REDUCING DESIGN RISK USING ROBUST DESIGN METHODS: A DUAL RESPONSE SURFACE APPROACH

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1. Introduction

Space transportation system conceptual design is a multidisciplinary process containing considerable element of risk. Risk here is defined as the variability in the estimated (output) performance characteristic of interest resulting from the uncertainties in the values of several disciplinary design and/or operational parameters. Uncertainties from one discipline (and/or subsystem) may propagate to another, through linking parameters and the final system output may have a significant accumulation of risk. This variability can result in significant deviations from the expected performance. Therefore, an estimate of variability (which is called design risk in this study) together with the expected performance characteristic value (e.g. mean empty weight) is necessary for multidisciplinary optimization for a robust design. Robust design in this study is defined as a solution that minimizes variability subject to a constraint on mean performance characteristics.

Even though multidisciplinary design optimization has gained wide attention and applications, the treatment of uncertainties to quantify and analyze design risk has received little attention. This research effort explores the "dual response surface" approach to quantify variability (risk) in critical performance characteristics (such as weight) during conceptual design.

2. Multidisciplinary Conceptual Design

In launch vehicle conceptual design studies, system performance can generally be determined by the use of computerized analysis tools available in many disciplines. However, these complex sizing and performance evaluation computer codes utilize iterative algorithms. In many cases, they are expensive and difficult to integrate and use directly for multidisciplinary design optimization (MDO). An alternative is to construct mathematical models that approximate the relationships between performance characteristics and design variables. These approximation models, called response surface models, may then used to integrate the disciplines using mathematical programming methods and for multidisciplinary system level optimization.

3. Response Surface Methods

A second-order approximation model of the form given below (Equation 1) is commonly used in approximation model building since in many cases it may adequately model the response surface especially if the region of interest is sufficiently limited.

$$Y = b_o + ?\, b_i\, x_i + ?\, b_{ii}\, x_i^{\,2} + ?\; ?\, b_{ij}\, x_i\, x_j \quad (1)$$

In equation 1, the x_i terms are the input variables that influence the response Y, and b_o, b_i, and b_{ij} are estimated regression coefficients. The cross terms represent two-parameter interactions, and the square terms represent second-order non-linearity. There are various response surface techniques that may be utilized to sample the design space efficiently to construct a second order approximation model. Some of these are, central composite designs (Montgomery, 1991; Myers, 1971; Khuri and Cornell, 1987) and D-Optimal designs (Craig, 1978; Roux et. al.,1996). Response surface methods using these designs have been applied to various multidisciplinary design optimization problems (Guinta et. Al, 1996; Lepsch et al, 1995; Unal et. al, 1996; Roux et al, 1996; Unal et al, 1998). The main advantage is that response surface methods can aid multidisciplinary design integration, and provide rapid design analysis and optimization capability in many applications. However, in these (and most) response surface model building applications, only the mean value for the performance characteristic (Y) was studied and optimized ignoring design risk or variability due to uncertain design parameter values (noise).

4. Dual Response Surfaces

Response surface methodology is designed to construct an approximation model for the response Y. This approximation model is then used to determine the best values of design parameters that optimize the response or the critical quality characteristic. In such problems typically the focus is on the mean value of Y where variance "S^2" is assumed to be small and constant. However, if the variance is not constant, only constructing a response surface model for the mean may not be adequate and optimization results can be misleading. Kim and Lin (1998) note that the assumption of constant variance is often not practically valid and in these events, classical response surface methods can be misleading.

An alternative to classical response surface methods is the "dual response surface" approach, which builds two models; one for the mean and one for the standard deviation (Vining & Myers, 1990; Lin & Tu, 1995; Wang, 1996; Del Castillo and Montgomery, 1993; Del Castillo, Fan & Semple, 1997; Tong, 2001, Tang and Xu, 2002).

$$Y_\mu = b_o + ?\ \ b_i\, x_i + ?\ \ b_{ii}\, x_i^{\,2} + ?\ \ ?\ \ b_{ij}\, x_i\, x_j + \varepsilon \qquad (2)$$

$$Y_\sigma = c_o + ?\ \ c_i\, x_i + ?\ \ c_{ii}\, x_i^{\,2} + ?\ \ ?\ \ c_{ij}\, x_i\, x_j + \varepsilon \qquad (3)$$

The dual response surface approach simultaneously considers the estimated mean (μ) and the standard deviation (σ) as a measure of design risk.

The steps in the dual response surface approach can be summarized as:

1) Conduct the experiments to sample the design space using a response surface technique such as central composite design or a D-Optimal design,
2) Repeat the experiments over the range of uncertain design (noise) parameters to capture variability,
3) Compute the mean and the variance for each experiment
4) Construct response surfaces for both the mean and variance,
5) Determine the best values of x_i to optimize the mean response subject to a constraint on the variance or determine the best values of x_i to minimize the variance subject to a constraint on mean response.

The dual response surface approach therefore can be utilized in approximation model building to quantify the variability in the mean value of the performance characteristic and for optimization considering both the mean response and variability to reduce design risk. Several studies successfully utilized the Dual Response methodology to optimization studies that considered the mean and the variability (Luner, 1994; Copeland & Nelson, 1996; Del Castillo, Fan & Semple, 1999, Dhavlikar, Kulkarni & Mariappan, 2002).

In this study, the dual response surface approach is applied to the conceptual design of a wing-body vehicle, configuration study. The results are presented and the strengths and limitations of the dual response surface approach are discussed.

5. Wing Body Launch Vehicle Configuration Study

An application of dual response surfaces is described for a configuration optimization study of a rocket-powered, single-stage-to-orbit launch vehicle. The vehicle has been sized by the Vehicle Analysis Branch (VAB) engineers to perform a 25,000 lb. payload delivery to the International Space Station from Kennedy Space Center. Near term structures and subsystem technologies are assumed in its design. The vehicle has a wing-body configuration with a slender, round cross-section fuselage and a clipped delta wing. The delta wing has elevon control surfaces for aerodynamic roll and pitch control. Small vertical fins, called tip fins, are located at the wing tips for directional control and a body flap extends rearward from the lower base of the fuselage to provide additional pitch control.

The purpose in this study is to determine the best values of the design parameters (that satisfy aerodynamic constraints) to minimize mean empty weight (WT) subject to a constraint on the variance. Therefore, empty weight is the critical performance characteristics to be optimized in this case. This multidisciplinary optimization and sensitivity study involved the following steps.

5.1. Identify Design Variables and Feasible Ranges

Four weight & sizing and aerodynamics design parameters were varied over a fixed range. The four common parameters included in aerodynamics and weights & sizing analysis were the fineness ratio (defined as the fuselage length divided by diameter), the wing area, the tip fin area, and the body flap area. The other parameters included were ballast-weight and mass-ratio for weights and sizing analysis and angle of attack and elevon deflection for aerodynamics analysis.

In this study, ballast-weight and mass-ratio were taken as the noise variables. Noise variables are those that one has little or no control on the values during operation. Therefore, one design goal is to reduce the variability in performance (weight in this case) due to the uncertain values of these parameters.

The ranges for the six weights & sizing parameters are given at Table 1.

Design Parameters	Range	
Fineness ratio (FR)	4	7
Wing area ratio (WA)	10	20
Tip fin area ratio (TP)	0.5	3
Body flap area ratio (BF)	0	1
Noise Parameters		
Ballast weight (BL)	0	0.04
Mass ratio (MR)	7.75	8.25

Table 1. Weights & Sizing Parameters and Ranges

5.2. Construct the Experimental Design Matrix

The next step is to construct an experimental design matrix that can enable the construction of a second-order response model for 4 parameters. Carpenter (1993) has conducted a study comparing the performance of various experimental design methods for approximation model building in terms of the quality of fit in the region studied and in terms of the number of design points required. His findings suggest that the D-optimality criteria as a good approach for constructing experimental designs for computer experiments. Other studies in the literature also found that the D-optimality criterion provides a rational means for creating experimental designs for an irregularly shaped response surfaces (Guinta et. al, 1996). Therefore, D-optimal designs are used in this study to construct an experimental design to sample the design space. The following section gives a background on D-optimal designs.

5.3. D-Optimal Designs

A statistical measure of goodness of a model obtained by least squares regression analysis is the minimum generalized variance of the estimates of the model coefficients. One way to construct a quadratic model using minimum point designs, leading to minimized variance of the least squares estimates, is to use the D-optimality criterion. Consider the problem of estimating the coefficients of a linear approximation model below by least squares regression analysis.

$y = b_o + ?\ b_i x_i$ (4)

Equation 4 can be expressed in matrix notation as:

$Y = XB + e$ (5)

Where Y is a vector of observations, e is the vector of errors, X is the design matrix and B is a vector of unknown model coefficients (b_o and b_i). The design matrix is a set of combinations of the values of the coded variables, which specifies the settings of the design parameters to be performed during experimentation. B can be estimated by using the least squares method as:

$B = (X'X)^{-1} X'Y$ (6)

A measure of accuracy of the column of estimators, B, is the variance-covariance matrix which is defined as;

$V(B) = \sigma^2 (X'X)^{-1}$ (7)

where σ^2 is the variance of the error. The V(B) matrix is a statistical measure of the goodness of the fit. Equation 7 indicates that V(B) is a function of $(X'X)^{-1}$ and therefore, one would want to minimize $(X'X)^{-1}$ to improve the quality of the fit. Statisticians have shown that minimizing $(X'X)^{-1}$ is equivalent to maximizing the determinant of X'X (Mitchell, 1974, Montgomery, 1991, Craig, 1978, Unal et al, 1996). Therefore, generating a design matrix which enables the construction of a good least squares approximation model translates to maximizing the determinant of the X'X matrix and experimental designs that maximize |X'X| are referred to as D-optimal designs. Here, "D" stands for the determinant of the X'X matrix associated with the model.

A number of authors have developed algorithms for obtaining D-optimal designs for specific models using mathematical programming methods (Mitchell, 1974, Craig, 1978). There are also numerous software packages available.

In this study, JMP ® software was utilized to construct the D-Optimal design matrix given in Table 2. With this design matrix, the four parameters are studied at three levels (values) as represented in coded form by, -1, 0 and +1. As an example, a -1 for fineness ratio corresponds to 4 (lower bound), a 0 corresponds to 5.5 (mid value) and +1 corresponds to 7 (upper bound). These coded values are then transformed into actual parameter values to be used in conducting the analysis. The following noise parameter matrix.

5.4. Conduct the Matrix Experiments

In this study, all of the geometry and subsystem packaging of the SSV were performed using a NASA-developed geometry modeling tool. The Aerodynamic Preliminary Analysis System (APAS) was used to determine vehicle aerodynamics. The weights and sizing analyses were performed using the NASA-developed Configuration Sizing (CONSIZ) weights/sizing package. This process was continued for the 45 rows of the D-optimal design matrix, each of which corresponds to a vehicle design generating the data.

For each of the 45 rows, experiments were repeated at 5 points corresponding to the five-point design matrix shown below to simulate the variability (Phadke, 1989) due to the uncertain values of the two noise variables (Ballast weight and Mass-Ratio). From the weight analysis, data points for empty weight were obtained (Table 2).

				BL	-1	+1	-1	+1	0
				MR	-1	-1	+1	+1	0
	FR	WA	TP	BF	Weight1	Weight2	Weight3	Weight4	Weight5
1	-1	-1	-1	-1	234798	266104	269950	309903	268058
2	-1	-1	-1	-1	234798	266104	269950	309903	268058
3	-1	-1	-1	1	244264	277534	281649	324255	279592
4	-1	-1	-1	1	244264	277534	281649	324255	279592
5	-1	-1	0	1	269903	308403	313455	363252	310966
6	-1	-1	1	-1	287841	329905	335853	390673	332920
7	-1	-1	1	-1	287841	329905	335853	390673	332920
8	-1	-1	1	1	299593	344325	350597	409106	347505
9	-1	-1	1	1	299593	344325	350597	409106	347505
10	-1	0	-1	-1	280089	320919	326475	379603	323736
11	-1	0	0	1	317505	366332	373475	437873	369956
12	-1	0	1	-1	338637	392009	400226	471188	396133
13	-1	0	1	0	344174	398758	407264	480087	403068
14	-1	1	-1	-1	333190	386010	393710	464042	389961
15	-1	1	-1	0	338136	392098	399987	471954	396060
16	-1	1	-1	1	343157	398199	406367	480012	402341
17	-1	1	0	-1	364494	424296	433686	514270	429055
18	0	-1	1	0	224385	255099	259353	298743	257245
19	0	0	-1	0	218940	248584	252729	290750	250729
20	0	0	0	1	237502	270968	275840	319109	273437
21	0	1	-1	1	252036	288707	294159	342098	291469
22	0	1	0	-1	262932	301882	307941	359117	304954
23	0	1	1	-1	281667	324663	331742	388679	328270
24	0	1	1	0	284972	328773	335938	393952	332402
25	0	1	1	1	288321	332893	340190	399307	336587
26	1	-1	-1	-1	171076	191965	194701	220827	193352
27	1	-1	-1	-1	171076	191965	194701	220827	193352
28	1	-1	-1	0	173638	195028	197805	224627	196434
29	1	-1	-1	1	176246	198150	200953	228456	199579
30	1	-1	-1	1	176246	198150	200953	228456	199579
31	1	-1	-1	1	176246	198150	200953	228456	199579
32	1	-1	0	-1	182001	204939	208028	236953	206510
33	1	-1	1	-1	194162	219452	222986	255109	221231
34	1	-1	1	-1	194162	219452	222986	255109	221231
35	1	-1	1	1	200132	226658	230332	264170	228520
36	1	-1	1	1	200132	226658	230332	264170	228520
37	1	0	-1	-1	190572	215197	218657	249927	216938
38	1	1	-1	-1	212127	241119	245476	282764	243327

39	1	1	-1	0	214254	243692	248117	286016	245935
40	1	1	-1	1	216406	246297	250762	289312	248572
41	1	1	0	0	225895	257754	262683	303939	260244
42	1	1	1	-1	236433	270443	275933	320256	273221
43	1	1	1	-1	236433	270443	275933	320256	273221
44	1	1	1	1	241231	276283	281946	327754	279152
45	1	1	1	1	327754	276283	281946	327754	279152

Table 2. Analysis Results

Using this data, mean empty weights and corresponding standard deviations (as a measure of design risk due to the uncertain values of BL and MR) were computed (Table 3).

	FR	WA	TP	BF	Mean	Std. Devn.
1	-1	-1	-1	-1	269763	26693
2	-1	-1	-1	-1	269763	26693
3	-1	-1	-1	1	281459	28434
4	-1	-1	-1	1	281459	28434
5	-1	-1	0	1	313196	33196
6	-1	-1	1	-1	335438	36584
7	-1	-1	1	-1	335438	36584
8	-1	-1	1	1	350225	38964
9	-1	-1	1	1	350225	38964
10	-1	0	-1	-1	326164	35398
11	-1	0	0	1	373028	42843
12	-1	0	1	-1	399639	47200
13	-1	0	1	0	406670	48404
14	-1	1	-1	-1	393383	46589
15	-1	1	-1	0	399647	47649
16	-1	1	-1	1	406015	48738
17	-1	1	0	-1	433160	53361
18	0	-1	1	0	258965	26439
19	0	0	-1	0	252346	25533
20	0	0	0	1	275371	29028
21	0	1	-1	1	293694	32048
22	0	1	0	-1	307365	34237
23	0	1	1	-1	331004	38108
24	0	1	1	0	335207	38808
25	0	1	1	1	339460	39525
26	1	-1	-1	-1	194384	17674
27	1	-1	-1	-1	194384	17674
28	1	-1	-1	0	197506	18115
29	1	-1	-1	1	200677	18549
30	1	-1	-1	1	200677	18549
31	1	-1	-1	1	200677	18549
32	1	-1	0	-1	207686	19528
33	1	-1	1	-1	222588	21665
34	1	-1	1	-1	222588	21665
35	1	-1	1	1	229962	22766
36	1	-1	1	1	229962	22766
37	1	0	-1	-1	218258	21099
38	1	1	-1	-1	244963	25124
39	1	1	-1	0	247603	25525
40	1	1	-1	1	250270	25932

41	1	1	0	0	262103	27767
42	1	1	1	-1	275257	29833
43	1	1	1	-1	275257	29833
44	1	1	1	1	281273	30796
45	1	1	1	1	298578	26709

Table 3. Summary Results for Mean Weight and Standard Deviations

5.5. Construct the Second-Order Response Surface Model

Least squares regression analysis is then used to determine the coefficients of the second order, dual response surface models for both the mean weight and the standard deviation. Table 4 shows the second order response surface model for the standard deviation.

$$Y_\sigma = c_o + ?\ c_i x_i + ?\ c_{ii} x_i^2 + ?\ ?\ c_{ij} x_i x_j + \varepsilon \qquad (8)$$

Term	Estimate
Intercept	28642.707
FR	-9513.122
WA	6827.781
TFA	3643.3254
BFL	542.11413
FR*FR	4753.1833
WA*FR	-3272.696
WA*WA	267.37427
TFA*FR	-1614.534
BFL*FR	-301.9769
BFL*WA	-207.5474
BFL*TFA	-91.53414
BFL*BFL	-450.2649

Table 4. Standard Deviation Response Surface Model

R-Square	0.9976
Adjusted R-Square	0.9965
RMS Error	3961.58

Table 5. Standard Deviation Model Regression Statistics

Table 5 displays regression analysis results. The model fit is very good in this case with an indicated Adjusted R-square value of 0.9965.

Table 6 shows the second order response surface model for the mean weight and model coefficients. Table 7 displays regression analysis results for the mean weight model. The model fit is also very good in this case with an indicated Adjusted R-Square value of 0.9944.

$$Y_\mu = b_o + ?\ b_i x_i + ?\ b_{ii} x_i^2 + ?\ ?\ b_{ij} x_i x_j + \varepsilon \qquad (9)$$

Term	Estimate
Intercept	271645.78

FR	-66299.86
WA	43696.134
TFA	24725.039
BFL	5095.908
FR*FR	34505.503
WA*FR	-17905.27
TFA*FR	-8992.935
BFL*FR	-723.6003
BFL*TFA	506.43229
BFL*BFL	-1715.667

Table 6. Mean Weight Response Surface Model

R-Square	0.9962
Adjusted R-Square	0.9944
RMS Error	30857.2

Table 7. Mean Weight Model Regression Statistics

These dual response surface equations can be used to rapidly determine the effect of varying design parameter values on the (weights) performance characteristics and for MDO.

5.6. Determine Design Parameter Values that Optimize the Response

The purpose in this study is to determine the optimum values of the design parameters to considering both the mean empty weight and variance. To obtain a robust design, one would seek to minimize the variability (risk) subject to a constraint on weight. Therefore, the optimization problem was set up as follows:

Minimize Y_σ

Subject to:

$Y_\mu = 331704$

$-1 = FR = 1$
$-1 = WA = 1$
$-1 = TP = 1$
$-1 = BF = 1$

This optimization problem was solved by utilizing three approaches; Excel Solver, GINO and Genetic Algorithms. Solver, available in Microsoft Excel®, is a gradient based optimization algorithm. GINO also uses a gradient based optimization algorithm and is available as an independent optimization software package (Liebman et al, 1986). Genetic Algorithms mimic natural search and selection processes leading to the survival of fittest individuals. In the range of optimization techniques, GA occupy a gap between calculus based methods and random search (Goldberg, 1989). They are in general less efficient than gradient based methods, however they can be applied to multi-modal problems with discontinuous topologies (Gage, 1994). The GA results in this study were obtained from

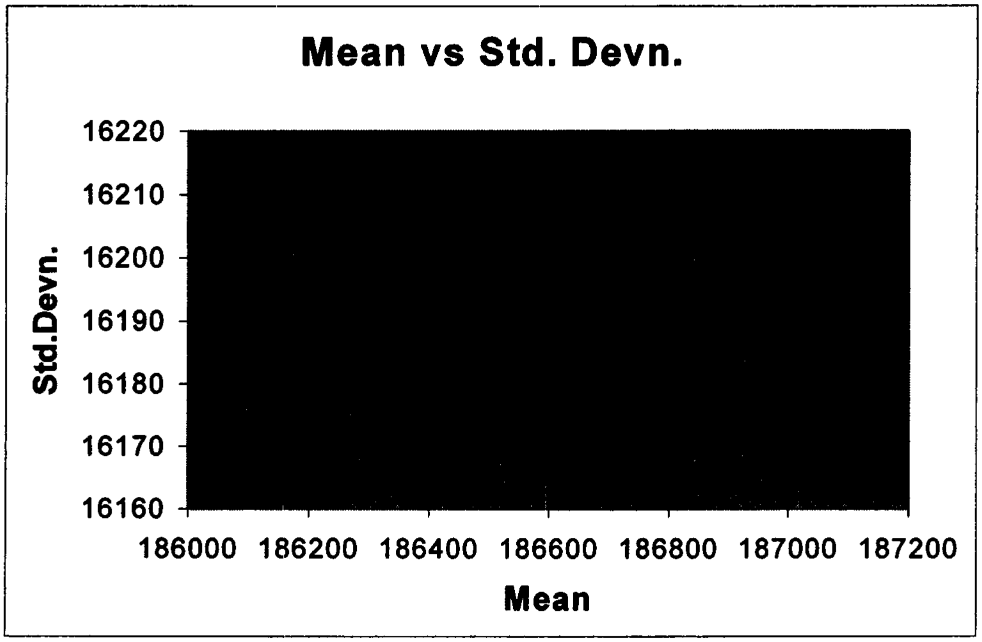
Genetik (floating point GA for minimization problems. Genetik V2.01 is available at: http://www.umoncton.ca/turk/genetik201.zip, for downloading.

Table 8 summarizes the optimization results. Solver and the Genetic Algorithm has found identical results, which is better than the GINO results in this case. Since Solver and GA are both utilized at VAB in prior studies, the results support their continued use in this type of optimization problems where the response surfaces usually have been found to have a saddle shape.

Excel Solver		GINO		Genetic Algorithm	
Parameter	Optimized Value	Parameter	Optimized Value	Parameter	Optimized Value
FR	0.455864	FR	0.518376	FR	0.4548447
WA	-1	WA	-1	WA	-1
TP	-1	TP	-1	TP	-1
BF	-1	BF	-1	BF	-1
Std.Devn	16164	Std.Devn	17552.66	Std.Devn	16164.16
Mean Wt	186465	Mean Wt	194570.55	Mean Wt	185465.48

Table 8. Optimization Results

Since the goal in this study was to search for optimization results considering both the mean and the variability, a mean and variance graph is plotted below. Table 9 indicates that both the mean and the variability are minimized at x'=(0.454844;-1;-1;-1) for this problem. Even though this is a desirable result, one would expect that for many optimization problems, there would be a trade off between the mean and variance.



Mean	Std. Devn.
187000	16180
186900	16175
186800	16171
186700	16168
186600	16165
186500	16164
186400	16165
186300	16167
186200	16175
186100	16196
186080	16217
186466	16164

Table 9: Mean versus Standard Deviation Plot

6. Conclusions

Space transportation system conceptual design is a multidisciplinary process containing considerable element of uncertainty. Uncertainties of one subsystem (and/or discipline) may propagate to another, through linking parameters and the final system output has an accumulation of risk. Risk here is defined as the variability in the expected system output performance characteristics.

This study investigated the use of dual responses to estimate variability resulting from uncertain values of several design parameters (called the noise factors) and conduct MDO considering both the mean and variance. The dual response surface approach is applied to the conceptual design of a wing-body vehicle, configuration study.

An orthogonal array based simulation approach is used to simulate the variability resulting from noise factors. With this approach, generation of the additional data points needed to construct a second response surface for the standard deviation was not costly in this case since the analysis was already set up to run the design points for constructing the response surface for the mean weight. The results here indicate that in many cases the second response surface can be constructed without much extra effort. Once this is done, a measure of design risk is obtained and optimization on risk basis can be conducted.

The results therefore suggest that the dual response surface approach can be utilized in approximation model building to estimate the variability in the mean value of the performance characteristic in conceptual design. Subsequently, multidisciplinary optimization studies can be conducted considering both the mean response and variability to reduce design risk and seek a robust design solution.

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8. Appendix A

In this study, an estimate of population mean and variance for empty-weight were computed based on the experimental results. Given the mean and variance, one could then compute a probability associated with a given weight value and construct a cumulative distribution function. In order to be able to do that, one needs to make an assumption on the underlying population distribution. The most commonly made assumption in many studies is the "Normal Distribution" assumption. However, if this assumption is not correct, the results and predictions made on probability will be misleading.

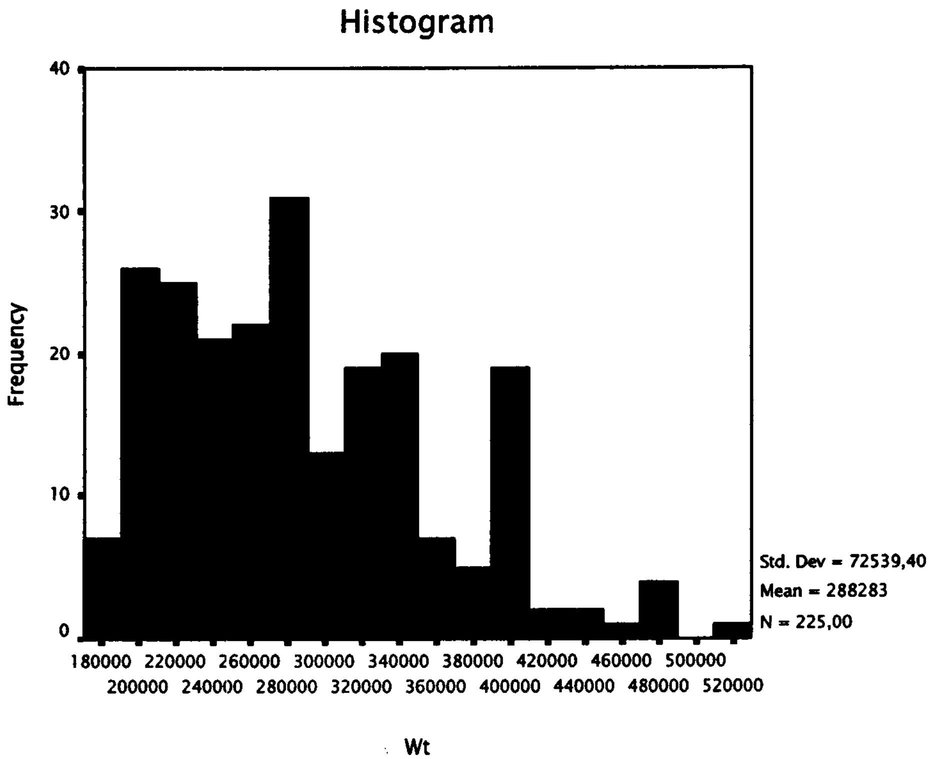
To test such an assumption a statistical test of normality was conducted. As the following results indicate, the weights data clearly is not normally distributed. Hence results based on such an assumption would be incorrect. A Kolmorgorov-Smirnov (KS) hypothesis test was conducted to test for normality of the underlying population distribution.

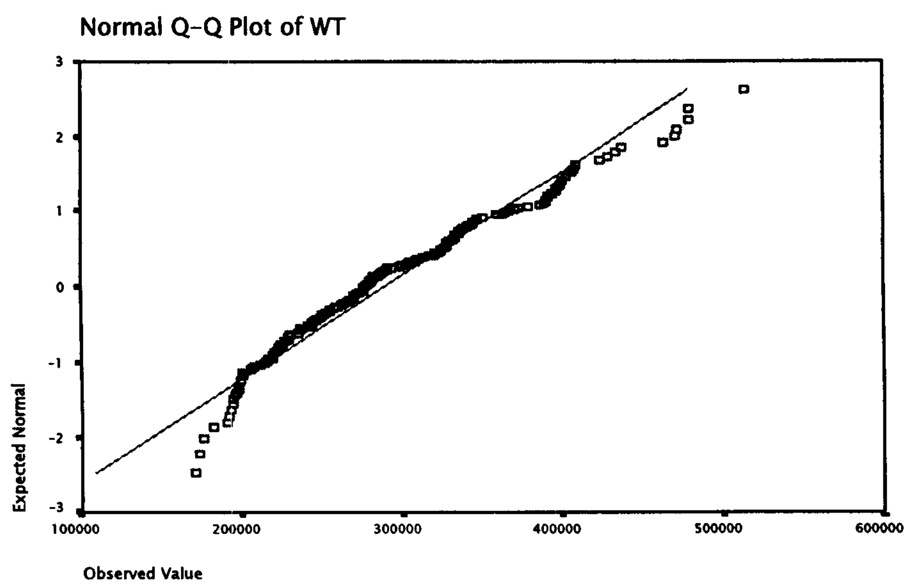
H_O: there is no difference between the distribution of the data set and a normal one
H_A: there is a difference between the distribution of the data set and normal

Test of Normality

Statistic	Degrees of Freedom	Significance
0.086	225	0.0003692

The Kolmorgorov-Smirnov statistic is significant. Hence the normality assumption is not satisfied ($p<0.05$). The hypothesis of normality is rejected (The distribution of data is significantly different from normal).


Histogram
Frequency
40
30
20
10
0
180000 220000 260000 300000 340000 380000 420000 460000 500000
200000 240000 280000 320000 360000 400000 440000 480000 520000
Wt
Std. Dev = 72539,40
Mean = 288283
N = 225,00


Normal Q-Q Plot of WT
Expected Normal
3
2
1
0
-1
-2
-3
100000
200000
300000
400000
500000
600000
Observed Value

Q-Q plot is a plot of our observed values against the expected values. If the data is from a normal distribution, the data points should fall on a straight line. In the Figure above , the expected normal distribution is the straight line and the line of little boxes is the observed values from our data. So, the distribution of data is not normal.