region #1.

Table 4-33 corresponds to the final model it is shown next.

%				
Results for	the Analysis of V	Variance for the	Basis Repres	entation Model
6	Coefficients	s and Variance In	nflation Fact	.ors
8				*******
-	t SE Coef T-t 0.00094403			
Term Coeffi	icients SE Coef	T-test P-value	e VIF	
1.0000 0.0	0.0010 0.0010	1.7793 0.0773	3 1.0000	
4.0000 -0.0	0.0014 -	-5.9183 0.0000	1.0000	
8.0000 0.0	0.0012	2.4503 0.0155	5 1.0000	
11.0000 -0.0	0.0013 -	-1.4432 0.1511	1.0000	
8				%
8	R^2 and Adju			%
R ² , R ² (ac 0.24195 0.22103				~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
° 2	Analysis of			• •
Source	DF SS	MS	 F	P
Regression	4 0.0058919	0.001473	11.5698	3.5191e-008
Residual Error	145 0.01846	0.00012731		
Total	149 0.024352			•
8				

Table 4-33 Final Output for the Piece-Wise Method using a Fourier basis for region #1

The model is not a good one; it only describes 24% of the variability of the data. Inferences using this model are not appropriate only two factor related terms were considered relevant by the model and two additional terms corresponding to the intercept of the model. The next plots (Figure 4-36 and Figure 4-37) show the lack of fit and variance problems that this model has. This is expected to happen in all the regions, due the basis selection.

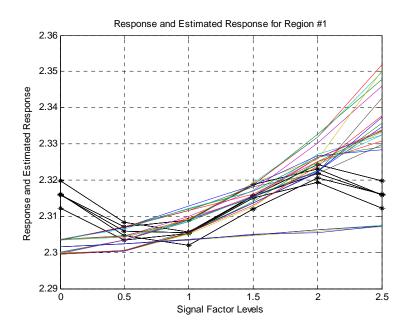


Figure 4-36 Response and estimated response for the region #1. The asterisks correspond to the estimated functions.

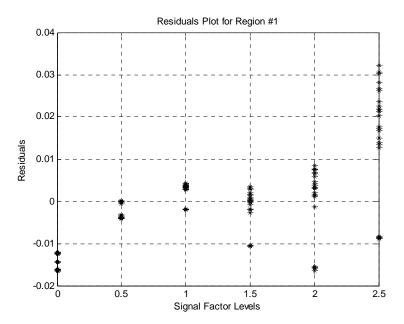


Figure 4-37 Residuals plot for region #1

4.3.3.2.2 Results for Region #2

Table 4-34 is the initial Matlab output; the stepwise plots and the final model are presented in the next pages.

Table 4-34 Initial Output for the Piece-Wise Method using a Fourier basis for region #2

```
٩
Results for the Analysis of Variance for the Basis Representation Model for the
region #2
                 ------
&_____
Type of Basis: fourier
Number of basis functions or knots if the basis is a Cubic Spline:
                                                                               2
                     ______
                         Coefficients and Variance Inflation Factors
§_____8
  Terms Coefficients SE Coef T-test
        CoefficientsSE CoefT-testP-valueVIF2.37110.0032493729.72000.00890250.00363282.45060.0159141.0937-0.0202650.0036328-5.57831.905e-0071.0937-0.0238390.0036328-6.56212.0578e-0091.09370.0319210.00549235.8126.6951e-0081.250.00656750.00614061.06950.287281.25-0.0161070.0061406-2.62310.0100091.25-0.0031610.0042543-0.743010.459131.05-0.00126250.0047565-0.265430.79121.1250.00254250.00475650.534540.594111.1250.0026050.00475650.547680.585081.125-1.2757e+0142.0057e+013-6.36065.3344e-00939.65
                                                             P-value
                                                                             VIF
     0
     1
     2
     3
      4
     5
     6
     7
     8
     9
    10
    11
    12-1.2757e+0142.0057e+013-6.36065.3344e-00913-3.3397e+0132.2424e+013-1.48940.13939
                                                                             39.65
                                                                              41.25
                                                       0.0014463

      7.3368e+013
      2.2424e+013
      3.2719
      0.0014463

      6.6529e+013
      2.2424e+013
      2.9669
      0.0037255

      -0.12477
      0.019917
      -6.2645
      8.3644e-009

      0.0121607
      0.00267
      0.00267
      0.012675

    14
                                                                              41.25
    15
                                                          0.0037255
                                                                              41.25
    16
                                      -1.4229
3 105
                                                                              39.45
    17
           -0.031685
                         0.022267
                                                           0.15772
                                                                             41.094
                       0.022267
                                            3.16860.00200652.92710.0041952
            0.070557
    18
                                                                             41.094
           0.065179 0.022267
    19
                                                                             41.094
                   R^2 and Adjusted R^2
                            _____
  R^2, R^2(adj)
 0.62116 0.5526
       ٩_____٩
                        Analysis of Variance

        o
        DF
        SS
        MS
        F

        Regression
        19
        0.20773
        0.010933
        9.061

        Residual Error
        105
        0.12669
        0.0012066

        Total
        124
        0.33442

                                                                    P
                                                         9.061 1.0325e-014
  _____
```

It is possible to observe that the model has a multicollinearity problem. In addition, the determination coefficient for the model is relatively low. The stepwise plots are shown in Figure 4-38.

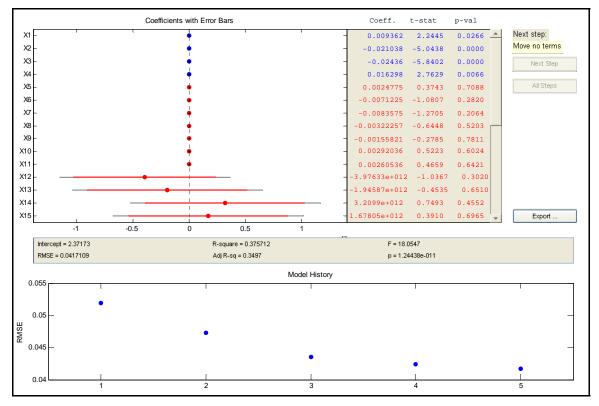


Figure 4-38 Final results for the Piece-Wise method using a Fourier basis for region #2.

Table 4-35 provides the details with respect the final model obtained after the execution of the stepwise procedure.

Results	for the A	nalysis of Va	ariance for th	e Basis Re	presentation Mc	del
5		Coefficients	and Variance	Inflation	Factors	
;						
	-		est P-valu 635.6675 0	e		
	Geoffision					
Term (1.0000		ts SE Coef	2.2447 0.0	lue VIF 266 1.0	000	
			-5.0424 0.0			
			-5.8393 0.0			
			2.7625 0.0			
1.0000	0.0103	0.0000	2.,025 0.0	1.0		
;·						
		R^2 and Adju				
R^2, I						
0.37563 0						
*						
		Analysis of				
Source	DF	SS		F	 Р	
Regression	4	0.12563	0.031406	18.0484	1.254e-011	
Residual Er						
Fotal	124	0.33444				
8						

Table 4-35 Final Output for the Piece-Wise Method using a Fourier basis for region #2

The final model is not a good one. Only around 35% of the total variability of the data is explained. Only the first four terms are relevant and the one that correspond to the cross-term in is the most relevant. In general, this model cannot be used to conclude with respect this region. Plots presented in figures 4-39 and 4-40 show the lack of fit presented by this model. The next section shows the results for region #3.

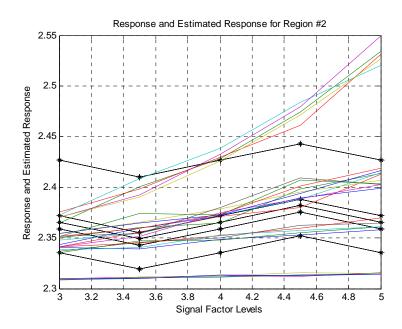


Figure 4-39 Response and estimated response for the region #2. The asterisks correspond to the estimated functions.

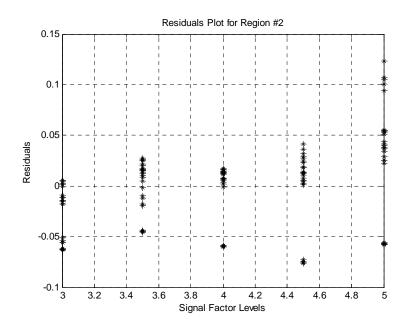


Figure 4-40 Residuals Plot for region #2

4.3.3.2.3 Results for Region #3

Table 4-36 corresponds to the initial model for this region

Table 4-36 Initial Output for the Piece-Wise Method using a Fourier basis for region #3

Results region	#3	malysi			Basis Repre	esentatio	on Mode	l for th
s Cype of	Basis:							
Jumber	of basis f	unctio	ns or knots	if the ba	sis is a Cuł	oic Splim	ne: 2	
					nce Inflatio	on Factor	ſS	
k	Coefficie			T-test	P-value			
Cerms O	2.469		0079599	310.18		=)	VIF 0	
1	0.046331		0088994	5.2061	9.6428e-00	-	L.0937	
2	-0.097173		0088994	-10.919			L.0937	
3	-0.076934		0088994		6.5947e-014		L.0937	
4	0.71764		0.17487	4.1039	8.0472e-00		295.61	
5	0.39114		0.19551	2.0006	0.048012		316.72	
6	-0.72718		0.19551	-3.7194	0.00032255		316.72	
7	-0.42635		0.19551	-2.1807			316.72	
8	-0.048996		.013455		0.00042265		1.25	
9	-0.027054		.015043	-1.7984	0.074979		1.25	
10	0.049308		.015043	3.2779	0.001418	7	1.25	
11	0.029391		.015043	1.9538	0.05338	, 2	1.25	
	2.0336e+014		33e+013	4.1389	7.0606e-00		172.63	
	L.1123e+014		33e+013	2.0249	0.04541		516.75	
	2.0631e+014		33e+013	-3.7557	0.00028408		516.75	
	L.2125e+014			-2.2072	0.02947		516.75	
16	0.32367		.078626		7.6768e-00		L02.45	
17	0.17611		.087907	2.0034	0.04771		L02.13	
18	-0.32841	. 0	.087907	-3.7359			L06.72	
19	-0.1929		.087907	-2.1944	0.030412	2	L06.72	
17	0.1923	, 0	.00/20/	2.1911	0.050112		100.72	
;								
			^2 and Adju					
 ב^ס	R^2(ad							
	1 0.69272	5,						
5.759C								
,		Δ	nalysis of					
<								
Source		DF	SS	MS		F	P	
Regress		19		0.1137		5.7129		
Residua	al Error	105	0.76031	0.0072			J	
otal		124	2.9221	0.0072				
. o cur								

This model has a better initial determination coefficient than the initial models for the first two regions. The model has a serious multicollinearity problem; in addition there are some terms that are not relevant in the model. The plots that correspond to the stepwise procedure are presented by Figure 4-41.

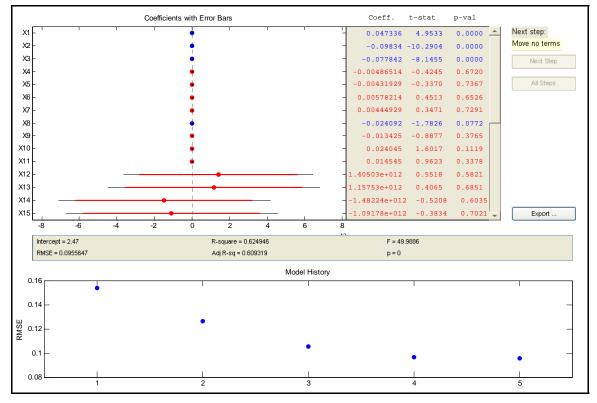


Figure 4-41 Final results for the Piece-Wise method using a Fourier basis for region #3.

Table 4-37 corresponds to the stepwise procedure it is shown in the next page.

<pre>%Results for</pre>	the Anal	ysis of V	Variance d	for the Ba	sis Repre	esentation Model
8	Co	efficient	ts and Va	riance Inf	lation Fa	actors
	ept SE 0.00			P-value 0		%
Term Coef 1.0000 0 2.0000 -0 3.0000 -0 8.0000 -0	0.0473 0.0983 0.0778	0.0096 0.0096 0.0096	4.9528 -10.2896 -8.1452	0 0.0000	1.0000 1.0000 1.0000)
%		2 and Ad	justed R^2	2		%
<pre>% R^2, R^2(0.62491 0.612 %</pre>	adj)					§
°	An		f Variance			%
Source Regression Residual Error	120	1.8261 1.096		L 49.9	F F 9819 (
Total %	124	2.9221				%

Table 4-37 Final Output for the Piece-Wise Method using a Fourier basis for region #3

This is model it is better than the previous ones in terms of the adjusted determination coefficient. The model describes 63% of the total variability of the data. This quantity is not excellent but is acceptable in some applications. Table 4-38 summarizes the obtained results.

Coefficient **Basis Term** Terms Value Related Represented Factor 0.0473 1 b_{10} X1 1 -0.0983 2 X2 1 b₂₀

b₃₀

 b_{02}

-0.0778

-0.0241

X1*X2

1

1

cos(wt)

3

8

Table 4-38 Results summary for region #3 of the Piece-Wise method using a Fourier basis

Terms 1 to 3 correspond to the factors without a sine or cosine term. By the magnitudes of the coefficient the factor, x_2 is the most relevant in this region.

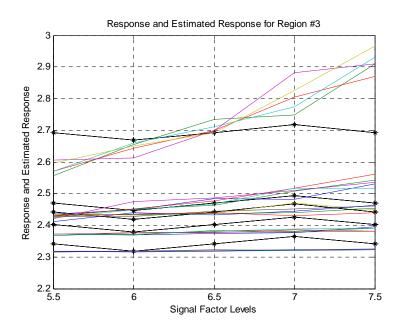


Figure 4-42 Response and estimated response for the region #3. The asterisks correspond to the estimated functions.

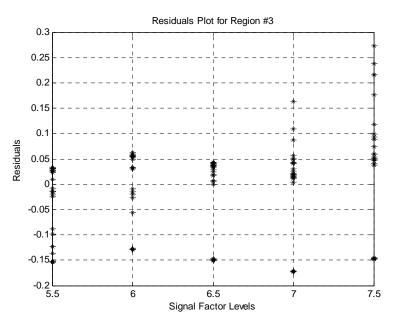


Figure 4-43 Residuals for region #3

The estimated responses plot presents a better fit compared to the previous two. The residuals plot shows the problem of non-constant variance for this model. The next section shows the results for the region #4, which is the last one due the number of knots used.

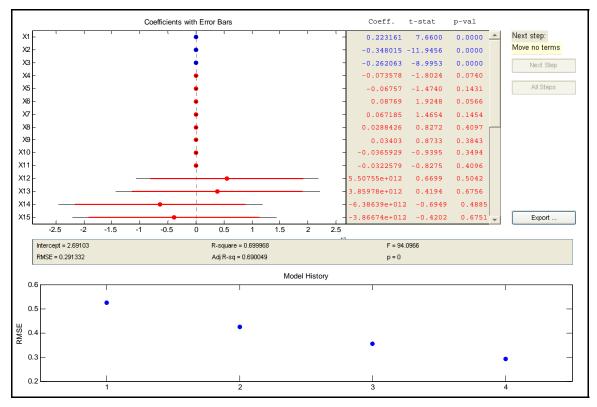
4.3.3.2.4 Results for Region #4

As done with all the regions in this procedure Table 4-39 corresponds to the initial model for this region.

Table 4-39 Initial Output for the Piece-Wise Method using a Fourier basis for region #4

%Results for th region #4 °	e Analy				entation Model	
*		 ,				%
Type of Basis:						
Number of basi %						0
8						%
0		Coefficients	s and Variar	ce Inflation	Factors	0
**	· · ·				·····	%
Terms Coeffi				P-value	VIF	
	833	0.019566			0	
	396	0.021875		2.2204e-016	1.0937	
2 -0.33		0.021875	-15.466	0	1.0937	
3 -0.25		0.021875	-11.576		1.0937	
4 -2.4		0.44484		4.1446e-007	226.15	
5 -2.3		0.49735		9.8854e-006	226.15	
6 2.8		0.49735		8.0325e-008	226.15	
7 2.3	266	0.49735		8.6648e-006	226.15	
8 0.024		0.025618			1.05	
9 0.029	249	0.028641	1.0212			
10 -0.031		0.028641	-1.1123		1.125	
11 -0.027				0.33928	1.125	
12 -6.3378e+		2077e+014	-5.2478	8.065e-007	420.55	
13 -6.1025e+		3503e+014	-4.5195	1.6321e-005	428.65	
		3503e+014	5.6077	1.6724e-007	428.65	
15 6.1479e+	014 1.	3503e+014	4.5531	1.4287e-005	428.65	
16 -1.3	836	0.26694		1.064e-006	195.45	
17 -1.3				2.1344e-005	203.59	
18 1.6	526	0.29845	5.5371	2.2862e-007	203.59	
19 1.3	385	0.29845	4.485	1.87e-005	203.59	
8		 R^2 and Adju				%
o						%
R ² , R ² 0.86579 0.84	(adj) 151					-
		SS	 MS	 F		6
Pegregaion	10	20 62/0				
Regression Residual Error	10F	27.0349 1 E020	1.337/ 0.042751	22.0202	U	
Residual Error Total	105	4.5938 34.2287	0.043/51	-		
10La1 %	⊥∠4					Q
°						

It is not surprising to obtain a model with the presence of the multicollinearity problem. In addition, some terms are not relevant in the model. For those reasons, once



again the stepwise procedure was used. The plots and final model are shown in the next pages.

Figure 4-44 Final results for the Piece-Wise method using a Fourier basis for region #4.

The details related with the final model for this region are shown in Table 4-40.

Table 4-40 Final Output for the Piece-Wise Method using a Fourier basis for region #4

```
______
    Results for the Analysis of Variance for the Basis Representation Model
    ______
                           Coefficients and Variance Inflation Factors
                      _____%
Term Intercept SE Coef T-test P-value
         2.691 0.026058 103.2727 0
    0

        Term
        Coefficients
        SE Coef
        T-test
        P-value
        VIF

        1
        0.22316
        0.029133
        7.66
        5.0999e-012
        1

        2
        0.24901
        0.029132
        11.046
        0
        1

        0.22316
        0.029133
        7.66
        5.0999e-012
        1

        -0.34801
        0.029133
        -11.946
        0
        1

        -0.26206
        0.029133
        -8.9952
        3.9968e-015
        1

      2
      3
     _____
                            ٩_____٩
                   R^2 and Adjusted R^2
     ______§
   R^2, R^2(adj)
 0.69996 0.69253
                            ______
                      Analysis of Variance
               _____
                                                                     -----%

        Source
        DF
        SS
        MS
        F
        P

        Regression
        3
        23.9589
        7.9863
        94.0954
        0

        Residual Error
        121
        10.2698
        0.084874
        0

        Total
        124
        34.2287
        0
```

The model obtained is the best one for the Fourier basis. The adjusted determination coefficient is close to a 70% and the model has an orthogonal design matrix. The next table shows the results summarized.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
1	b ₁₀	0.22316	X1	1
2	b ₂₀	-0.34801	X2	1
3	b ₃₀	-0.26206	X1*X2	1

Table 4-41 Results summary for region #4 of the Piece-Wise method using a Fourier basis

The relevant terms correspond to the terms that not are multiplied by a sine or cosine term. This is exactly what happened with the previous region. The term that corresponds to the factor x_2 is the most relevant in this model. Figure 4-45 shows the estimated responses as constant lines; this behavior is caused by the elimination of all the terms related to the signal factor. The residuals plot shows the same problems presented by the models of the previous regions.

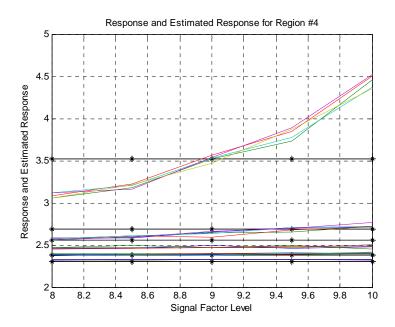


Figure 4-45 Response and estimated response for the region #4. The asterisks correspond to the estimated functions.

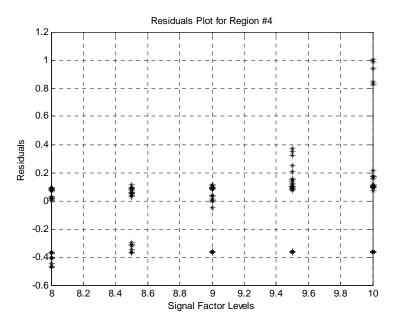


Figure 4-46 Residuals plot for region #4

The next section summarizes the results for the Piece-Wise method without the continuity constraint.

4.3.3.3 Results Summary for the Piece-Wise Method without the Continuity

Constraint

After performing, the Piece-Wise method for the theoretical case study is important to summarize and make some remarks with respect the results obtained. The next tables show a summary for the two bases used by region. These tables also present the results for the pseudo-MSE for both bases.

Monomial	Number of		Number of Data	Adjusted
Basis	Terms	MSE	Points	R^2
Region 1	7	0.00033438	250	0.75496
Region 2	5	0.004758	125	0.69203
Region 3	5	0.015969	75	0.78489
Region 4	5	0.063951	75	0.83619
Pseudo-				
MSE	0.012418718			

Table 4-42 Summary for the Piece-Wise procedure using a Monomial Basis

Table 4-43 Summary for the Piece-Wise procedure using a Fourier Basis

Fourier	Number of		Number of Data	Adjusted
Basis	Terms	MSE	Points	R^2
Region 1	7	0.00012672	150	0.22469
Region 2	7	0.0017288	125	0.35902
Region 3	8	0.0090161	125	0.61098
Region 4	4	0.084874	125	0.69253
Pseudo-				
MSE	0.023173788			

From tables 4-42 and 4-43 one can notice the difference in the adjusted determination coefficients for both bases. The monomial basis has a better performance compared to the Fourier basis. This result was expected due the behavior of the response functions that do not have a periodical behavior. The pseudo-MSE for the monomial basis it is approximately the half of the pseudo-MSE of the Fourier basis. Both bases worked better in their respective regions 3 and 4. Also for both bases, the factor x_2 was the most relevant for the last region. In general, the method worked out decently well for this case in specific when the monomial basis was used. The next section of this chapter

presents the results for the Piece-Wise method with the incorporation of the continuity constraints.

4.3.4 Piece Wise Method with the Continuity Constraint

In order to ensure the continuity among the regions for all the curves, a set of constraints were imposed to the models. As mentioned on Chapter 3, these constraints are incorporated to the models using a series of indicator variables, after the stepwise procedure. The number of those variables is equal to the number of experimental conditions minus one. The reasoning of subtracting one experimental condition is to create a reference or a base for the rest of the indicator variables. Then the restrictions to these indicator variables are the averages of the responses at the last level of the signal factor of the previous region. The restricted least of squares algorithm it is used to find the regression coefficients for each region. The following sections are going to present the implementation of this procedure, it is important to understand that the terms considered for the final regressions are the same terms selected by the stepwise procedure for the models without the continuity constraint. The results obtained are next.

4.3.4.1 Monomial Basis

4.3.4.1.1 Results for Region #1

The results obtained for this region are exactly the same results obtained for the model without the continuity constraint, because this region does not involve the restrictions. The next tables show the results summary for this region.

Table 4-44 Final Matlab Output for Region #1

Results for t	the Analy	vsis of Va	ariance fo				Model
	Cc	oefficient	s and Var		lation Fac		
erm Intercep							
0 2.3039	90.	.0016865	1366.095	2 0			
Term Coefi	Eicients	SE Coef	T-test	P-value	VIF		
6.0000 0	.0031	0.0020	1.5809	0.1152	16.2281		
7.0000 0			2.0958	0.0371	16.2281		
8.0000 0	.0041	0.0002	23.9729	0	1.0000		
9.0000 0			3.6945				
10.0000 -0							
11.0000 -0	.0024	0.0005	-4.5972	0.0000	16.2281		
	R′		justed R^2				
R^2, R^2(a	(ibe						
0.76087 0.7549	5.						
	Ar	nalysis of	E Variance				
ource	DF	SS	MS		 F	 Р	
egression	б	0.25854	0.0430	9 128	.8631	0	
esidual Error	243	0.081255	0.0003	3438			
otal	249	0.33979					

Table 4-45 Results Summary for Region #1

Terms	Coefficient Represented	Value	Related Factor	Basis Term
6	b ₂₁	0.0031	X2	t
7	b ₃₁	0.0041	X1*X2	t
8	b ₀₂	0.0041	1	t^2
9	b ₁₂	0.0005	X1	t^2
10	b ₂₂	-0.00019	X2	t^2
11	b ₃₂	-0.0024	X1*X2	t^2

As mentioned previously the model has the multicollinearity problem but both factors were considered as relevant.

4.3.4.1.2 Results for Region #2

The results of the analysis of variance for this region are shown on the next tables Table 4-46 Matlab Output for Region #2

<pre>%% Analysis of Variance for the Final Model with the restricted coefficients for the region #2 %*</pre>									
。 Type of Basis: monomial Number of basis functions or knots if the basis is a Cubic Spline: 2 **									
°	Coefficients and Variance Inflation Factors								
Term									
0	2.4561	0.0196	125.0281	0					
8	0.0242	0.0042	5.7108	0	1				
9	0.0205	0.0047	4.3445	0	2.0345				
10	-0.0194	0.0047	-4.1053	0.0001	2.0345				
11	-0.0239	0.0047	-5.0538	0	2.0345				
ind 1	-0.0725	0.0281	-2.5766	0.0112	3.2552				
ind 2	-0.0024	0.0281	-0.0856	0.9319	3.2552				
ind 3	-0.115	0.0281	-4.0868	0.0001	3.2552				
ind 4	-0.0686	0.0232	-2.9517	0.0038	2.2207				
	R^	2 and Adjuste	ed R^2						
ô		R^2							
		0	0						
0 0 %% Analysis of Variance %%									
Source	DF	SS	MS	F	P				
Regression	8	-0.4375	-0.0547	0	1				
Residual Erro	r 116	0.5644	0.0049						
Total %	124	0.1269							

This model is completely inadequate if is compared to the model without the continuity constraints. Inferences with this model are not reliable. The next section presents the results for the third region.

4.3.4.1.3 Results for region #3

As done on the previous sections the results for the third region are in the following tables.

umber of basi	monomial s functions or				
		cients and W	ariance Infl		
Term	Coefficient	SE Coef		P-value	VIF
0	2.5404	Inf	0	1	
8	0.2427	Inf	0	1	0
9	0.2433	Inf	0	1	0
10	-0.0349	Inf	0	1	9.7965
11	0.0349	Inf	0	1	9.7965
ind 1	-0.1244	Inf	0	1	0
ind 2	0.2654	Inf	0	1	0
ind 3	-0.1938	Inf	0	1	0
ind 4	-0.0563	Inf	0	1	0
					1.0e+015 *
		2 and Adjus	ted R^2		
			adj R^2		
		0.7069			
		is of Varian	ice		
Source	DF	SS	MS	F	P
Regression	8	2.4026	0.3003	19.8983	6.77E-15
Residual Erro	or 66	0.9961	0.0151		
Total	74	3.3988			

Table 4-47	Matlab	Output for	the region #3

The multicollinearity problem is extremely severe. The effect of the indicator variables in the model was very adverse on it inference capabilities.

4.3.4.1.4 Results for region #4

The results for the last region analyzed are presented on the next couple of tables.

ype of Basis: umber of basis		nots if the	basis is a (Cubic Splin	e: 2	
	Coefficie	ents and Var	iance Inflat	tion Factor	S	-
	Coefficient					6
0	2.631	Inf	0	1		
8	0.6381	Inf	0	1	0	
9	0.5668	Inf	0	1	0	
10	-0.0288	Inf	0	1	9.7965	
11	0.0288	Inf	0	1	9.7965	
ind 1	-0.2854	Inf	0	1	0	
ind 2	0.4175	Inf	0	1	0	
ind 3	-0.0417	Inf	0	1	0	
ind 4	-0.2173	Inf	0	1	0	
					1.0e+015	*
		and Adjuste	d R^2			°,
		R^2				0
			0.3311			
	Analysis	of Variance				-
Source	DF	SS		F		P
Regression	8	7.1038	0.888	3 5.5	794	2.11E-
	66	10.5039	0.1592	2		
Total	74	17.6077				

Table 4-48 Matlab Output for Region #4

Similar to the previous two regions the cost of the imposition of the continuity constraint has been a dramatic loss on inference capabilities. It is important to mention that the constraint was not incorporated to the models obtained using the Fourier bases because from the shape of the response functions it is clear that this type of basis is not appropriate. The Table 4-49 summarizes the results obtained

				Number	
Monomial	Number of			of Data	Adjusted
Basis	Terms	SSE	MSE	Points	R^2
Region 1	7	0.081255	0.00033438	250	0.75496
Region 2	9	0.5644	0.0049	125	0
Region 3	9	0.9961	0.0151	75	0.6714
Region 4	9	10.5039	0.1592	75	0.3311
Pseudo- MSE	0.024737				

Table 4-49 Results Summary for the Piece-Wise method with Continuity Constraints

The next and last section of this chapter summarizes and compares the obtained results for all the methods applied on this case. The comparison it is based on the Pseudo MSE presented on Chapter 3.

4.4 Comparison of Results for the Three Methods for the Theoretical Case Study

After completing the discussion of the three methods individually, it is important to make some comparisons in order to verify the adequacy of the methods to determine which procedures are better. In general, the conclusions driven by the three procedures were the same. Both factors and their interaction were considered as relevant by every procedure. An important inference obtained by the Point-Wise procedure is the significance of a curve component that was not captured or considered in the experiment. The main purpose of the pseudo-MSE as explained in Chapter 3 is to ease the comparison of the three methods. The following table presents a summary of the pseudo-MSE for all the methods used to analyze the experiment.

Method	Basis Used	Total SSE	Total Number of Parameters	Total Number of Data Points	Pseudo MSE
Point-Wise	N/A	5.48682	84	525	0.01244177
Basis Representation	Monomial	8.9124	7	525	0.01720541
Basis Representation	Fourier	20.5355	20	525	0.04066436
Basis Representation	Cubic Spline	5.7778	8	525	0.01117563
Piece-Wise without continuity constraints	Monomial	6.246615	22	525	0.01241872
Piece-Wise without continuity constraints	Fourier	11.56372	26	525	0.02317379
Piece-Wise with continuity constraint	Monomial	12.14566	34	525	0.024737

Table 4-50 Pseudo-MSE for all the methods applied to the theoretical case study

The procedures that involved a Fourier bases are less effective in comparison with the other procedures. They have the highest SSE totals. As previously mentioned this behavior was expected due the nature of the response functions. The Point-Wise method, the Piece-Wise using a monomial basis and the basis representation using the cubic spline basis provided the best results in terms of the pseudo-MSE, considering the number of terms that each model has. It is highly desired that the final models have the lowest quantity of terms as possible, this in order to have a simple model able to describe the data under study. The basis representation model with the cubic spline basis provided the second lowest number of terms and the second lowest pseudo-MSE can be considered the selected model for this case.

This model has a good determination coefficient (approximately 83%), a low number of terms and a low SSE. The Piece-Wise method can be an alternative if is desired to investigate some specific regions of the signal factor. With the monomial basis in some regions, the factor x_2 was the most relevant and in other regions the cross-term had the greatest impact. This is very interesting because the factors can affect the response functions differently depending on the levels of the signal factor. This can be a real contribution for some engineering applications. The Piece Wise method provided a good fit for all the regions but the inferential capabilities of this method are questionable. The work with the theoretical case study was completed successfully. The three methods were executed, analyzed and compared. The results were consistent among the methods and conclusions could be obtained for each procedure. The next chapter presents the application of all the techniques used in the theoretical case study in a real world application, the analysis of the reflection coefficient of rectangular slot ring antennas.

An Applied Case Study: Reflection Coefficient Analysis for Rectangular Slot Ring Antennas

5.1 Introduction

Recently the Design of Experiments (DOE) has been used in the analysis and characterization of Antennas [13]. In this chapter, the methods applied to the Theoretical case study are going to be applied to an experiment in order to analyze the behavior of the Reflection Coefficient for this structure in a range of frequencies. A set of runs where simulated in order to collect data for the analysis.

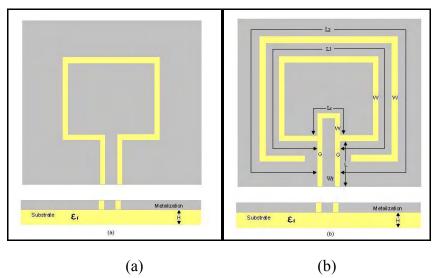


Figure 5-1 (a) A single RSRA. (b) Two concentric RSRA. Two examples of the antennas used for the experiments

5.2 **Experiment Description**

Initially, some simulations were performed for the single Rectangular Slot Ring Antenna (RSRA) shown in Figure 5-1(a). Two different substrates were used. One with a relative permittivity of 3 and a thickness of 0.76 mm and the other with a relative permittivity of 6.15 and a thickness of 0.635 mm. The perimeter and the width of the slot of the antenna were varied in order to have an initial data to compare with. In the frequencies where the observations were made the reflection coefficient was very high for both substrates.

In order to improve the matching of the antenna to 50 Ω an open circuit stub is implemented in a new set of antennas. Then, a third set of antennas with an open circuit stub and an exterior ring are simulated. For some, cases a low reflection coefficient was achieved as it is shown in Figure 5-2.

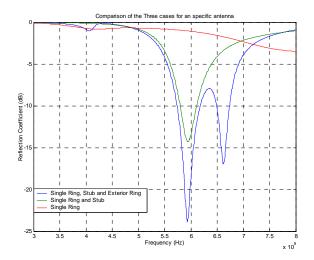


Figure 5-2 A case where a low reflection coefficient is observed with the structure proposed.

According to Figure 5-1(b), the parameters that can be varied are the substrate permittivity (ε_r), the substrate thickness (*H*), the slot ring perimeters (L_1 y L_2), the slot width (*W*), the open circuit stub (L_s), the fed slot width (*G*) and the fed conductor width (W_f). The factors to be considered in this design with its respective levels are shown in Table 5-1.

Factor	Low level	High level
${\mathcal E}_r$	3	6.15
W	0.25mm	1mm
L_1	$1 \lambda_g$	$2 \lambda_g$
L_2	$2.2 \lambda_g$	2.6 λ_g
L_s	$0.25 \lambda_g$	$0.3 \lambda_g$

Table 5-1 Factors and levels considered for the experiments

The factors L_1 , L_2 , and L_s depend on λ_g . For these DOE designs the design frequency (f_d) is 5.77 GHz. The other variables such as W_f and G depend on the

substrate permittivity and are obtained as follows. For $\varepsilon_r = 3$ and H = 0.76 mm a 50 Ω CPW line is used with a slot width *G*, of 0.25 mm, a central conductor width W_{f_r} of 6.435 mm and slot length *L*, of 10.32 mm. For $\varepsilon_r = 6.15$ and H = 0.635 mm a 50 Ω CPW line is used with a slot width *G*, of 0.25 mm, a central conductor width W_{f_r} of 1.725 mm and slot length *L*, of 7.634 mm. Considering all the experimental conditions of the five factors, it is necessary to run 32 simulations. In order to make regression coefficients comparable, factor physical dimensions need to be transformed into coded factors: low level as -1 and high level as 1. Additionally, the combination of ε_r and *W* will be coded as shown in Table 5-2.

\mathcal{E}_r	W	Indicator Variable
-1	-1	T_1
1	-1	T_2
-1	1	T_3
1	1	T_4

Table 5-2 Coding for the combination of \mathcal{E}_r and W

Only one of these combinations is present in the model:

$$y = B_0 + B_1 T_1 + B_2 T_2 + B_3 T_3 + B_4 L_1 + B_5 L_2 + B_6 L_s$$
(5.1)

Where y is the response to be analyzed, in this case it is the reflection coefficient; T_i , i = 0,...4 is one of the experimental condition shown in table 5.2, and only three of these variables are shown in Equation 5.1 because are indicator variables that used T₄ as the base and B_j , j = 0,...3 are the regression coefficients in the model. The range of frequency where the experiments were performed is from 5.7 GHz to 6GHz.

5.3 **Results for the Applied Case Study**

5.3.1 Point-Wise Method

Figure 5-3(a) shows some of the 32 responses that correspond to each experimental condition. The frequency range in the graphs is form 3 GHz to 8 GHz. The Point-Wise method was applied. Only in some frequency intervals the model was reliable enough to derive reasonable conclusions. The selection of the frequency range was based in the adjusted determination coefficient for the model and the frequency of design. This coefficient measures the variability of the data explained by the model and its value is between zero and one. Figure 5-3(b) shows the determination coefficients for the frequency considered.

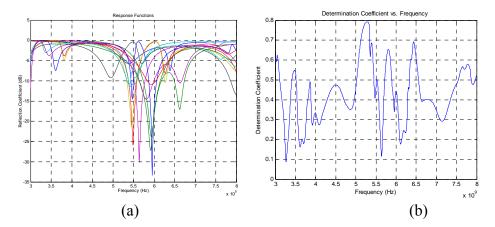


Figure 5-3 (a) Observed responses, (b) Determination Coefficient.

The selected region is from 5.7 to 6 GHz. This range corresponds to the frequencies used for the design of the antenna. The Figure 5-4 shows the response functions for the selected range.

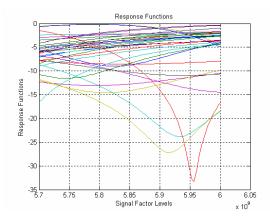


Figure 5-4 Response functions for the selected range of frequencies

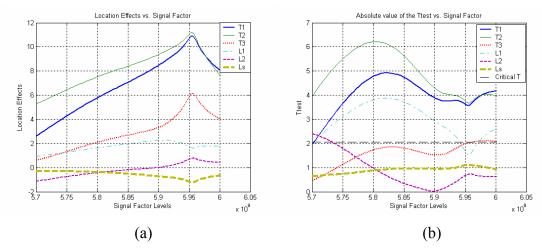


Figure 5-5 (a) Factor effects, (b) Absolute value of the T test.

From Figure 5-5(b) it is possible to infer that the factors T_2 , T_1 and L_1 are the most significant effects in the selected region. Because T_1 and T_2 are indicator variables that represent levels of the same factor T, which is a combination of ε_r and W they cannot coexist. T_2 has the strongest influence on the response and that is the level that has to be selected over this region. The others factors such as L_s , L_2 , and T_3 have low impact on the reflection coefficient. The intercept is not shown in the figures in order to ease the visualization of the effects; this is because the magnitude of the intercept is greater than the rest of the effects. In Figure 5-5(a), the four highest effects are positive for this reason it is necessary to set these factors to their low level in order to minimize the reflection coefficient as it is desired. Some additional plots related with the implementation of this method are presented in the next figures.

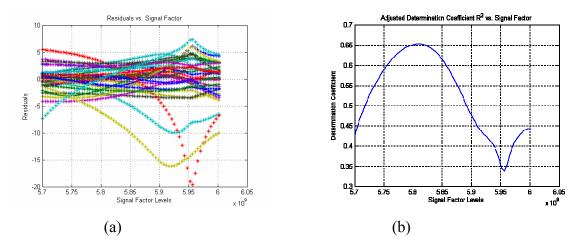


Figure 5-6 Residuals and Adjusted Determination Coefficients Plots

From Figure 5-6(a) it is possible to observe that the residuals look constant for almost all the responses. A few ones make some changes for frequencies that are higher than 5.9 GHz. The Figure 5-6(b) shows the determination coefficients for the selected range of frequencies. This coefficients drop dramatically for frequencies higher than 5.85 GHz. Table 5-3 shows the pseudo-MSE generated by the applications, necessary to ease the comparison of the methods.

Total SSE	Total Number of	Total Number of	Pseudo MSE
	Parameters	Data Points	
22985.9	476	2176	13.521

Table 5-3 Pseudo-MSE for the Applied Case Using the Point-Wise Method

5.3.2 Basis Representation Method

5.3.2.1 Monomial Basis

This type of basis was the first attempt to fit the selected range of frequencies the following series of figures tables and outputs shows the results obtained. The first monomial base used was expanded two times (k = 2) terms in the following form

$$y(t) = B_{00} + B_{10}T_1 + B_{20}T_2 + B_{30}T_3 + B_{40}L_1 + B_{50}L_2 + B_{60}L_s + (B_{01} + B_{11}T_1 + B_{21}T_2 + B_{31}T_3 + B_{41}L_1 + B_{51}L_2 + B_{61}L_s)t + (B_{02} + B_{12}T_1 + B_{22}T_2 + B_{32}T_3 + B_{42}L_1 + B_{52}L_2 + B_{62}L_s)t^2$$
(5.2)

The Table 5-4 shows all the terms and the factors associated with them.

Terms	Coefficient	Related Factor	Basis Term
	Represented		
0	B_{00}	1	1
1	B ₁₀	T1	1
2	B ₂₀	T2	1
3	B ₃₀	T3	1
4	B ₄₀	L1	1
5	B ₅₀	L2	1
6	B ₆₀	Ls	1
7	B ₀₁	1	t
8	B ₁₁	T1	t
9	B ₂₁	T2	t
10	B ₃₁	T3	t
11	B ₄₁	L1	t
12	B ₅₁	L2	t
13	B ₆₁	Ls	t
14	B ₀₂	1	t^2
15	B ₁₂	T1	t^2
16	B ₂₂	T2	t^2
17	B ₃₂	Т3	t^2
18	B ₄₂	L1	t^2
19	B ₅₂	L2	t^2
20	B ₆₂	Ls	t^2

Table 5-4 Relation between the Matlab's output column "Term" and the coefficients of Equation 5.2

The initial output for this expansion it is presented in Table 5-5.

Table 5-5 Initial results for the applied case using the basis representation method with a Monomial Basis (K = 2)

&_____& Results for the Analysis of Variance for the Basis Representation Model <u>%</u>_____% Type of Basis: monomial Number of basis functions or knots if the basis is a Cubic Spline: &_____& Coefficients and Variance Inflation Factors <u>%</u>_____% Term Intercept SE Coef T-test P-value 1249.2824 691.0816 1.8077 0.070789 0 Term Coefficients SE Coef T-test P-value VIF -2356.3 977.34 -2.411 0.015993 3.61E+07 1 2 -2585.8 977.34 -2.6458 0.00821 3.61E+07 3 -31.053 977.34 -0.03177 0.97466 3.61E+07 -1140.1 345.54 -3.2995 0.000985 2.40E+07 4 5 -138.89 345.54 -0.40194 0.68777 2.40E+07 -18.24 345.54 -0.05279 0.95791 2.40E+07 6 7 -4.18E-07 2.36E-07 -1.771 0.076694 87744 8 7.83E-07 3.34E-07 2.3446 0.019135 1.44E+08 8.72E-07 3.34E-07 2.6089 0.009146 1.44E+08 9 10 -4.23E-09 3.34E-07 -0.01266 0.9899 1.44E+08 3.87E-07 1.18E-07 3.2783 0.001061 9.62E+07 11 12 4.16E-08 1.18E-07 0.35248 0.72451 9.62E+07 13 8.62E-09 1.18E-07 0.072996 0.94182 9.62E+07 3.47E-17 2.02E-17 1.719 0.085767 87744 14 -6.48E-17 2.86E-17 -2.2712 0.023236 3.61E+07 15 16 -7.32E-17 2.86E-17 -2.5636 0.010427 3.61E+07 17 1.71E-18 2.86E-17 0.060034 0.95213 3.61E+07 18 -3.28E-17 1.01E-17 -3.252 0.001164 2.41E+07 19 -3.06E-18 1.01E-17 -0.30352 0.76152 2.41E+07 -9.58E-19 1.01E-17 -0.09486 0.92443 2.41E+07 20 &_____% R^2 and Adjusted R^2 §_____§ R^2, R^2(adj) 0.58379 0.57992 &_____% Analysis of Variance 8------8
 Source
 DF
 SS
 MS
 F
 P

 Regression
 20
 32673.959
 1633.698
 151.131
 0

 Residual Error
 2155
 23295.1436
 10.8098
 100.8098
 100.8098
 Total 2175 55969.1026 &_____& The outputs shows that a serious multicollinearity problem. As an attempt to solve this situation, some terms are eliminated. The final output for the simplified model is shown next.

Table 5-6 Stepwise procedure results for the applied case using the basis representation method with
a Monomial Basis (K = 2)

The m	ode	l is not a go	od one di	ue a multi	collinearit	v problem		
8								20
Resu %	ilts	s for the Ana		Variance	for the Bas: 	is Representa	tion Model	2
Ŭ						flation Facto	rs	U
% Term		Intercept		T-test				20
0		16.5949						
Term		Coefficients	SE Coef	T-test	P-value	VIF		
	1	-1123.7	698.67	-1.6083	0.10792	1.80E+07		
	2	-1353.1	698.67	-1.9367	0.052914	1.80E+07		
	4	-1140.1	349.32	-3.2638	0.0011166	2.40E+07		
	5	-34.019	4.7184	-7.2099	7.71E-13	4385.1		
	6	14.536	4.7184	3.0806	0.0020918	4385.1		
	7	-4.65E-09	1.14E-09	-4.0794	4.68E-05	2.0005		
	8	3.70E-07	2.39E-07	1.5475	0.12188	7.22E+07		
	9	4.58E-07	2.39E-07	1.9172	0.055343	7.22E+07		
	10	4.99E-10	3.44E-11	14.494	0	1.5001		
	11	3.87E-07	1.19E-07	3.2428	0.0012015	9.62E+07		
	12	5.78E-09	8.06E-10	7.1742	9.95E-13	4385.1		
	13	-2.58E-09	8.06E-10	-3.203	0.0013796	4385.1		
	15	-3.01E-17	2.04E-17	-1.4768	0.13988	1.81E+07		
	16	-3.85E-17	2.04E-17	-1.8859	0.059443	1.81E+07		
	18	-3.28E-17	1.02E-17	-3.2168	0.0013154	2.41E+07		
8								alo
<u>.</u>				Adjusted 1				•
	2,	R^2(adj) 0.57068						б 0,
ō			Analysis	of Varia	nce			ō
% Source Regres Residu Total	2	DF Dn 15 Error 2160 2175	3210 2386	SS 6.4339 2.6688 9.1026	MS	F 193.7473	P 0	-10
8								ړ ۵

Table 5-6 is the result after using the stepwise procedure of the application. The graphs that correspond to the stepwise procedure are shown in Figure 5-7.

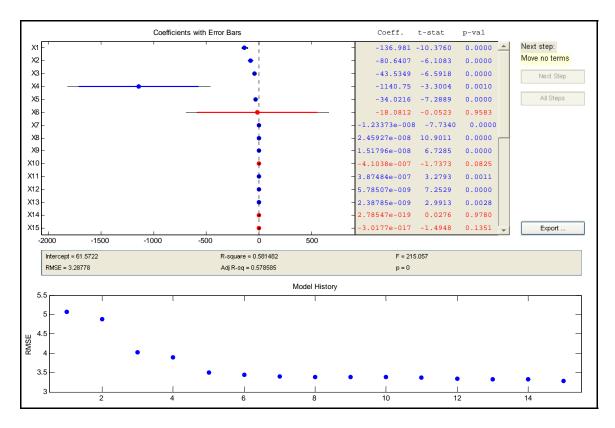


Figure 5-7 Final Results for the Monomial Basis Representation Model with k =2.

The results for the basis representation method are not reliable with the use of a monomial basis with k = 2. A severe multicollinearity problem is present and for that reason, the inferences that can be drawn for the model are not correct. It is not appropriate to use this model to describe the region under study. In general, the monomial basis is not a good one to analyze the range of frequencies selected in this experiment. In the next section, a Fourier Basis is used to analyze the experiment under study.

5.3.2.2 Fourier Basis

As a second option a Fourier basis it is going to be used in order to analyze the experiment under study. The expansion of terms selected was k = 2 and the general model has the form shown in Equation 5.3

$$y(t) = B_{00} + B_{10}T_1 + B_{20}T_2 + B_{30}T_3 + B_{40}L_1 + B_{50}L_2 + B_{60}L_s + (B_{01} + B_{11}T_1 + B_{21}T_2 + B_{31}T_3 + B_{41}L_1 + B_{51}L_2 + B_{61}L_s)\sin(\omega t) + (B_{02} + B_{12}T_1 + B_{22}T_2 + B_{32}T_3 + B_{42}L_1 + B_{52}L_2 + B_{62}L_s)\cos(\omega t) + (B_{03} + B_{13}T_1 + B_{23}T_2 + B_{33}T_3 + B_{43}L_1 + B_{53}L_2 + B_{63}L_s)\sin(2\omega t) + (B_{04} + B_{14}T_1 + B_{24}T_2 + B_{34}T_3 + B_{44}L_1 + B_{54}L_2 + B_{64}L_s)\cos(2\omega t) +$$
(5.3)

Table 5-7 relates the terms in Equation 5.3 with the Matlab output

Terms	Coefficient Represented	Related Factor	Basis Term
0	B ₀₀	1	1
1	B ₁₀	T1	1
2	B ₂₀	T2	1
3	B ₃₀	T3	1
4	B ₄₀	L1	1
5	B ₅₀	L2	1
6	B ₆₀	Ls	1
7	B ₀₁	1	sin(wt)
8	B ₁₁	T1	sin(wt)
9	B ₂₁	T2	sin(wt)
10	B ₃₁	T3	sin(wt)
11	B ₄₁	L1	sin(wt)
12	B ₅₁	L2	sin(wt)
13	B ₆₁	Ls	sin(wt)
14	B ₀₂	1	cos(wt)
15	B ₁₂	T1	cos(wt)
16	B ₂₂	T2	cos(wt)
17	B ₃₂	T3	cos(wt)
18	B ₄₂	L1	cos(wt)
19	B ₅₂	L2	cos(wt)
20	B ₆₂	Ls	cos(wt)
21	B ₀₃	1	sin(2wt)
22	B ₁₃	T1	sin(2wt)
23	B ₂₃	T2	sin(2wt)
24	B ₃₃	Т3	sin(2wt)
25	B ₄₃	L1	sin(2wt)
26	B ₅₃	L2	sin(2wt)
27	B ₆₃	Ls	sin(2wt)
28	B ₀₄	1	cos(2wt)
29	B ₁₄	T1	cos(2wt)
30	B ₂₄	T2	cos(2wt)
31	B ₃₄	T3	cos(2wt)
32	B44	L1	cos(2wt)
33	B ₅₄	L2	cos(2wt)
34	B ₆₄	Ls	cos(2wt)

Table 5-7 Relation between the Matlab's output column "Term" and the coefficients of Equation 5.3

The initial output for this model as follows.

Table 5-8 Initial results for the applied case using the basis representation method with a Fourier Basis (K = 2) $\,$

		sis of Va	riance for		s Representat	
mber of k		ns or knot			a Cubic Splin	
	C	oefficient	ts and Var	iance Inf	lation Factor	S
Term 0	Intercept -10.625	SE Coef	T-test	P-value		
Term	Coefficients	SE Coef	T-test	P-value	VIF	
1.0000	6.9295	0.2009	34.4951	0		
2.0000	8.1937	0.2009	40.7881	0	1.5012	
3.0000	2,9021	0.2009	14.4464	0	1.5012	
4.0000					1.0008	
5.0000		0.0710	-2.4093	0.0161	1.0008	
6.0000	-0.5764 1.0962	0.0710	-8.1153	0.0000	1.0008	
8.0000						
9.0000		0.2846	-3,9343	0.0001	2.0012	
	-1.3876	0.2846	-4.8749	0.0000	2.0012	
11.0000	-0.1000	0.1006	-0.9933	0.3207	1.0006	
12.0000	-0.1000 -0.4431	0.1006	-4.4025	0.3207 0.0000	1.0006	
13.0000	0.2775 1.0479	0.1006	2.7572	0.0059	1.0006	
14.0000	1.0479	0.2005	5.2266	0.0000	4.0028	
15.0000	-1.9657	0.2835	-6.9326	0.0000	2.0018	
16.0000		0.2835	-5.3249	0.0000	2.0018	
17.0000						
	-0.4797	0.1002	-4.7855	0.0000	1.0010	
19.0000		0.1002	-3.3454	0.0008 0.1032	1.0010	
20.0000 21.0000	0.1634	0.1002				
22.0000		0.1997	-1.2443	0.2135	2.0022	
23.0000			1 1139	0.2655	2.0022	
24.0000						
25.0000		0.0998	0.5025	0.6154	1.0012	
26.0000		0.0998	-0.3623	0.7172	1.0012	
27.0000		0.0998				
28.0000	0.7567	0.2021	3.7446	0.7963 0.0002	4.0005	
29.0000	-1.3524 -0.9047	0.2858	-4.7323	0.0000	2.0003	
30.0000	-0.9047	0.2858	-3.1657	0.0016	2.0003	
31.0000						
32.0000		0.1010	-0.4864	0.6267	1.0002	
33.0000 34.0000	0.1408		-3.5227 1.3934		1.0002 1.0002	
	R	^2 and Ad	justed R^2	 ?		
R^2, .58046 (R^2(adj) .5738					
	A	nalysis o	f Variance	 2		
urce gression sidual En tal	DF 34 cror 2141 2175		485 95 2541 1	MS 55.525 0.9674	F 87.1239	Р 0

The stepwise procedure was implemented in order to improve the model. The final output and the stepwise procedure graphs are shown in the next.

Table 5-9 Stepwise procedure results for the applied case using the basis representation method with a Fourier Basis (K = 2)

			Coefficien	ts and Var	iance Inf	lation Facto	ors	
	m Int	ercept S	SE Coef T	-test P	-value			
	0 -	10.6173	0.14224	-74.644	0			
	Term	Coefficient	s SE Coef	T-test	P-value	VIF		
	1.0000			34.4180	0	1.5006		
	2.0000	8.1853	0.2012	40.6898	0	1.5006		
	3.0000	2.8931	0.2011	14.3834	0	1.5003		
	4.0000		0.0711		0	1.0003		
	5.0000	-0.1703	0.0711	-2.3951	0.0167	1.0005		
	6.0000	-0.5736		-8.0665	0.0000	1.0001		
	7.0000 8.0000	1.1084 -1.8821		5.4980 -6.6015	0.0000 0.0000	4.0005 2.0006		
	8.0000 9.0000			-6.6015 -4.0012	0.0000	2.0006		
	10.0000	1 2045	0 2051	-4.8916	0.0001	2.0003		
	12.0000	-0.4507		-4.4708	0.0000	1.0004		
	13.0000	0.2775	0.1008	2.7534	0.0059	1.0001		
	14.0000	0.6100	0.1419	4.2974	0.0000	2.0005		
	15.0000	-1.5093	0.2459	-6.1389	0.0000	1.5007		
	16.0000	-1.0726	0.2459 0.1004	-4.3629	0.0000	1.5007		
	18.0000			-4.7585	0.0000	1.0003		
	19.0000		0.1004	-3.2367	0.0012	1.0006		
	28.0000	0.7715	0.2023	3.8130	0.0001	4.0002		
	29.0000			-4.7593	0.0000	2.0002		
	30.0000	-0.9227 -1.0480	0.2861	-3.2246	0.0013	2.0002		
						2.0001		
	33.0000		0.1012		0.0005	1.0001		
			R^2 and Ad	justed R^2				
		R^2(adj)						
Ο.	57676 0							
ou	rce	DF	SS		MS	F	P	
eg	ression	22 ror 2153	32280.6	522 14		133.36	0	
les 'ot		ror 2153 2175	23688. 55969.		11.0026			

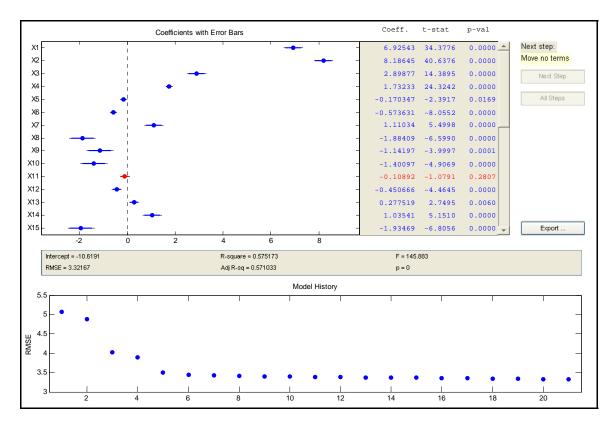


Figure 5-8 Final Results for the Fourier Basis Representation Model with k =2.

The final model obtained is not good at all, but at least it is able to describe approximately the 60% of the variability of the data. The most relevant terms of this model are summarized in Table 5-10.

Terms	Coefficient Represented	Value	Related Factor	Basis Term
1	B ₁₀	6.9223	T1	1
2	B ₂₀	8.1844	T2	1
3	B ₃₀	2.8924	Т3	1
4	B ₄₀	1.7321	L1	1
5	B ₅₀	-0.1706	L2	1
6	B ₆₀	-0.576	Ls	1
7	B_{01}	1.0883	1	sin(wt)
8	B ₁₁	-1.8406	T1	sin(wt)
9	B ₂₁	-1.1086	T2	sin(wt)
10	B ₃₁	-1.3759	T3	sin(wt)
12	B ₅₁	-0.4436	L2	sin(wt)
13	B ₆₁	0.2771	Ls	sin(wt)
14	B ₀₂	0.6157	1	cos(wt)
15	B ₁₂	-1.5345	T1	cos(wt)
16	B ₂₂	-1.0821	T2	cos(wt)
18	B ₄₂	-0.4798	L1	cos(wt)
19	B ₅₂	-0.3346	L2	cos(wt)
28	B_{04}	0.7603	1	cos(2wt)
29	B ₁₄	-1.3564	T1	cos(2wt)
30	B ₂₄	-0.9099	T2	cos(2wt)
31	B ₃₄	-1.0496	Т3	cos(2wt)
33	B ₅₄	-0.3557	L2	cos(2wt)

Table 5-10 Results Summary for Fourier Basis Representation for the Applied Case

The terms presented in the table shows that the most relevant factors in the experiment are T1, T2, T3, and L1. These factors are the same factors considered as relevant by the Piece-Wise approach. As mentioned before the factor Ls is completely non-relevant to the experiment. Most of the terms that include Ls were eliminated by the stepwise procedure. The plots that correspond to the residuals, estimated response are presented in the next figures.

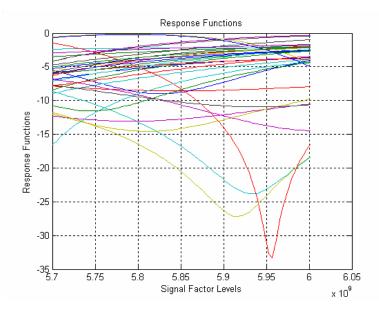


Figure 5-9 Responses for the Basis Representation Final Model with a Fourier Basis for the Applied Case Study.

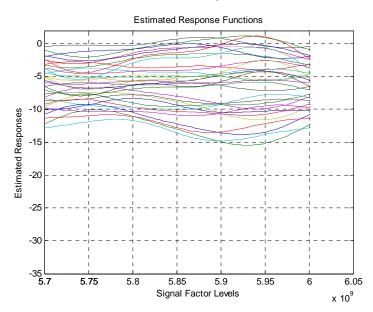


Figure 5-10 Estimated responses for the Basis Representation Final Model with a Fourier Basis for the Applied Case Study.

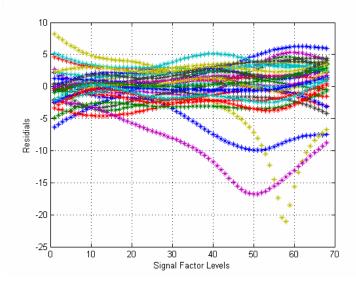


Figure 5-11 Residuals for the Basis Representation Final Model with a Fourier Basis for the Applied Case Study.

From Figure 5-10 it is possible to observe the lack of fit of the models. The selected basis is unable to fit the local features of some of the responses. The metrics for this procedure are summarized in the following table

Table 5-11 Metrics for the Applied Case Using the Basis Representation Method using a Fourier Basis with k=2

Total SSE	Total Number of	Total Number of	Pseudo MSE	
	Parameters	Data Points		
23617.8	26	2176	10.985	

5.3.2.3 Piece-Wise Method without the Continuity Constraint

In order to complete the comparison among the methods, the Piece-Wise method is applied for this applied case study. Only the Fourier basis it is going to be used. The main reason for this is the poor performance of the monomial basis and the cubic spline in the previous method. Due the high computational effort of the knots search procedure the quantities of knots tested were 1, 2, and 3. Table 5-12 shows the results of the search procedure.

Fourier Basis	K=2			
Number of knots	Objective function		optimal knots	
3	23066	10	22	35
2	23085	14	31	*
1	23142	24	*	*
Minimal	23066			

Table 5-12 Knots Search for the Piece-Wise method for the applied case study

The selected knots were 10, 22, and 35. The general model in each region is exactly the same model presented as Equation 5.3. Figure 5-12 presents the four regions delimited by the knots search.

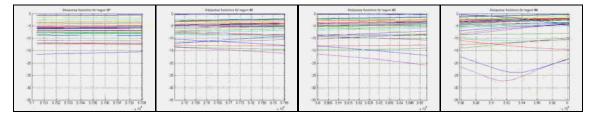


Figure 5-12 Plots for all the regions delimited before using the Piece-Wise procedure for the applied case study with a Fourier basis

The next sections show the results for this procedure in detail. As done in the previous chapter the initial model, stepwise procedure and the final model are presented per each region.

5.3.2.3.1 Results for Region #1

Table 5-13 corresponds to the initial model is shown next.

Table 5-13 Initial Output for the Piece-Wise Method using a Fourier basis for region #1

for the	for the An region #1	alysis of Varia:			tation Model	à
Type of	Basis: f	ourier				4
umber	DI DASIS IU 	nctions or knot	s 11 the bas: 	15 15 a Cubic	Spline: 2	
		Coefficient	s and Variand	- Treflation D		
\$					actors	9
Term		ients SE Coef			VIF	
0	-8.8963		-33.606		0	
1	3.2922			2.2204e-016	1.5476	
2	5.746		15.348	0	1.5476	
3	0.89029		2.3781	0.018062 1.088e-014	1.5476	
4	1.08				1.0317	
5	-0.9667		-7.3035	2.818e-012	1.0317	
6	-0.29931		-2.2613	0.024493	1.0317	
7	0.012943		0.035984	0.97132	4.1143	
8	-0.0038653		-0.0075988	0.99394	2.0857	
9	-0.0068824	0.50867	-0.01353 -0.030728	0.98921	2.0857	
10	-0.015631			0.97551	2.0857	
11	0.0015116		0.008405	0.9933	1.0476	
12	0.0031899		0.017737	0.98586	1.0476	
13	0.0024999	0.17984	0.0139	0.98892	1.0476	
14	0.14078	0.3885	0.36237	0.71735	4	
15	-0.41488		-0.75511	0.4508	2	
16	-0.28839	0.54943	-0.52489	0.60007	2	
17	-0.1692	0.54943	-0.30796	0.75834	2	
18	-0.089061	0.19425	-0.45848	0.64696	1	
19	-0.097349	0.19425	-0.50114	0.61666	1	
20	-0.00076938			0.99684	1	
21	-0.060006	0.3885	-0.15445	0.87736	4	
22	0.17901	0.54943	0.32581	0.7448	2	
23	0.12407	0.54943	0.22582	0.8215	2	
24	0.072177	0.54943	0.13137	0.89558	2	
25	0.038809	0.19425	0.19979	0.84179	1	
26	0.042464	0.19425	0.2186	0.82712	1	
27	0.00034518	0.19425	0.001777	0.99858	1	
28	0.0044164	0.35969	0.012278	0.99021	4.1143	
29	-0.0021857		-0.0042968	0.99657	2.0857	
30	-0.0028494		-0.0056017	0.99553	2.0857	
31	-0.0053194		-0.010457	0.99166	2.0857	
32	0.00032012			0.99858	1.0476	
33	0.00083329	0.17984	0.0046334	0.99631	1.0476	
34	0.00078824		0.0043829	0.99651	1.0476	
						9
;						
R^2, 0.5986	R^2(adj 0.55072)				
		Analysis of	Variance			c
Source		DF SS	MS	F	 P	1
Regress	ion	34 2309.438			0	
-		1548.606			v	
Fotal		3858.044		•		
k	J		-			

The obtained model has many non-relevant terms. The stepwise procedure was executed in order to simplify the model and eliminate the terms that are not contributing to the model.

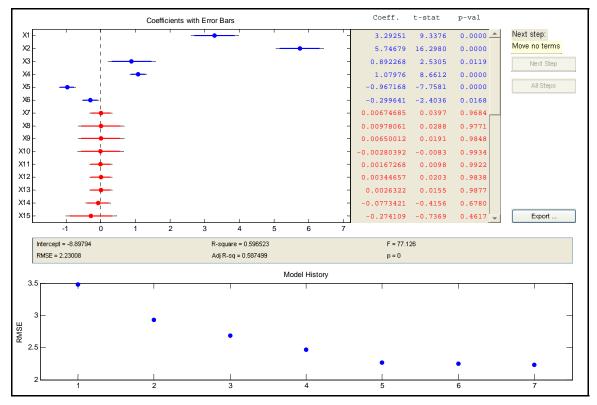


Figure 5-13 Stepwise Plots for the Region #1 of the Applied Case Study Using A Fourier basis (K=2)

The final model obtained after the stepwise procedure it is shown in Table 5-14.

8 Regu		the Ar	nalvgig of '	 Variance fo	 r the	Bagig Rer		tion Mo	% del
8									%
o.				ts and Vari					0.
Zerm	Intercer	ot s		 -test P-					8
0	-			-35.6873					
Term	Coeff	ficient	ts SE Coef	T-tes	t	P-value		VIF	
1	3.29	925	0.35261	9.337	6	0		1.5	
2	5.74	68	0.35261	16.29	8	0		1.5	
3	0.892	227	0.35261	2.530	5	0.01188		1.5	
4	1.07	798	0.12467	8.661	22.	2204e-016		1	
5	-0.967	17	0.12467	-7.758	1 1.	2279e-013		1	
6	-0.299	964	0.12467	-2.403	6	0.016818		1	
8									%
Q_			R^2 and Ad	justed R^2					Q.
R^2,	R^2(a								ô
0.59652	0.5887	79							
8			Analysis o						%
8									%
Source					-	F	P		
				1 383.5		77.126	0		
			1556.63		733				
Total		319	3858.04	45					
8									%

Table 5-14 Final Output for the Piece-Wise Method using a Fourier basis for region #1

After the stepwise procedure all the terms that stayed in the model, are terms that do not are multiplied by a sine or cosine term. Of those terms, the less relevant is the term that correspond to the factor Ls. The factors L1, L2 and the combinations of W and ε_r have a considerable relevance in this model as shown in Table 5-15. The model is not very good. Only explains around a 60% of the total variability of the data, but most of their terms are relevant. The next section shows the results for the next region.

Table 5-15 Results Summary for Region #1

Terms	Coefficient Represented	Value	Related Factor	Basis Term
0	B ₀₀	-8.8973	1	1
1	B ₁₀	3.2925	T1	1
2	B ₂₀	5.7468	T2	1
3	B ₃₀	0.8923	T3	1
4	B_{40}	1.0798	L1	1
5	B ₅₀	-0.9672	L2	1
6	B ₆₀	-0.2996	Ls	1

5.3.2.3.2 Results for Region #2

Table 5-16 presents the initial model obtained for this region.

e of Ba	sis: fourier basis functions	or knots i	f the basis	is a Cubic Splin	ne: 2	
	Coeffic	tients and N	Variance Infl	ation Factors		
Terms	Coefficients	SE Coef	T-test	P-value	VIF	
0	-9.5316	0.22526	-42.313 15.372	0	0	
1	4.897	0.31857	15.372	0	1.5341	
2	6.8848	0.31857	21.612	0 3.8761e-007	1.5341	
3	1.6482	0.31857	5.1738	3.8761e-007	1.5341	
4	1.4254 -0.60844	0.11263	12.655	0	1.0227	
5	-0.60844	0.11263	-5.4021	3.8761e-007 0 1.2216e-007 0.0035689	1.0227	
6	-0.33045		-2.9339	0.0035689 0.56647	1.0227	
7	0.18672	0.3254	0.57381	0.56647	4.0266	
8	-0.43232	0.46018	-0.93945	0.34815 0.50173	2.0172	
9			-0.67246	0.50173	2.0172	
10	-0.22049	0.46018	-0.47915	0.63213 0.55745	2.0172	
11	-0.095537	0.1627	-0.5872	0.55745	1.0092	
12	-0.094815	0.1627	-0.58276	0.56043 0.92048	1.0092	
13	0.016254	0.1627			1.0092	
14	-0.084179	0.31159	-0.27016 0.41936	0.7872	4.0808	
15	0.18479	0.44065	U.41936		2.0572	
16	0.13143	0.44065	0.29826 0.21808	0.76569	2.0572	
17	0.096099				2.0572	
18	0.043491	0.15579 0.15579	0.27916		1.0314	
19	0.040125				1.0314	
20 21	-0.011005	0.100/9	-0.070637	0.94373	1.0314	
21 22	0.060941 -0.14238	0.31692	0.19229 -0.31768	0.84762 0.75092	4.0685 2.0464	
22					2.0464	
23 24	-0.10187 -0.072093	0.44819			2.0464	
25	-0.031265	0.15846			1.0252	
26	-0.031201	0.15846	-0.1969		1.0252	
27	0.0049886	0.15846			1.0252	
28	-0 070607	0 32021	_0 2205		4.0555	
29	0.16057	0.45284	0.35457		2.0369	
30	0.11457	0.45284 0.45284 0.45284	0.35457 0.253	0.80042	2.0369	
31	0.082108	0.45284	0.18132		2.0369	
32	0.082108 0.036335	0.1601	0.22695	0.8206	1.02	
33	0.034946	0.1601	0.21827	0.82735	1.02	
34	0.034946 -0.0073094	0.1601	-0.045654	0.96361	1.02	
			Adjusted R'	2		
0.	R ² , R ² (ad 69342 0.66355	j)				
		Analysi	ls of Variand	:e		
Sou		 DF	SS	 MS	F P	
Rec	gression	34 3759	9.7825 11	0.5818 23.2	164 0	

There is a lot of term that are not contributing to the model. The stepwise procedure is executed in order to eliminate those terms and simplify the model. The plots that correspond to the procedure are shown next.

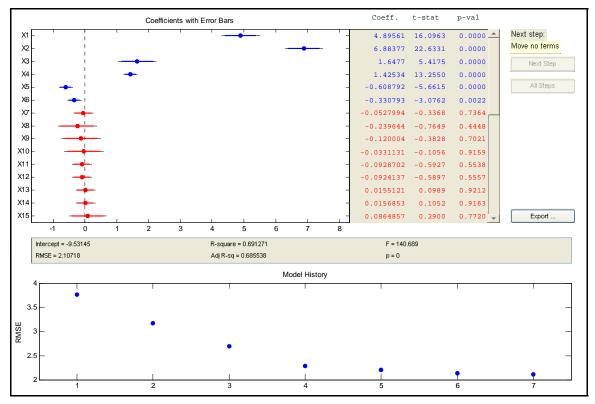


Figure 5-14 Stepwise Plots for the Region #2 of the Applied Case Study Using A Fourier basis (K=2)

The details for the final model are shown in Table 5-17.

% Re	sults for	the An	alysis of Var	riance for the	e Basis Repre	sentatio	n Model
% o.			Coefficients	and Variance	Inflation Fa	ctors	%
6							6
Term	Interce	pt S	E Coef T-te	est P-value	9		
0	-9.532	15	0.21506 -4	44.3193 0			
Ter	m Coefi	ficient	s SE Coef	T-test	P-value	VIF	
1	4.89	956	0.30415	16.096	0	1.5	
2	6.88	338	0.30415	22.633	0	1.5	
3	1.64	177	0.30415	5.4175 1	.0798e-007	1.5	
4	1.42	253	0.10753	13.255	0	1	
5	-0.608	379	0.10753	-5.6615 2	.9772e-008	1	
6	-0.330	079	0.10753	-3.0762	0.0022493	1	
8							%
<u> </u>			R ² and Adjus	sted R^2			
	R^2(a 27 0.6863	5,					
%			Analysis of N	/ariance			%
Source	`	DF	SS	MS	ਸ	P	Ŭ
				624.6897	-	-	
			1673.96	4.4402	110.0072	0	
			5422.0981	1.102			
8							%

Table 5-17 Final Output for the Piece-Wise Method using a Fourier basis for region #2

Terms	Coefficient	Value	Related	Basis Term
	Represented		Factor	
0	B_{00}	-9.5315	1	1
1	B ₁₀	4.8956	T1	1
2	B ₂₀	6.8838	T2	1
3	B ₃₀	1.6477	Т3	1
4	B_{40}	1.4253	L1	1
5	B ₅₀	-0.6088	L2	1
6	B ₆₀	-0.3308	Ls	1

Table 5-18 Results Summary for Region #2

The same terms selected by this procedure in the previous region were selected for this one. Those terms are the terms that relate W and ε_r , and the terms that correspond to L1 and L2. There is a term that corresponds to Ls but it has the lowest magnitude among the other coefficients. This model is better than the previous one in terms of the adjusted determination coefficient, which is close to a 70%. The execution of the Piece-Wise method on region #3 is shown in the next section.

5.3.2.3.3 Results for Region #3

Table 5-19 corresponds to the initial model obtained for this region.

Table 5-19 Initial Outp	ut for the Piece-Wise	Method using a Fouri	er hasis for region #3
Table 3-17 Initial Outp		, memou using a roun	c_1 basis for region πs

	on #3			ariance for		-		
pe of		fourie						
			ns or k			Cubic Spline:		
		 ~						
		Coe	efficie	nts and Vari		lon Factors		
	Terms			s SE Coef	T-test	P-value	VIF	
	0	-10.2		0.24538	-41.796	0	0	
	1	б.4		0.34702	18.65	0	1.5294	
	2	7.99	18	0.34702	23.03	0	1.5294	
	3	2.42	.79	0.34702	6.9965	1.1869e-011	1.5294	
	4	1.80	58	0.12269	14.719	0	1.0196	
	5	-0.287	22	0.12269	-2.341	0.019746	1.0196	
	6	-0.439	49	0.12269	-3.5821	0.00038498	1.0196	
	7	-0.168	84	0.34988	-0.48256	0.62969	4.0435	
	8	0.338	25	0.4948	0.68361	0.49463	2.0285	
	9	0.230	96	0.4948	0.46677	0.64093	2.0285	
	10	0.150		0.4948	0.30455	0.76088	2.0285	
	11	0.0896		0.17494	0.51274	0.60843	1.0154	
	12	0.0571		0.17494	0.32679	0.74401	1.0154	
	13	-0.0379		0.17494	-0.21698	0.82834	1.0154	
	14	-0.125		0.34414	-0.36594	0.71461	4.0626	
	15	0.267		0.48669	0.55018	0.58252	2.0426	
	16	0.18		0.48669	0.38136	0.70315	2.0426	
	17	0.129		0.48669	0.26591	0.79045	2.0120	
	18	0.123		0.17207	0.39704	0.69156	1.0232	
	19			0.17207	0.30195			
		0.0519			-0.13457	0.76285	1.0232	
	20	-0.0231		0.17207		0.89302	1.0232	
	21	0.027		0.33756	0.080074	0.93622	4.072	
	22	-0.0512		0.47739	-0.10743	0.9145	2.052	
	23	-0.0347		0.47739	-0.07274	0.94205	2.052	
	24	-0.0214		0.47739	-0.044851	0.96425	2.052	
	25	-0.0138		0.16878	-0.082105	0.93461	1.0286	
		-0.00768		0.16878	-0.045561	0.96368	1.0286	
	27	0.00679		0.16878	0.040274	0.9679	1.0286	
	28	0.0950		0.35623	0.26682	0.78975	4.0098	
	29	-0.194		0.50378	-0.38658	0.69928	2.0062	
	30	-0.134	80	0.50378	-0.26615	0.79027	2.0062	
	31	-0.0900		0.50378	-0.17872	0.85825	2.0062	
	32	-0.0504	99	0.17811	-0.28352	0.77693	1.0033	
	33	-0.0350	83	0.17811	-0.19697	0.84396	1.0033	
	34	0.0195	56	0.17811	0.10979	0.91263	1.0033	
				R^2 and Adju				
	R^2,	R^2(a						
	0.70805		19					
				Analysis of	Variance			
	 Source		DF	SS	MS	F	 P	
	Regressi	on	34	5674.8544				
	Residual		381	2339.9442			-	
	Fotal		415	8014.7985		-		

Once again, the model has a good quantity of terms that are not contributing to the model. The stepwise procedure once again provides a new simplified model. The plots that correspond to this procedure are shown in Figure 5-15.

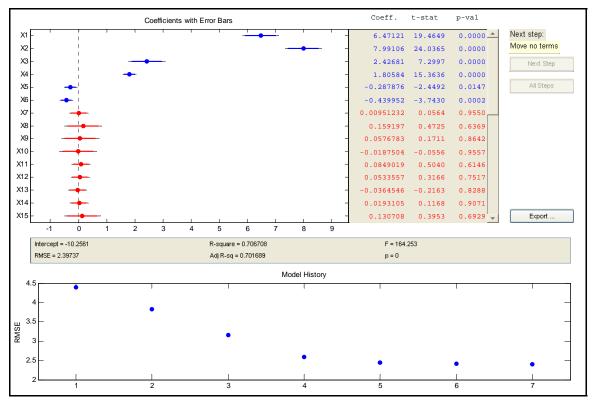


Figure 5-15 Stepwise Plots for the Region #3 of the Applied Case Study Using A Fourier basis (K=2)

The details for the final model are presented in Table 5-20.

8									%
Re	sults fo	or the	Analysis of	E Variance f	for the	Basis 1	Represent	ation	Model
8									%
			Coefficient	ts and Varia	ance Int	flation	Factors		
8									%
	-			-test P-v					
0	-10.25	61	0.23508	-43.628	0				
Term	Coeffic	ients	SE Coef	T-test]	P-value	VIF		
1	6.47	12	0.33245	19.465	5	0	1.5		
2	7.99	11	0.33245	24.037	1	0	1.5		
3	2.42	268	0.33245	7.2997	1.51	55e-012	1.5		
4	1.80)58	0.11754	15.364	ł	0	1		
5	-0.287	88	0.11754	-2.4492	2 0	.014738	1		
6	-0.439	95	0.11754	-3.743	0.00	0020787	1		
8									%
			R^2 and Ad	justed R^2					
% ¤^ว	 R^2(a								%
	0.7024	5,							
%			Analysis of						%
8									%
Source		DF	SS	MS	5	F	P		-
				4 944.02			28 0		
				31 5.74					
Total			8014.798						
8									%

Table 5-20 Final Output for the Piece-Wise Method using a Fourier basis for region #3

Once again, the constant terms were selected by the procedure. The model explains a 70% of the variability of the data. This is almost equal to the model for region #2. The next table presents a summary of these results. The next table summarizes these results.

Terms	Coefficient	Value	Related	Basis Term
	Represented		Factor	
0	B ₀₀	-10.2561	1	1
1	B ₁₀	6.4712	T1	1
2	B ₂₀	7.9911	T2	1
3	B ₃₀	2.4268	Т3	1
4	B40	1.8058	L1	1
5	B ₅₀	-0.2879	L2	1
6	B ₆₀	-0.4400	Ls	1

Table 5-21 Results Summary for Region #3

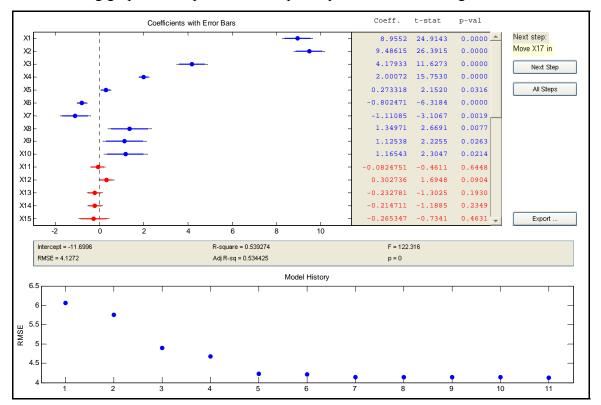
The next section presents the results for the region #4, which is the last one.

5.3.2.3.4 Results for Region #4

In the same way as in the previous section the Matlab output for the initial model it is presented first.

Table 5-22 Initial Output for the Piece-Wise Method using a Fourier basis for region #4

	basis function	s or knots if	the basis i	s a Cubic Spli	ne: 2
				Inflation Facto	
 Terms	Coefficients				VIF
0		0.25535			0
1	8 9599	0 36112	24.811	0	1.5052
2	9.4994	0.36112	26.305	0	1.5052
3	4.1743	0.36112 0.36112 0.36112	26.305 11.559	0	1.5052
4	2.0027	0.12768	15.686	0 0.02973	1.0035
5	0.27792			0.02973	1.0035
б	-0.80924 -1.0964	0.12768	-6.3382	3.4821e-010 0.0023407	1.0035
7			-3.0509	0.0023407	4.0118
8	1.342	0.50822	2.6406	0.0084026 0.030077	2.0077
9	1.1039	0.50822	2.1721	0.030077	2.0077
10	1.1733	0.50822	2.3086	0.021167 0.62113	2.0077
11 12	-0.088834 0.30719	0.17968	-0.4944 1.7096		1.0042 1.0042
12	-0.23103		1 2050	0.19881	1.0042
14	-0.035729		-0.098469		4.0071
15	-0.22989		-0.44801		
16	0.23196	0.51315	0.45204		2.0046
17	-0.70884		-1.3814		
18	0.28085	0.18142	1.548		1.0025
19	-0.25225		-1.3904		1.0025
20	0.048552	0.18142	0.26762	0.78905	1.0025
21	0.37463	0.35712	1.0491	0.2944	4.0127
22	-0.32811	0.50504		0.51605	2.0088
23	-0.43287	0.50504	-0.8571	0.39159	2.0088
24	-0.26835	0.50504	-0.53135	0.59529	2.0088
25	0.03991	0.17856	0.22351 -0.25421	0.82318	1.0048
26	-0.045391	0.17856	-0.25421	0.79939	1.0048
27	0.07497	0.17856	0.41986 0.587	0.67467	1.0048
28	0.21428	0.36505	0.587	0.55734	4.0025
29 30	-0.041564 -0.28299	0.51626	-0.080509 -0.54815	0.93585 0.58371	2.0016
30	-0.010145	0.51626	0.010651	0.98433	2.0016 2.0016
32	0.020609	0.18253	-0.019651 0.11291	0.91013	
33	0.033339	0.18253	0.18266		1.0009
34	0.017307	0.18253	0.094817	0.92448	1.0009
	R^	2 and Adjuste	ed R^2		· · _ · _ · _ · · _ · · · · · ·
	R^2(adj) 0.53157				
	An	alysis of Var	iance		
rce	DF	SS	MS	 F	 Р
ressior		21120.4829	621.1907		0



The following graphs correspond to the stepwise procedure for this region.

Figure 5-16 Stepwise Plots for the Region #4 of the Applied Case Study Using A Fourier basis (K=2)

The final model details are presented in the Table 5-23

		Coefficients		nce Inflation	Factors	
Term	Intercept	SE Coef				
0	-11.6996	0.25416	-46.032	0		
Term	Coefficients	SE Coef	T-test	P-value	VIF	
1	8.9552	0.35944	24.914	0	1.5018	
2	9.4861	0.35944	26.391	0	1.5018	
3	4.1793	0.35944	11.627	0	1.5018	
4	2.0007	0.12701	15.753	0	1	
5	0.27332	0.12701	2.152	0.031625	1	
б	-0.80247	0.12701	-6.3184	3.9053e-010	1	
7	-1.1108	0.35757	-3.1067	0.0019431	4	
8	1.3497	0.50568	2.6691	0.0077231	2.0018	
9	1.1254	0.50568	2.2255	0.026262	2.0018	
10	1.1654	0.50568	2.3047	0.02138	2.0018	
5		R^2 and Adju	usted R^2			
	R^2(adj) 0.53487					
,		Analysis of				
Source	DF	SS	 MS	F	 Р	
legressi	on 10	20835.036 5 17800.28	5 2083. 328 17	5036 122.3 .0338		

Table 5-23 Final Output for the Piece-Wise Method using a Fourier basis for region #4

This model has more terms considered relevant due the behavior of some of the response functions in this region. For the previous regions, all the curves behave as constant functions. However, in this region some of the responses differ from that pattern. This is shown in the next figure.

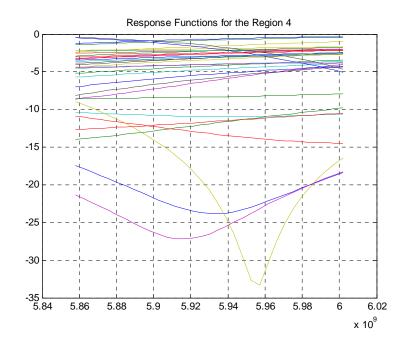


Figure 5-17 Response Functions for Region #4

For the behavior of the response functions in this region, the adjusted determination coefficient is close to a 50%. Table 5-24 summarizes the terms that were considered as relevant by this model.

Terms	Coefficient	Value	Related Factor	Basis Term
	Represented			
0	B ₀₀	-11.6996	1	1
1	B ₁₀	8.9552	T1	1
2	B ₂₀	9.4861	T2	1
3	B ₃₀	4.1793	T3	1
4	B40	1.9987	L1	1
5	B ₅₀	0.2807	L2	1
6	B ₆₀	-0.8025	Ls	1
7	B ₀₁	-1.1108	1	sin(wt)
8	B ₁₁	1.3497	T1	sin(wt)
9	B ₂₁	1.1254	T2	sin(wt)
10	B ₃₁	1.1654	T3	sin(wt)

Table 5-24 Results Summary for Region #4

This model considered the same factors that were pointed out as relevant in the previous regions. However, due the low determination coefficient this results are not

reliable. In general, this procedure worked out in the same way than the basis representation model. The next section presents a summary of the results obtained using the Piece-Wise method.

5.3.2.4 Results Summary for the Piece-Wise Method without the Continuity

Constraints

The Piece-Wise method was performed in order to analyze this applied case study. The next table shows a summary of the results obtained.

	Number of		Number of Data	Adjusted
Fourier Basis	Terms	SSE	Points	R^2
Region 1	7	4.9733	320	0.58879
Region 2	7	4.4402	384	0.68636
Region 3	7	5.7474	416	0.70241
Region 4	11	17.0338	1056	0.53487
Pseudo-MSE	10.90628925			

Table 5-25 Summary of the Piece-Wise Method for the Applied Case Study

All the models contained almost the same quantity of terms for all the regions. The only exception was the model for the region #4. The adjusted determination coefficients obtained were relatively low. In general, in all the regions the terms T1, T2, T3, L1 and L2 were considered as the most relevant ones. The next section is a comparison of the three methods under for the case that corresponds to this chapter.

5.3.3 Piece-Wise Method with the Continuity Constraints

As done with the theoretical case study the procedure used to force the curves from two adjacent regions to be joined at the knot was applied to this case. In this case, 31 indicator variables were incorporated to the model. The consequences of the high number of variables added to the model were dramatic. The effects on the design matrix were fatal. The variance-covariance matrices are completely ill-conditioned. For that reasons the obtained models are completely useless to analyze or infer with respect the factors of this

experiment. For the reasons previously mentioned the results for this part of the piecewise method are not presented.

5.4 Comparison of Results for the Three Methods for the Applied Case

Study

The three methods were utilized to analyze the experiment. The pseudo-MSE it is used as a metric of comparison for the methods. The next table shows the pseudo-MSE for the three methods.

Method	Basis Used	Total SSE	Total Number of Parameters	Total Number	Pseudo MSE
				of Data Points	
Point-Wise	N/A	22985.9	476	2176	13.521
Basis Representation	Fourier	23617.8	26	2176	10.985
Piece-Wise without Continuity Constraints	Fourier	23328.55	37	2176	10.9063

Table 5-26 Pseudo-MSE Table for all the methods applied for the applied case study

The Point-Wise method provides the lowest total SSE but total of number of parameters was so high that the pseudo-MSE became the highest one among the methods. The basis representation method and the Piece-Wise procedure worked out almost in the same way. The three methods considered ε_r , W, L₁, and L₂ as the most relevant parameters for the design of a rectangular slot ring antenna considering as a measure of interest the reflection coefficient. The next chapter presents the conclusions and future work for the whole research.

6 Computer Applications

6.1 Introduction

One of the objectives of this research is the development of a series of tools to ease the implementation of the concepts developed and presented on the previous chapters in the industry. The following sections describe the applications developed for each of the methods developed in this study.

6.2 Point-Wise Method GUI

In order to ease the use of these tools, graphical user interfaces were created. For each method, a Matlab GUI was created. Figure 6-1 shows the GUI for the Point-Wise method. This GUI provides to the user with all the plots in order to complete the desired analysis. In addition, the "pseudo MSE" is included in the final output of this form. The next page shows the MS Front Page document created to be used as the help for this application. The user only needs to press the "help" button of the application and the html document appears as part of the Matlab help.

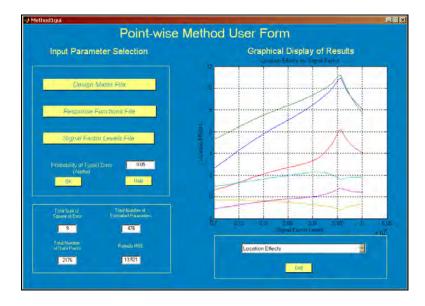


Figure 6-1 Snapshot of the Point-Wise Method user form

6.2.1 Point-Wise Method GUI Help

In order to use the Piece-Wise procedure you need to complete the following series of steps

- Press the "Design Matrix File" button- Select the **text** file with the design matrix
- Press the "Response Functions File" button- Select the text file with the responses
- Press the "Signal Factor Levels File" button- Select the **text** file with the responses
- In addition to the files that must be uploaded, a probability must be entered in the edit box provided.
- The "OK" button must be pressed in order to execute the procedure

Note: Each row of the response functions file must correspond to the row of the design matrix, otherwise errors can occur in the analysis.

The following figure shows a snapshot of the GUI for the Piece-Wise procedure

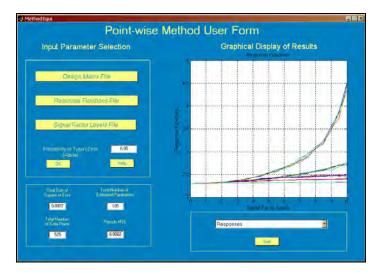


Figure 6-2 Snapshot of the user form for the Point-Wise method presented in the help file of the application

The popup menu has the options required. The user has to select the graphs in order to see them in the axes. In addition, the grid can be added to the graphs if is desired.

6.3 **Basis Representation Method GUI**

For the Basis Representation Method also a graphical user interface was created. This is quite different with respect the previous one. This GUI has three main sections. The first section, which is located at the left side of the GUI, is the input parameter section. In this section, the user loads the files with the data. After loading the files, the user has to select the type of basis that is going to be used and the number of basis that are desired. If the basis is a Cubic Spline the user has to enter the desired knots for the spline. The second section of this application is the results section, which is right in the center of the application. All the results for the method are presented in this section, including the results after the stepwise procedure. The last section of the GUI includes the controls to initialize the stepwise procedure, the outputs for the "pseudo MSE" and the help button. In the next page the html document for the help it is presented

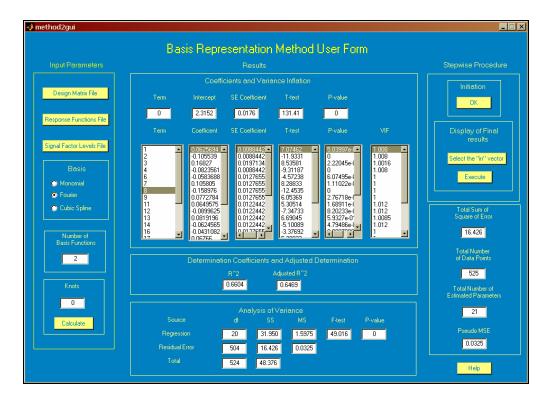


Figure 6-3 Snapshot of the Basis Representation Method user form

6.3.1 Basis Representation Model GUI Help

The design matrix must include the column for the intercept estimation. This column of ones must be the first one in the design matrix. The number of rows of the design matrix and the responses matrix must be the same. In addition, the number of columns of the responses matrix and the length of the signal factor vector must be equal. Otherwise, error messages will appear indicating the errors.

In order to use the GUI for the Basis Representation Model it is required to follow the next sequence of steps.

- Load the file for the design matrix (x)
- Load the file for the responses matrix (y)
- Load the file for the signal factor levels (t)
- Select the type of basis to be used
 (i) If the basis is a monomial, or Fourier basis fill the "knots" edit text with a zero.
 (ii) If the basis is a Cubic Spline fill the "Number of Basis Functions" edit text with a zero
- The knots have to be enclosed using brackets ([]) and each element must be separated using spaces or commas. The knots selected must be equal to some levels of the signal factor vector.
- Press the "Calculate" Button to execute.

Note: If you select decide to select other type of basis unselect the previous one.

Figure 6-4 the GUI for the basis Representation Method in detail.

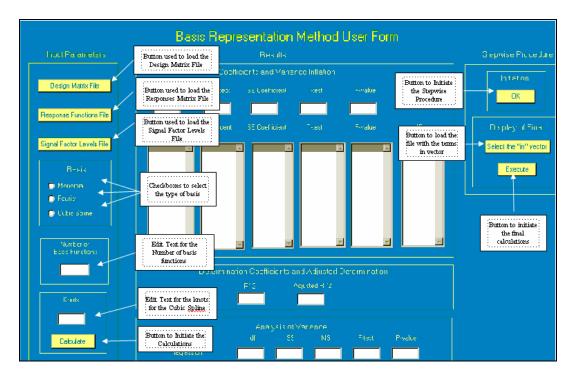


Figure 6-4 Snapshot of the Basis Representation user form used in the help file of the application

To use the stepwise procedure of this application it is necessary to complete the following steps

• Press the "Initiate" button of the application

This Button activates the Matlab stepwise procedure that opens three GUIs that are shown in Figure 6-5

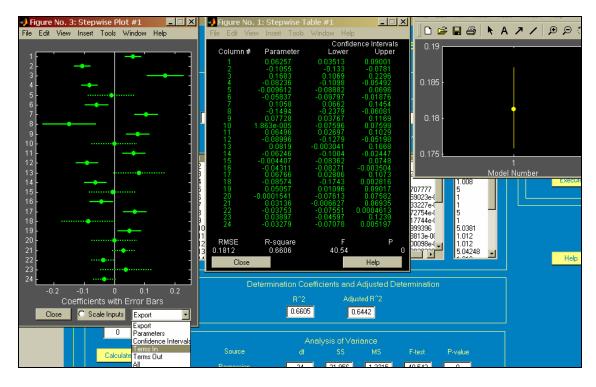


Figure 6-5 Snapshot of the stepwise procedure of the Basis Representation user form, presented in the help file

After eliminating al the terms that are not going to be included in the final model; use the export option of the stepwise plot and select the option "Terms in". This option is going to save that vector of indices in the workspace. Select the vector and create a text file with those indices.

- Press the "Select the "in" vector" button of the application
- Select your file with the Terms in indices
- Press the "Execute" button to present the final results in the GUI

6.4 Piece-wise Method GUI

For this method a GUI was develop in order to ease their implementation. This GUI is similar to the previous ones, but all the results of all the procedures conducted are presented on the Matlab's workspace instead on the GUI. The Piece Wise method is a more complicated procedure compared to the previous two. It can be summarized in three main steps, which are the following

- Knots Search
- Unconstrained Piece Wise Method and variable selection via stepwise procedure
- Constrained Least of Squares

The performance metrics for the model such as the Pseudo-F ratio will appear on the user form. The plot for the knot search it is part of the GUI but the regression plots will appear as separate figures. The next section presents the help for this application.

6.4.1 Piece Wise Method GUI Help

The design matrix must include the column for the intercept estimation. This column of ones must be the first one in the design matrix. The number of rows of the design matrix and the responses matrix must be the same. In addition, the number of columns of the responses matrix and the length of the signal factor vector must be equal. Otherwise, error messages will appear indicating the errors.

In order to use the GUI for the Basis Representation Model it is required to follow the next sequence of steps.

- Load the file for the design matrix (x)
- Load the file for the responses matrix (y)
- Load the file for the signal factor levels (t)
- Select the type of basis to be used
- Define the number of basis functions
- If the knot search it is going to be executed the "Number of Knots" field must be defined
 - o Press the "Start Knot Search Button

		Piece	vvise ivi	ethod Us	ser Forr	n		
Input Parameters Design Matrix File Response Functions File Signal Factor Levels File Basis Type	1 0.9 - 0.8 - 0.7 - 0.6 -						nconstrained Piece Wilse strained Least of Squares Total Sum of Square of Error	
Mononial Fourier Number of Basis Functions	0.5 - 0.4 - 0.3 - 0.2 - 0.1 -						Total Number of Dote Points Total Number of Estimated Parameters	
Number of Knots	00	0.2	0.4	0.6	0.8	1	Pseudo MSE	
Help		Objective Fi	inction	Optimal F	(nots			

Figure 6-6 Piece Wise Method user form used in the help file of the application

- To execute the unconstrained piece wise method press the button "Unconstrained Piece Wise"
 - A question dialog it is going to appear asking you if you completed the knot search
 - If the answer to this question is "not" then the program, it is going to ask you to enter the knots using the Matlab's vector notation on the command window.
 - The stepwise command GUI it is going to appear for each region of the problem (the number of knots plus one), to move to the next stepwise you must press any key
 - You must export the "in terms" of each stepwise procedure to the workspace
- To execute the Constrained Least of Squares press the button "Constrained Least of Squares"
 - A question dialog it is going to appear asking you if you completed the knot search

- If the answer to this question is "not" then the program, it is going to ask you to enter the knots using the Matlab's vector notation on the command window.
- The program will require you to enter the in terms of the stepwise procedure for each region, using the Matlab's workspace
- o All the required graphs are going to appear as separate figures
- The GUI should look like the next figure if you completed all the steps mentioned

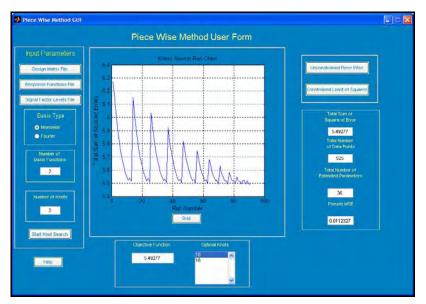


Figure 6-7 Piece Wise Method GUI after Execution

This chapter presented the main aspects of the applications developed in order to ease the implementation of the concepts of this research in industry. The technical details of the applications are on the appendixes. The next chapter presents the conclusions and future work for this research.

7 Conclusions and Future Work

7.1 Conclusions

The main contribution of this research is the demonstration of how powerful can be the functional data analysis in order to analyze industrial experiments. The development of new methods of analysis such as the basis representation method and the Piece-Wise methods are also considerable contributions. The three methods were consistent, with respect the factors considered as relevant in both of the experiments. The point wise procedure can lead to good results but sometimes the interpretation of the graphs can be complex. The basis representation method is more complex than the Point-Wise in terms of computational effort, but the results obtained can be easily interpreted because is a linear regression model. The Piece-Wise can be an option for experiments in which some regions need to be analyzed in detail. The greatest disadvantage that this method has with respect the previous two is the necessity of the knot search. This knot search can take a lot of computational effort in order to find the best locations for the knots. In addition to the knot search, the procedures to ensure the continuity of the curves among the regions can have a serious impact on the inferential capabilities of the models. A possible advantage of the Point-Wise method over the basis representation and the Piece-Wise method is the non-dependence in a basis selection. In addition, the Point-Wise method is very efficient in terms of computational effort. In general, the three methods complete their task. They are able to find the most relevant factors that can affect the functional response. The following table presents a summary of the respective advantages and disadvantages for each of the methods studied in this research.

Method	Advantages	Disadvantages
Point-Wise	 Computationally Efficient Independent of a basis selection Useful for model selection and determination 	 Depends on graphical interpretation High number of terms to be calculated and analyzed No functional form is obtained for the estimated response A multiplicity problem that increases with the number of levels of the signal factors
Basis Representation	Simple interpretationLow number of terms	 Basis Dependent Could be computationally intensive
Piece-Wise	 Simple interpretation Deeper analysis in each region 	 Basis Dependent Computationally extensive due the knot search The approach used for to establish the continuity constraint induces a severe multicollinearity problem

Table 7-1 Summary of the Advantages and Disadvantages for the Three Methods Used in this Research

It is possible to observe that all the methods have advantages and disadvantages. The final decision with respect the method to be applied is going to depend in the nature of the problem. If the problem has a high number of levels for the signal, the Piece-Wise method can be a problem in terms of the knot search part of the procedure. It is recommended to use the Piece-Wise method only for situations in which is required to analyze response functions by regions or when the signal factor does not has a high number of levels. The other two procedures can be applied practically in every desired situation.

7.2 Future Work

There is a lot of work to be done; in specific for the basis representation, and the Piece-Wise methods. More types of bases can be integrated to those methods. Bases such as wavelet, exponential, polygonal and constant could be used for those methods. New procedures in order to complete the knots search are extremely necessary in order to make more efficient this search in order to ease the implementation of the Piece-Wise

method. In addition, procedures to obtain the curves continuity between regions need to be developed in order to ensure the continuity without affecting the quality of the regressions. In the cases studied some problems were founded with respect the regressions. To be specific the assumption of constant variance was not followed by most of the models. Different approaches for the parameter estimation could be tested in order to overpass the difficulties presented by the use of the least of squares regression.

In addition to all the work completed in this research, there is a lot of work been doing by many researchers. Statisticians and engineers must develop some robust and practical techniques in order to demonstrate the strengths that the functional data analysis can provide to industrial experiments.

8 References

- Montgomery, D.C. (2001), Design and Analysis of Experiments (5th edition), New York: Wiley
- Ramsay, J.O., Silverman, B.W. (1997), Functional Data Analysis, New York: Springer-Verlag
- Nair, V.N., Taam, W., Ye, K.G. (2002), "Analysis of Functional Response Form Robust Design Studies", Journal of Quality Technology, Vol. 34, No. 4
- Faraway, J.J., "Regression Analysis for a Functional Response", Technometrics, Vol. 39, No. 3
- Montgomery, D. C. (1994), Applied Statistics and Probability for Engineers, New York: Wiley
- 6. Fan, J., Lin, S. (1998), *"Test of Significance When Data Are Curves"*, Journal of the American Statistical Association, Vol. 93, No. 443, Theory and Methods
- Cuevas, A., Febrero, M., Fraiman R., (2002), "Linear Functional Regression: the case of fixed design and functional response", The Canadian Journal of Statistics, Vol. 30, No. 2
- 8. Ramsay, J.O., Silverman, B.W., (2002), *Applied Functional Data Analysis Methods and Case Studies*, New York: Springer-Verlag
- Abramovich, F., Antoniadis, A., Sapatinas, T., Vidakovic, B. (2002), "Optimal Testing in Functional Analysis of Variance Models" www.isye.gatech.edu/~brani/Wavelets/02-02.pdf

- Montgomery, D.C., Peck Elizabeth A., Vining G. Geoffrey (2001), *Introduction to Linear Regression Analysis* (3rd edition), New York: Wiley
- Ramsay, J.O., and Dalzzel, C.J. (1991), "Some Tools for Functional Data Analysis" (with discussion), Journal of the Royal Statistical Society, Ser. B, 539-572
- Cuevas, A.; Febrero, M. y Fraiman, R. (2002) "Linear functional regression: The case of fixed design and functional response." The Canadian Journal of Statistics, Vol. 30, nº 2, pp. 285-300.
- Salazar, J. (2002), "Desarrollo de un sensor para el sistema Crosswell Radar Tomography para detección de residuos bajo tierra." M.S Thesis. ,University of Puerto Rico, Mayagüez, P.R.

Appendix 1 Details form Theoretical Case

In this first appendix, the details for the theoretical case study are going to be presented. As mentioned in chapter 4 a VBA Macro was used to generate the response curves for the experiment. An snapshot of the excel spreadsheet used to generate the data used for the experiment is presented in figure A.1.1

	В	С	D	E	F	G	Н	I	J	К	L	M	N	0
1	To recalculate press CTRL+ALT+F9													
2	81	-1	-1	1	1	0								
3	×2	-1	1	-1	1	0			Eu	inctiona	al Resno	nnses		
4	t	Resp(-1,-1)	Resp(-1,1)	Resp(1,-1)	Resp(1,1)	Resp(0,0)					n neop	511505		
5	0.00	-0.0261	-0.0317	0.0091	0.0096	-0.0112								
6	0.50	0.0083	-0.0187	0.0162	0.0410	-0.0012	10.0	1				1	1	
7	1.00	0.0588	0.0259	0.0643	0.1031	0.0091							11	
8	1.50	0.1501	0.1103	0.1601	0.1567	0.0201							/	
9	2.00	0.1971	0.2334	0.2546	0.2106	0.0390	8.0	+						
10	2.50	0.3150	0.3488	0.4008	0.3042	0.0511						I I		
11	3.00	0.4577	0.4776	0.6850	0.3574	0.0668								
12	3.50	0.5032	0.7030	0.9834	0.4220	0.0809	6.0	+				+		- 1
13	4.00	0.8000	0.7273	1.3696	0.5324	0.0925						1.7		
14	4.50	0.9602	1.0304	1.9202	0.5827	0.1156						r -		
15	5.00	1.1380	1.0008	2.5596	0.6782	0.1456	4.0							- 1
16	5.50	1.2901	1.0618	2.7642	0.7191	0.1226					/		-	
17	6.00	1.4991	1.3723	4.7049	0.8467	0.1637	_				المسر ا		Λ	
18	6.50	1.8385	1.6184	4.8250	0.7877	0.1767	2.0	+			<u> </u>			
19	7.00	2.2173	1.2114	7.5715	0.8247	0.1964	_			- Ka			J. X. Y	~~
20	7.50	2.0659	1.6399	7.7693	0.8033	0.1857			100			\uparrow \land \land $$	T C C	
21	8.00	2.7472		12.0100		0.2281	0.0	4 <u>-</u> 6-6-6				+		
22	8.50	3.1385		16.5359	1.0229	0.2215								
23	9.00	3.3522		21.6583	0.9768	0.2457								
24	9.50	4.8005	2.0264	34.1406	1.1356	0.2248	-2.0	+				1		
25	10.00	4.7947	2.0241	78.4544	1.0729	0.2330	0	.00	2.00	4.00	6	.00	8.00	10.00
26														
27								Value (X)	axis Resp	o(-1,1) 🗕	Resp(1,-1)	 R esp	(1,1) — E	lesp(0,0)
28														

Figure A.1.1 Snapshot of the MS Excel spreadsheet used to generate the experiment for the theoretical case study.

The details of the VBA macro are shown in the next figure.

```
Response
(General)
                                                                                 -
   Private Function Response(t, x1, x2) As Single
        t = Abs(t)
       If t > 10 Then t = 10
       f0 = x1 - 0.5
       f1 = 2 * x1 * x2 + 0.75
f2 = 2 * x1 <sup>^</sup> 2 + x2 <sup>^</sup> 2 - x1 * x2 + 0.25
       ft = f0 + f1 * t + f2 * t ^ 2
        g0 = 2 * x1 ^ 2 + x2 ^ 2 + 50
       g1 = 2 * x1 * x2 + 2.25
       g2 = x2 + 0.5
       gt = g0 + g1 * t + g2 * t ^ 2
       Eps = (Sqr(-2 * Log(Rnd(1)))) * Sin(2 * 3.1415926 * Rnd(2))
       Response = ft / gt * (0.075 * Eps + 1)
   End Function
```

Figure A.1.2 Snapshot of the VBA macro used to generate the functions for the Theoretical Case

Study

The numerical results of the five runs used to test the methods of analysis are shown in the next tables.

0 -1 -1 1 1 -1 1 -1 1 0 -0.00974 -0.02955 -0.02701 0.009643 0.009401 0.00794 -0.0224 0.019626 0.043568 -0.00134 0.06313 0.025469 0.06363 0.090566 0.009705 0.127897 0.100342 0.161652 0.156327 0.022091 0.200127 0.224025 0.305872 0.194455 0.037763 0.326992 0.311946 0.463723 0.275638 0.049903 0.420874 0.53448 0.644597 0.346922 0.060038 0.584393 0.649618 1.028072 0.44136 0.083804 0.716669 0.792269 1.342418 0.488681 0.097133 0.905562 0.973432 1.876639 0.620892 0.10853 1.011142 1.104563 2.604896 0.637629 0.125836 1.414877 1.307627 2.891856 0.660031 0.137948 1.584432 1.408364 4.208405 0.762732 0.147079 1.987885 1.452143 5.395805 0.805077 0.165387 1.972278 1.817569 5.612346 0.789524 0.185538 2.574979 1.568784 8.346522 0.824069 0.200709 3.219038 1.631887 11.24417 0.936698 0.226127 3.20401 1.78047 14.04148 0.822115 0.239182 4.195609 1.822697 23.79627 0.99046 0.238341 4.922475 1.931292 31.7241 1.120306 0.258074 5.06598 2.007657 76.81027 1.042286 0.301072

Table A.1.1 Data for Run #1 of the Theoretical Case Study

х1

х2

x1 x2

Table A.1.2 Data for Run #2 of the Theoretical Case Study

-1	-1	1	1	0
-1	1	-1	1	0
-0.02506	-0.02814	0.009319	0.009185	-0.01058
0.008322	-0.01996	0.016525	0.042236	-0.00128
0.059312	0.031915	0.066759	0.101967	0.010312
0.129266	0.110564	0.162704	0.160596	0.022341
0.201625	0.196582	0.297258	0.245443	0.035951
0.337096	0.410005	0.505396	0.262178	0.048042
0.482517	0.498941	0.758635	0.389001	0.070933
0.591822	0.534093	1.003673	0.375722	0.087029
0.643676	0.806376	1.354527	0.469875	0.104813
1.00613	1.125653	1.717689	0.516822	0.095494
1.170984	1.049902	2.573347	0.574457	0.131791
1.342684	1.340854	3.061642	0.715934	0.153145
1.618439	1.325836	4.053267	0.698535	0.155132
1.730971	1.521352	4.867299	0.742636	0.180463
2.270578	1.611667	6.525233	0.774761	0.201395
2.707817	1.724198	7.626052	0.961136	0.20375
2.880525	1.861544	11.79702	0.771159	0.224973
3.502698	1.802845	15.2124	0.936421	0.234723
4.021999	1.798873	25.33165	0.9183	0.260367
4.248888	1.776384	36.97179	1.017769	0.244292
5.298789	2.191868	80.79288	0.982667	0.204118

Table A.1.3 Data for Run #3 of the Theoretical Case Study

x1 x2

x1 x2

-1	-1	1	1	0
-1	1	-1	1	0
-0.02906	-0.0308	0.009129	0.008319	-0.01112
0.007969	-0.02145	0.015479	0.045803	-0.00132
0.069092	0.028228	0.060468	0.095082	0.009102
0.126612	0.111507	0.166558	0.145239	0.02142
0.237457	0.197497	0.296702	0.239752	0.033853
0.318097	0.354262	0.484636	0.270072	0.044545
0.393697	0.534973	0.726386	0.331751	0.057815
0.549785	0.640372	1.121206	0.454334	0.087166
0.710146	0.726084	1.453431	0.460759	0.101167
0.808599	0.957632	1.990109	0.537481	0.130697
1.163068	1.204151	2.432114	0.600821	0.123196
1.359438	1.159892	3.061314	0.71798	0.131949
1.61253	1.480099	4.293924	0.700131	0.163548
1.919435	1.377092	5.037033	0.840747	0.191638
2.395726	1.520627	6.030873	0.827303	0.20146
2.943201	1.732558	8.75532	0.91076	0.213701
3.085407	1.704156	12.55411	0.992311	0.200034
3.58548	1.698999	14.7318	0.968709	0.220278
3.319357	2.134924	24.04517	1.009499	0.255059
4.549213	1.680975	33.67556	0.938481	0.271797
5.10281	1.868435	68.98808	1.00252	0.290429

Table A.1.4 Data for Run #4 of the Theoretical Case Study

-1	-1	1	1	0
-1	1	-1	1	0
-0.02799	-0.03028	0.009709	0.007986	-0.00927
0.008035	-0.01951	0.017758	0.045331	-0.00115
0.065106	0.025831	0.073214	0.090301	0.009807
0.125944	0.114701	0.14619	0.13574	0.022432
0.248526	0.228625	0.280081	0.227296	0.037364
0.303013	0.315163	0.44326	0.285834	0.04778
0.463151	0.499487	0.706184	0.392888	0.069485
0.535819	0.74476	0.94271	0.430409	0.081568
0.725761	0.725605	1.387714	0.511043	0.087297
0.894978	1.100409	1.932457	0.588839	0.109323
1.183528	1.064585	2.804713	0.697142	0.118582
1.294208	1.413398	3.53286	0.714377	0.14214
1.582925	1.391951	3.64095	0.772333	0.15273
1.798324	1.431159	4.88521	0.777191	0.210812
2.390928	1.477567	7.834334	0.859378	0.19127
2.40153	1.627087	8.339213	0.828463	0.206762
3.173717	1.803808	12.6681	0.876307	0.247802
3.622976	2.131194	13.56933	0.954295	0.205997
4.017898	1.859688	24.40208	0.999199	0.248427
5.028654	2.13463	39.10254	0.926936	0.258994
5.236986	1.646408	82.36643	1.182261	0.240994

x1	-1	-1	1	1	0
x2	-1	-1	-1	1	0
XZ	-	•	-		-
	-0.02562	-0.03041	0.009371	0.010595	-0.01093
	0.007637	-0.02082	0.016673	0.03829	-0.00113
	0.06271	0.029197	0.06654	0.0964	0.008378
	0.13141	0.105038	0.166515	0.143538	0.023743
	0.237821	0.215558	0.234498	0.218809	0.029061
	0.313876	0.359247	0.487976	0.303875	0.047052
	0.390985	0.499875	0.706666	0.364817	0.067519
	0.502899	0.586057	0.920314	0.38907	0.073615
	0.751922	0.733302	1.312079	0.519346	0.108103
	0.902728	1.033647	1.842729	0.566822	0.101534
	1.052538	1.229487	2.519927	0.601609	0.113821
	1.245388	1.35897	3.404696	0.723718	0.147072
	1.867583	1.409289	4.152516	0.72506	0.140835
	2.014749	1.475526	4.782989	0.823508	0.164042
	2.303423	1.353883	6.889404	0.883207	0.204301
	2.627156	1.462087	9.424388	0.922087	0.218063
	3.046413	1.651445	11.1958	0.964646	0.207535
	3.347896	1.686946	14.79526	0.90296	0.234474
	4.331627	1.846729	22.23893	0.866161	0.259719
	4.78677	1.991228	38.17537	1.049412	0.260177
	5.896906	2.030268	67.59177	1.095003	0.281483

Table A.1.5 Data for Run #5 of the Theoretical Case Study

In the next pages the graphical representation of the response functions at each experimental condition for all the runs are presented.

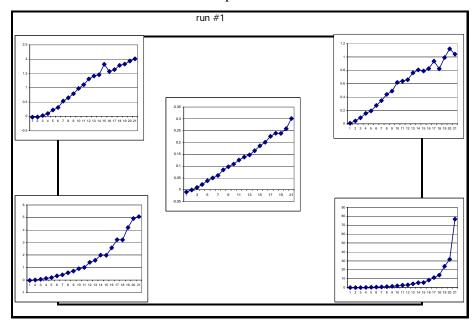


Figure A.1.3 Graphical Representation for run #1

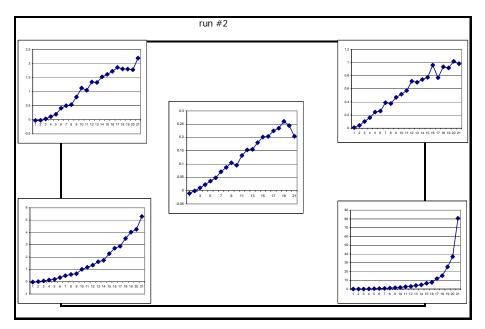


Figure A.1.4 Graphical Representation for run #2

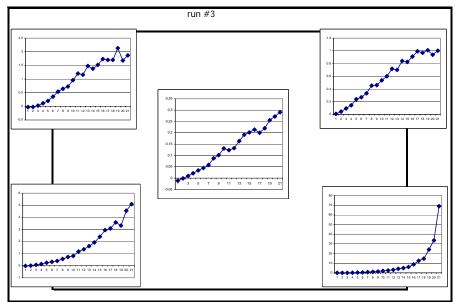


Figure A.1.4 Graphical Representation for run #3

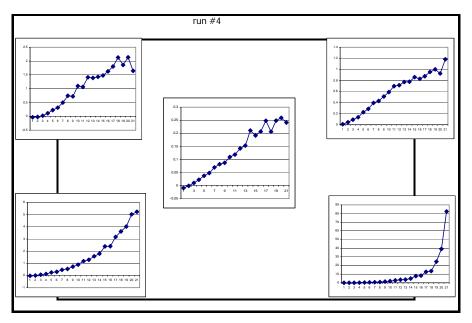


Figure A.1.5 Graphical Representation for run #4

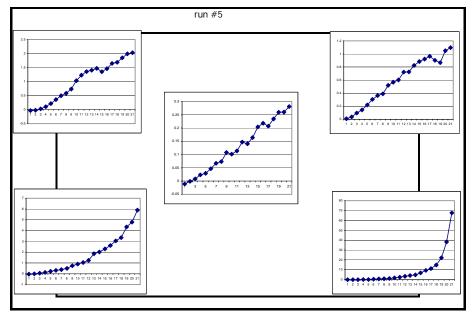


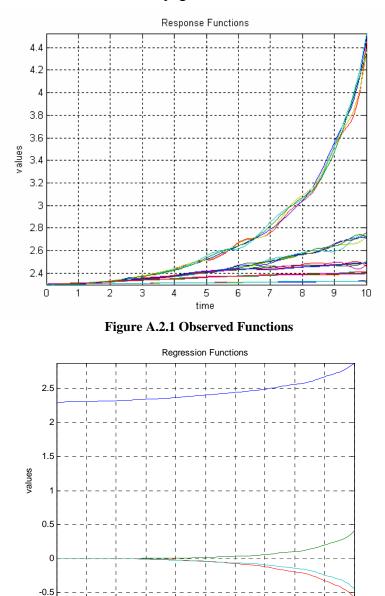
Figure A.1.6 Graphical Representation for run #5

It is important to mention once again that the origin of the function used to generate this theoretical experiment was completely unknown by the analyst of the experiment until the end of the investigation. Also is relevant to mention that Dr. Noel Artiles León, member of the thesis committee, created the function used.

Appendix 2 Results of the Classical Functional Data Analysis for Both Cases

Results of the FDA procedure to the Theoretical Case Study

The classical functional data analysis proposed by Ramsay was also used to analyze the cases studied. In order to complete this part of the analysis the Matlab functions that complement the book Functional Data Analysis were used. The graphical results for the Theoretical Case are shown in the next pages.



time
Figure A.2.2 Effects plot using the FDA Methodology

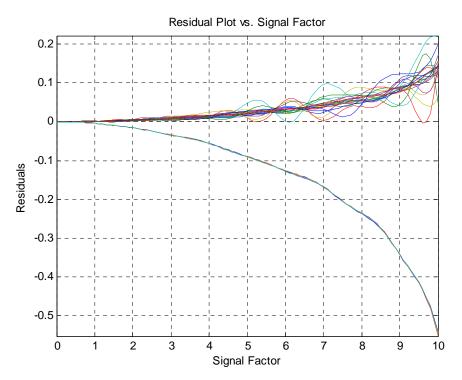


Figure A.2.3 Residuals Plot using the FDA Methodology

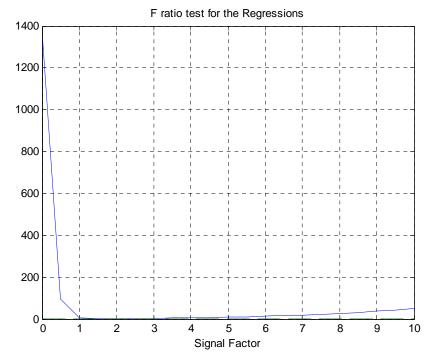


Figure A.2.4 F- Ratio Plot using the FDA Methodology

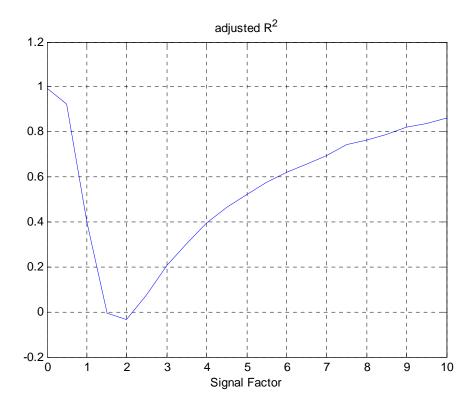


Figure A.2.5 Adjusted Determination Coefficient Plot using the FDA Methodology

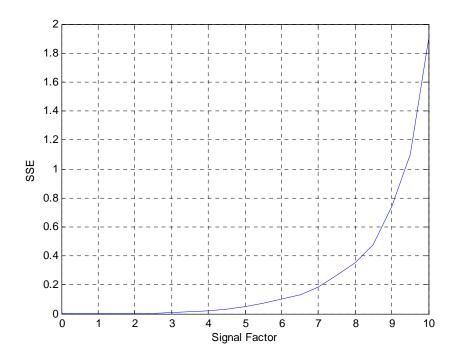


Figure A.2.6 SSE Plot using the FDA Methodology

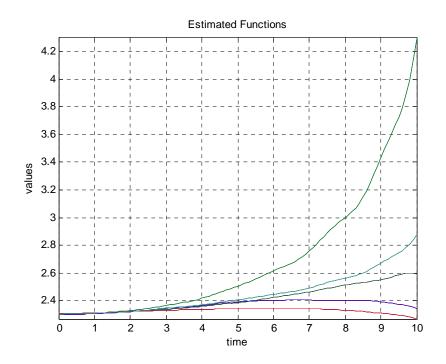


Figure A.2.7 Estimated Responses Plot using the FDA Methodology

It is possible to observe that the plots presented in this section are almost identical to the plots presented with use of the Point-Wise method. The main difference is that the plots look smoother than the previous ones. This is the effect of the use of techniques such as smoothers, registration and roughness of penalty approach among others. However, the basic interpretation and characterization of the response are basically the same.

Results of the FDA procedure to the Applied Case Study

The classical FDA was also applied to the applied study case in order to verify the performance of the Point-Wise procedure. The following graphs are the results obtained.

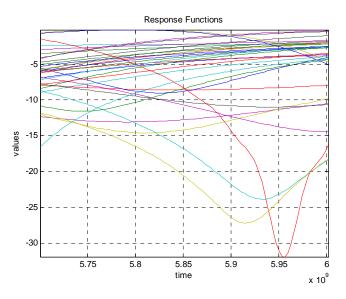


Figure A.2.8 Response Function for the Applied Case Study

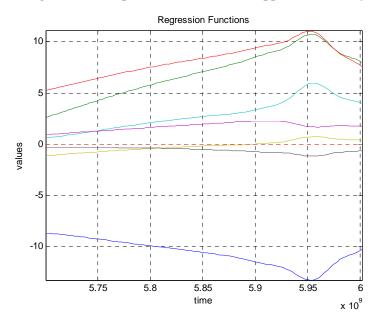


Figure A.2.9 Location Effects for the Applied Case Study using FDA

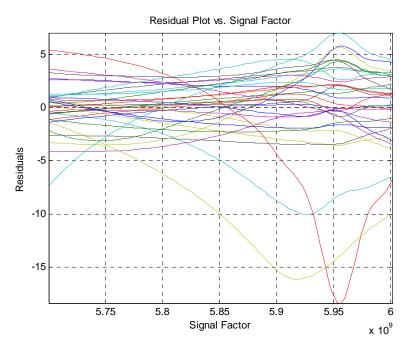


Figure A.2.10 Residuals for the Applied Case Study Using FDA

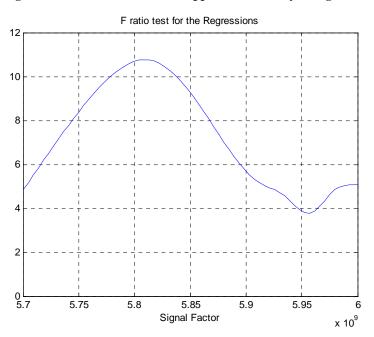


Figure A.2.11 F ratio test for the Regressions for the Applied Case Study

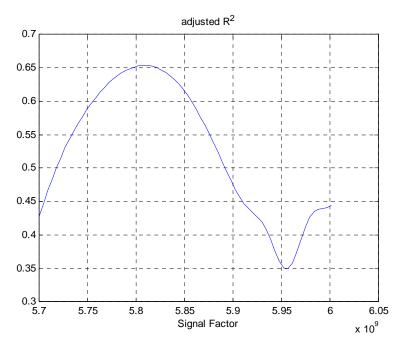


Figure A.2.12 Adjusted Determination Coefficient Plot for the Applied Case Study Using FDA

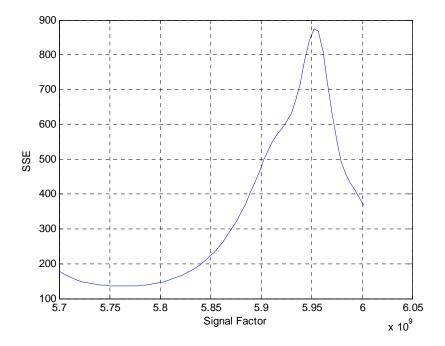


Figure A.2.13 SSE Plot for the Applied Case Study Using the FDA Procedure

Appendix 3 Response functions, Residuals and Estimated functions plots for the Basis Representation Model Using The Theoretical Case Study Plots for the Monomial Basis Representation

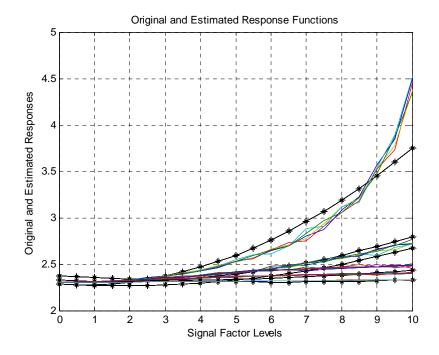


Figure A.3.1 Responses and estimated responses for the Basis Representation Final Model with a Monomial Basis for the Theoretical Case Study. The asterisks correspond to the estimated functions.

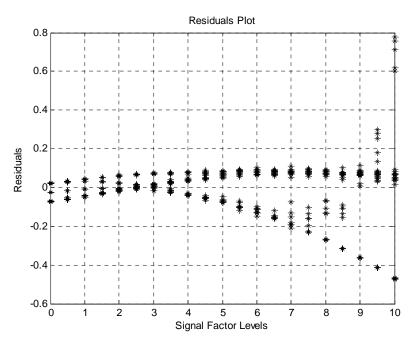


Figure A.3.2 Residuals for the Basis Representation Final Model with a Monomial Basis for the Theoretical Case Study

The following plots correspond to the Fourier Basis Representation model for the theoretical case study.

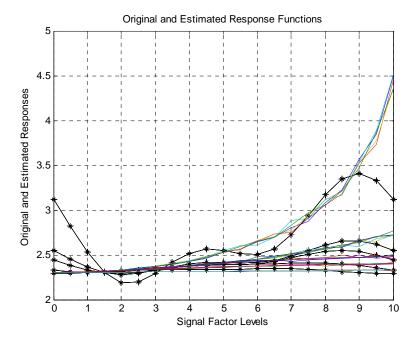


Figure A.3.3 Responses and estimated responses for the Basis Representation Final Model with a Fourier Basis for the Theoretical Case Study. The asterisks correspond to the estimated functions.

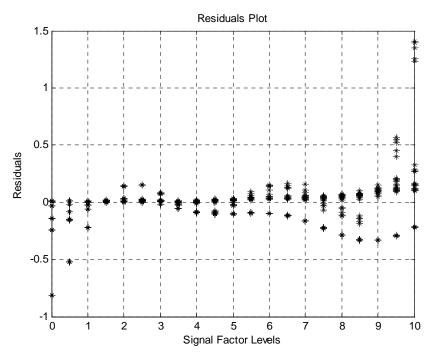


Figure A.3.5 Residuals for the Basis Representation Final Model with a Fourier Basis for the Theoretical Case Study

To conclude this appendix the graphs for the Cubic Spline Basis Representation Model are presented.

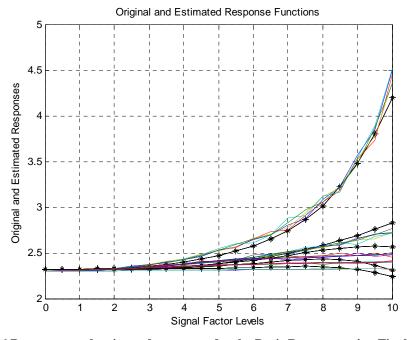


Figure A.3.6 Responses and estimated responses for the Basis Representation Final Model with a Cubic Sppline Basis for the Theoretical Case Study. The asterisks correspond to the estimated

functions

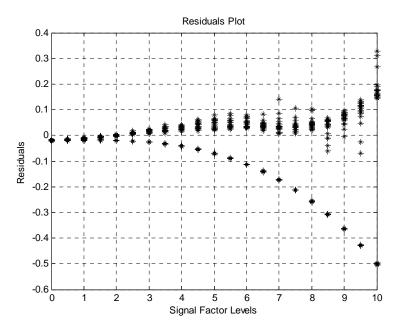


Figure A.3.7 Residuals for the Basis Representation Final Model with a Cubic Spline Basis for the Theoretical Case Study

Appendix 4 Response functions, Residuals and Estimated functions plots for the Basis Representation Model Using The Applied Case Study The following plots correspond to the point wise analysis to the selected region in the applied case study. The selected region as mentioned in Chapter 5 is from 5.7 to 6 GHz.

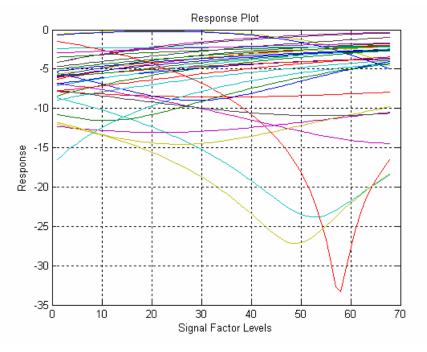


Figure A.4.1 Plot of all the response functions for the applied case study

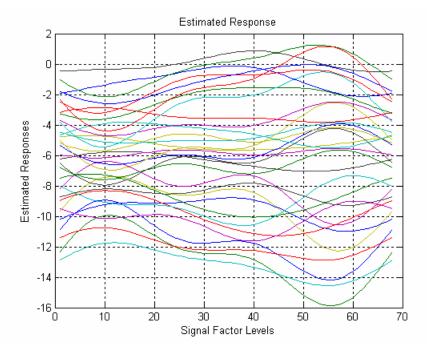


Figure A.4.2 Estimated Responses Plot for the Applied Case Study Using a Fourier Basis (K=2)

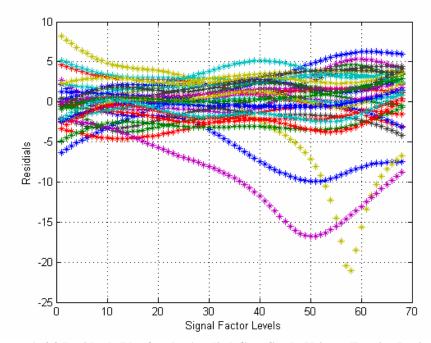


Figure A.4.3 Residuals Plot for the Applied Case Study Using a Fourier Basis (K=2)