DEVELOPMENT OF A STOCHASTIC SIMULATION SOFTWARE FOR STUDYING FACTORS THAT CONTRIBUTE TO VARIATION IN A HARD DRIVE PRODUCTION PROCESS

INTRODUCTION

In manufacturing system, variation always happens in every process, even though manufacturing companies would like to eliminate it from their manufacturing process. We cannot remove it from the process, but we can control it. In order to reduce the variation in manufacturing processes, we have to investigate the cause of variation that could be from incoming parts, manufacturing processes, testers, or operators.

We consider the case of a company who is a supplier of hard disk drives. We want to improve their manufacturing process for the next product generation (Ursa02). Ursa02 has almost the same configuration and component as the previous product (Ursa01). However, Ursa02 has some new technology incorporated to increase its performance. Because of having almost the same configuration and components, the company decided to leverage Ursa01's process line to produce Ursa02s. Ursa02 processes not only higher technology and performance, but it also requires more precision in manufacturing processes. The company has to reduce the variation in process to support new products. Especially, head pitch (Hp) and spring force (Sp) parameters are critical for its customers. Figures 1 and 2 show sigma roadmaps of Hp and Sp, respectively, that show standard deviations required for Ursa01 and Ursa02. The company has some standard deviation margin, which is a difference between incoming part sigma requirements (*Supplier commitment*) and their finish product sigma requirements (*Customer requirement*). The sigma roadmap of Ursa02 is tighter than Ursa01, however they have almost the same configuration (*Ursa generation*). Our study is base on Ursa01 data.

Our company wants to know a percent contribution of variation of each factor to their process and an analysis tool that our company can do what-if analysis. A simulation is a tool to do a what-if analysis. Barton (2001) states that "a simulation modeling is a popular method for predicting the performance of complex systems, particularly systems that include random phenomena." Simulation has many benefits, for example, alternative system designs can be compared to see which configurations best meet the requirements. However, its disadvantages are expense and sometimes a long time to develop a model. Each simulation run produces only estimates of a model's true characteristics for a particular set of input parameters (Law and Kelton 2000).

For simulation software, we use Crystal Ball which is a commercial stochastic simulation language that runs on a spread sheet such as Microsoft Excel simulation. Crystal Ball allows us to model the relationship between input factors and key performance outputs that we are interested in. Therefore, we can calculate a percent contribution of variation of each input factor. For ease of input/output display, we develop Visual Basic Application (VBA) subroutines to interface between Excel and Crystal Ball.

The main causes of variation are due to parts and the process. The relationship that we have received from the design team is only variations in parts, but we have to investigate variations in the process. Our company measure product on incoming part from supplier and finish product before send to customers (See Figure 3). We don't have any measurement tool to measure each process. We have to develop a measurement tool that they have to assess the variation in each process to be the input factors of analysis tool.

We choose the optical measurement system which our company has to develop to measure on the key performance input of Hp and Sp parameters. We design a new fixture referring their original one to measure on specific location and develop machine code to control it.

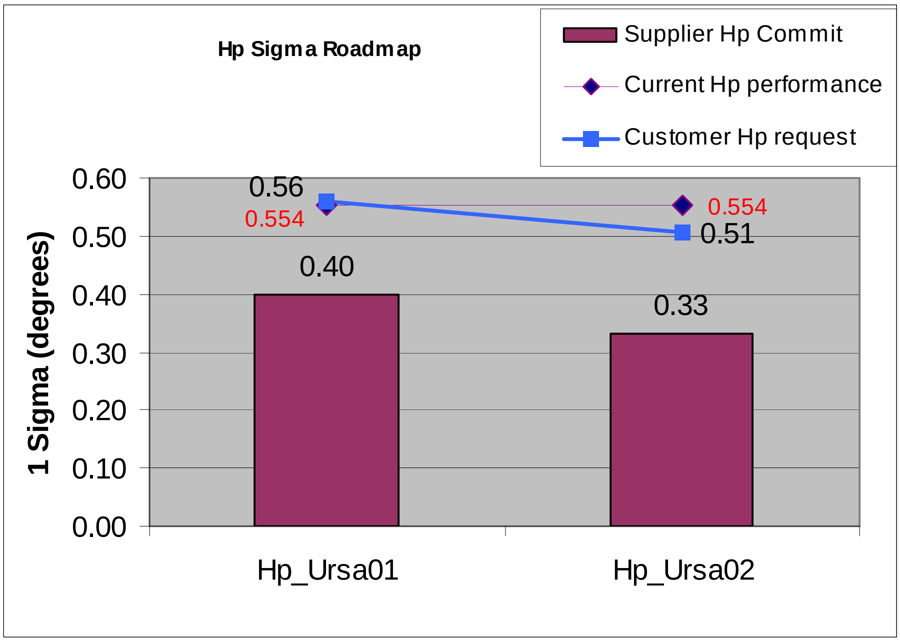


Figure 1 Sigma roadmap for the head pitch parameter.

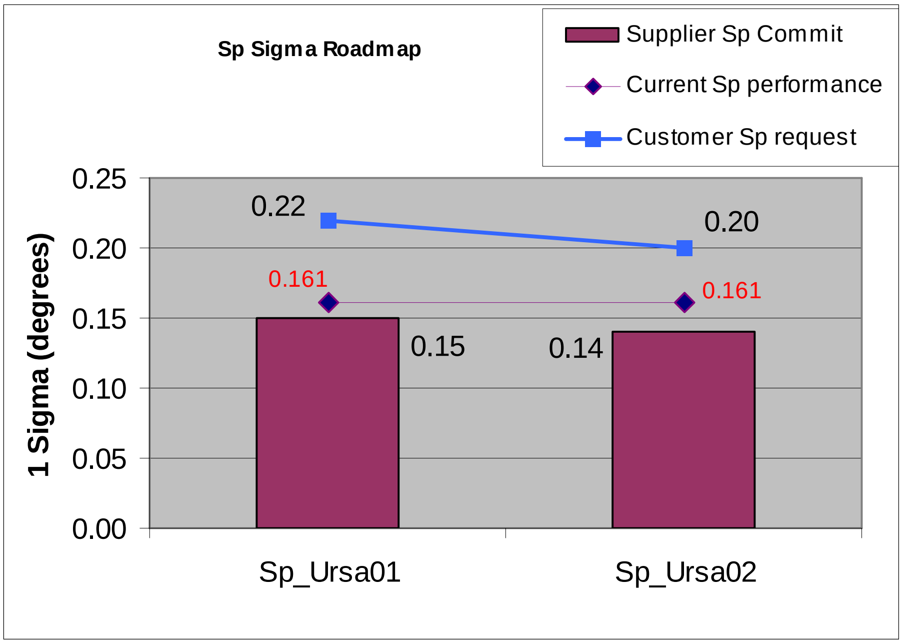


Figure 2 Sigma roadmap for the spring force parameter.

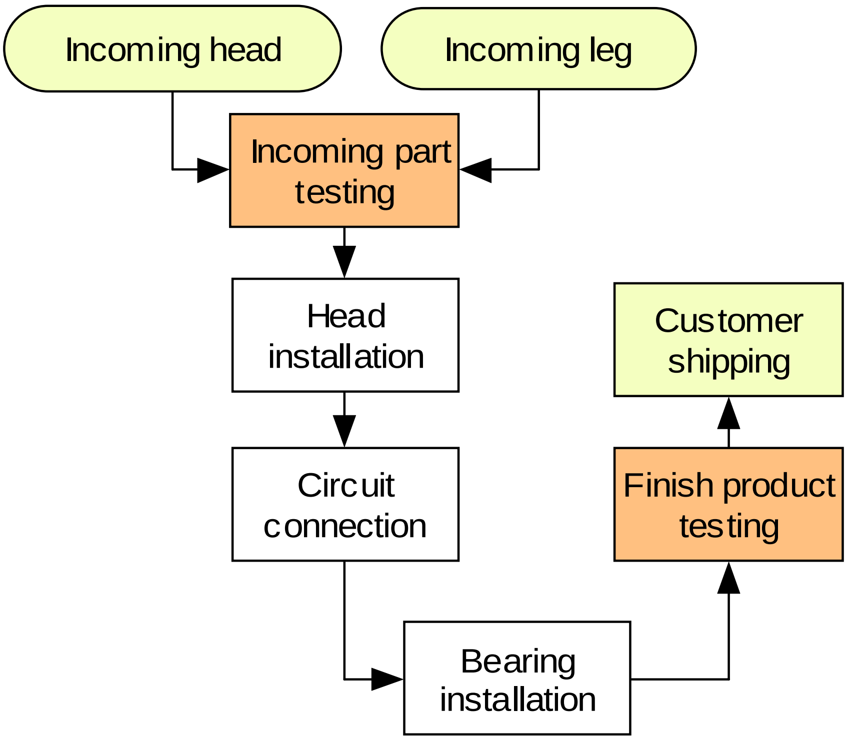


Figure 3 Flow process chart of Ursa01 and Ursa02.

OBJECTIVE

Our purposes are:

1. To develop the VBA interface with Crystal ball simulation package and Excel.
2. To predict the percent contribution of each factor that adds up variation to the critical output parameters.
3. To develop a measurement tool for measuring critical product performance each of process step.
4. To reduce a percents contribution of variation from error term in our model.

SCOPES

We assume the following conditions:

1. We focus on the production of Ursa01.
2. The data used in this research is real data multiplied by some constant.
3. We ignore the variation of the final tester.
4. The parallelism of material is perfect in our model.

BENEFITS

This research will improve quality of product. It will determine the causes of variation add up in process.

LITERATURE REVIEW

The literature review consists of four parts: simulation methodology, design of experiments techniques, basic overview of the laser micrometer operation and six sigma improvements.

Simulation Methodology

Evans and Olson (2002) define that simulation is a process of building a mathematical or logical model of a system or a decision problem, and experimenting with the model to obtain insights into the system's behavior or to assist in solving the decision problem. It is particularly useful when problem exhibit significant uncertainty which generally is quite difficult to deal with analytically.

A model is an abstraction or a representation of a real system, idea, or object. It can be classified into three different dimensions.

1. *Prescriptive vs. Descriptive model:* Prescriptive models, such as linear programming models provide an optimal solution. On the other hand, descriptive models explain the behavior of systems, predict future events for planning process, and assist decision makers in choosing the best solution or system design.
2. *Deterministic vs. Probabilistic model:* In deterministic models, all data are known, or assumed to be known, with certainty. It does not have any random inputs, unlike probabilistic models (stochastic model) that have at least some random input components.
3. *Continuous vs. Discrete models:* In mathematical programming, this dichotomy refers to the types of variables in the model. For example, linear programming models are continuous, integer programming models are discrete. It may also refer to how model variables change over time. A discrete-event system is the system in which its state variables change instantaneously at separated point in time. On the other hand, state variables change continuously with respect to time in a continuous simulation model.

Simulation is used to analyze many real-world complex problems which cannot be solved analytically. It uses computers to evaluate a model numerically, and data are gathered in order to estimate the desired characteristics of the model.

A simulation consists of ten steps as shown in Figure 4 (Law and Kelton 2000).

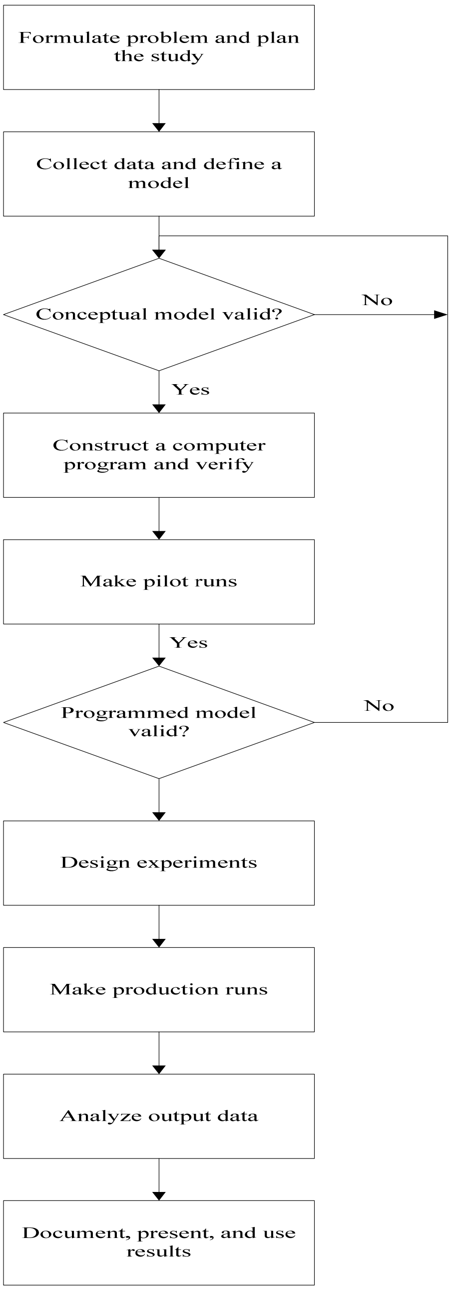


Figure 4 Steps in a simulation study.
Source: Law and Kelton (2000).

Design of Experiments Techniques

The design of experiments (DOE) techniques is the way that experimenters perform experiments to discover something interesting for a particular process or system. Sanchez (2005) states that there are three fundamental concepts in DOE: control, replication, and randomization. Control means that an experiment is conducted in a systematic way, rather than by using a trial-and-error approach. Replication is a way to gain enough data to achieve narrow confidence intervals and powerful hypothesis tests, or for graphical methods to reveal the important characteristics of a simulation model. Randomization provides a probabilistic guard against the possibility of unknown, hidden sources of bias surfacing to create problems with data.

Telford (2001) states that "experimental design is an effective tool for maximizing the amount of information gained from a study while minimizing the amount of data to be collected." In experimental design, factors are the inputs parameters and structural assumptions composing a model, and responses are the output performance measures (Law and Kelton, 2000). Estimating how changes in input factors affect responses of the experiment is one of the main goals of experimental design. Barton (2001) says that "factorial designs are based on a grid, with each factor tested in combination with every level of every other factor". When there are k input factors and two values, or levels, are identified for each factor, there are 2^k different combinations of the input factors, called 2^k factorial design. Anderson (2004) states that changing only one factor at a time cannot detect interaction of factors. In factorial design, it enables the experimenter to investigate the individual effects of each factor (or the main effect) and to determine whether the factors interact, and factors are varied together, instead of one at a time (Montgomery 2005). The main effect measures the average difference in response when an individual factor changes, or moves from its low level (-) to its high level (+). An interaction can be computed when the effect of one factor depends on the level of one or more factors (Kelton, 2000).

Generally, for 2^k factorial design, when the number of factors of interest increases, the number of runs required increases rapidly (Montgomery 2005). A fractional factorial design, which requires only a subset of the runs, can be used if the experimenter can reasonably assumes that three- or higher-order interaction are negligible. Montgomery (2005) also states that fractional factorials are used in screening experiments, which consist of many factors to be considered and the objective is to identify factors that have large effects. In fractional factorial design, there are three types of designs of resolution, resolution III, IV, and V designs, to quantify the overall severity of confounding. Two effects are not confounded with each other if the sum of their ways is strictly less than the design's resolution (Law and Kelton 2000). A design is of resolution R if no p-factor effect is aliased with another effect containing less than R-p factors (Montgomery 2005). Aliases mean that it is impossible to differentiate between two or more effects. Law and Kelton (2000) state that there will often be at least two-way interactions of interest in simulation study, so resolution IV may be inadequate. In resolution V design, two-way interactions are not confounded with each other.

Our study will use 2^{k-p} fractional factorial design, or a $1/2^p$ fraction of the 2^k design. This design contains 2^{k-p} runs. The 2^{k-p} design may be constructed by writing down a basic design of a *k-p* full factorial, then adding *p* generators columns that are the interactions relevant to those *k-p* factors. Selection of *p* independent generators is important so that effects of potential interest are not aliased with each other. The defining relation for a fractional factorial, which consists of the *p* generators and their 2^p-p-1 generalized interactions, will always be the set of all columns that are equal to the identity column *I,* which always has plus sign. The alias structure may be found by multiplying each effect with the defining relation. Table 1 shows an example of 2^{7-4} design with resolution III. There are only eight runs for seven factors, and four generators *I* = ABD, ACE, BCF, and ABCG (Montgomery 2005).

Table 1 The 2^{7-4} design with resolution III.

	Basic Design						
Run	A	B	C	D=AB	E=AC	F=BC	G=ABC
1	-	-	-	+	+	+	-
2	+	-	-	-	-	+	+
3	-	+	-	-	+	-	+
4	+	+	-	+	-	-	-
5	-	-	+	+	-	-	+
6	+	-	+	-	+	-	-
7	-	+	+	-	-	+	-
8	+	+	+	+	+	+	+

Basic Overview of the Laser Micrometer Operation

The semiconductor laser emits a laser beam, which is first reflected by the rotating polygonal mirror. This causes the laser beam to continuously scan, starting at the top going to the bottom. Therefore, the red laser beams shown in Figure 5 actually occur sequentially, starting at the top, instead of all at once as shown. The scanned laser beam is then reflected by mirror, and passes through the collimator lens so that the beams run parallel to each other.

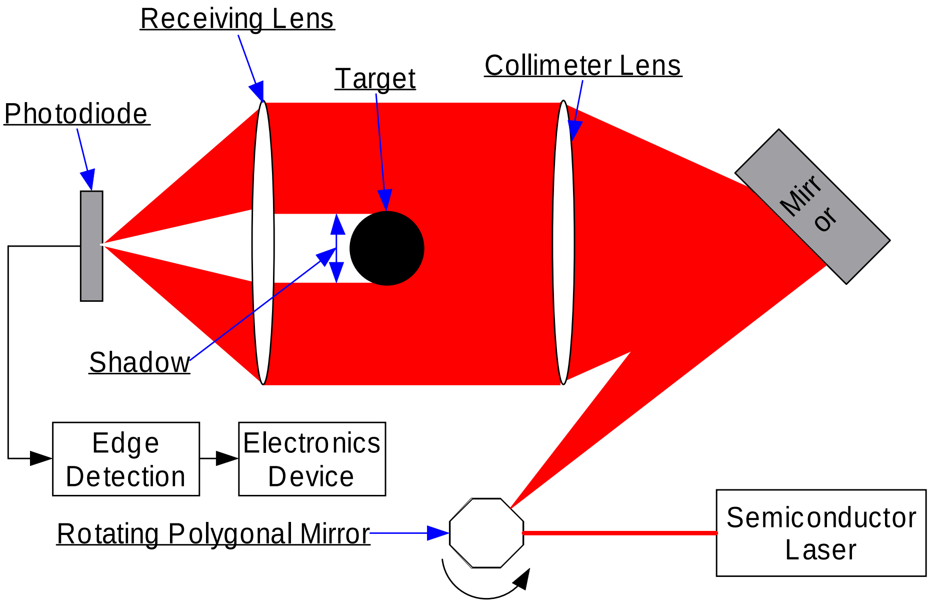


Figure 5 Basic Laser Micrometers.

These parallel beams are directed at the target, and only beams that do not hit the target pass through the receiving lens, which converge with the laser beams on to a photodiode. The beams collected are converted to an electrical signal which corresponds to the light-dark pattern produced. The dark region corresponds to the shadow shown in Figure 5. Since the laser micrometer knows how fast the laser beams scan, it can determine the width of the shadow, which is the diameter of the part, by multiplying the time it sees a dark region by the distance scanned per unit of time.

The laser micrometer tells the computer the distance between two edges. Edges are numbered from top to bottom, starting at one. The first edge is where the laser starts scanning at the top, which is either the top of the laser micrometer's scan field or the first place the laser beam is not blocked, whichever is lowest. The last (highest numbered) edge is where the laser stops scanning, which is either the bottom of the laser micrometer's scan field or the last time the laser's beam is not blocked, whichever is highest.

Six Sigma Improvements

Sigma is a statistical unit of measure that reflects process variability. The sigma measurement is correlated to such characteristics as defects-per-unit, parts-per-million defective, and the probability of a failure/error as shown in Table 2.

Table 2 Defect per million for each Sigma.

Process Capability (σ)	Defect per million (ppm)
2	308,537
3	66,807
4	6,210
5	233
6	3.4

Source: George L.M. (2005)

Tonner (2003) defines the meaning of Six Sigma as follows: it is a methodology that provides businesses with the tools to improve the capability of their business processes. This increase in performance and decrease in process variation leads to defect reduction and vast improvement in profits, employee morale and quality of product.

DMAIC is a structured problem-solving methodology used in Six Sigma. The letters are an acronym for the five phases of Six Sigma improvement: Define-Measure-Analyze-Improve-Control. These phases lead a team logically from defining a problem through implementing best practices to make sure the solutions stay in place (George .L.M. *el at* 2005). DMAIC is a valuable tool to find permanent solutions, but using DMAIC does involve time and expense. DMAIC is appropriate for the following scenarios:

1. The problem is complex.
2. The solution risks are high (risks of implementation are high).

Each step of DMAIC can be further explained as follows:

- *D: Define* is a phase that have the team reach an agreement on the scope, goal, and financial and performance targets of the project. For this phase, it has 3 steps to follow:
    a. Redefine the project charter and launch team.
    b. Validate the scope of project.
    c. Collect Voice of the Customer (VOC).

- *M: Measure* is a phase that thoroughly understands the current state of process and collects reliable data on process speed, quality and cost that we will use to expose the underlying causes of the problem. For this phase, it has 5 steps to follow:
    a. Determine outputs and inputs to the process.

b. Articulate the process through value stream mapping.
c. Validate the measurement system (Is it repeatable? Reproducible?).
d. Create and execute a data collection plan.
e. Assess capability and performance of the process.

- *A: Analyze* is a phase that verify causes affecting the key input and out variables tied to the project goal ("Finding the critical Xs"). For this phase, it has 5 steps to follow:

a. Determine critical inputs.
b. Perform data analysis.
c. Perform process analysis.
d. Determine root causes.
e. Prioritize root cause.

- *I: Improve* is a phase that learns from pilots of the selected solutions and execute full-scale implementation. For this phase, it has 5 steps to follow:

a. Generate potential solutions.
b. Selection and prioritize solutions.
c. Apply Six Sigma best practices.
d. Perform risk assessment.
e. Pilot solution.

- *C: Control* is a phase that complete project work and hand off improved process to the process owner, with procedures for maintaining the gains

a. Institute ongoing metrics & control charts.
b. Document standard operating procedures.
c. Create process control plans.
d. Create project storyboard.
e. Transition ownership of the process.

MATERIALS AND METHODS

Materials

1. Hardware

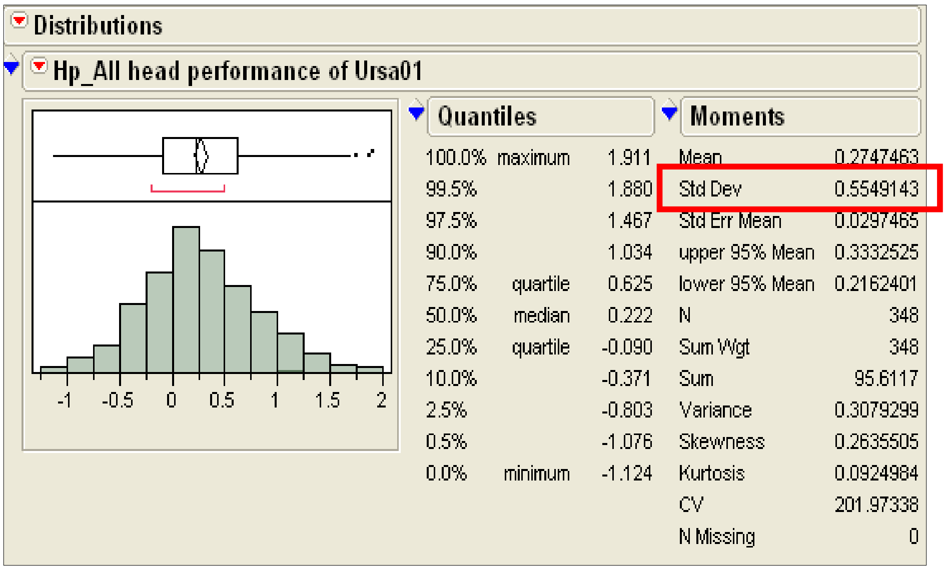
1.1 Microsoft Windows 95 (OSC-2), Windows 98, Windows ME, NT 4.0 (Service Pack 5 or later), Windows 2000, Windows XP.
1.2 75 – 250 MB free disk space.
1.3 64MB RAM (recommended 128MB RAM or higher).
1.4 Minimum Pentium Processor, 300Mhz or higher.

2. Software

2.1. Crystal Ball version 7: Simulation spreadsheet software used to generate random numbers and analyze a roadmap model.
2.2. Minitab version 14: Statistical software used for analyzing the statistical data.
2.3. Microsoft Excel 2003: Spreadsheet software used to contain and calculate models.

Methods

In order to improve quality in a hard disk drive supply chain, each manufacturing factories have to commit their product variation on critical parameters such as head pitch (Hp) and spring force (Sp). They should not exceed their commitments; otherwise quality of the whole supply chain is adversely affected. Ursa01 data show assembly processes add variation into critical product performances (See Figure 6 and 7). Hp standard deviation of Ursa01's performance is 0.5549 degree. Comparing with Hp sigma roadmap on Figure 1 (0.56 degree), it is under customer requirement for product Ursa01, but it is over commitment for Ursa02 (0.51 degree). For Sp standard deviation, 0.1615 gram is under customer requirement for product Ursa01 (0.22 gram) and Ursa02 (0.20 gram) on Figure 2.



Distributions

Hp_All head performance of Ursa01

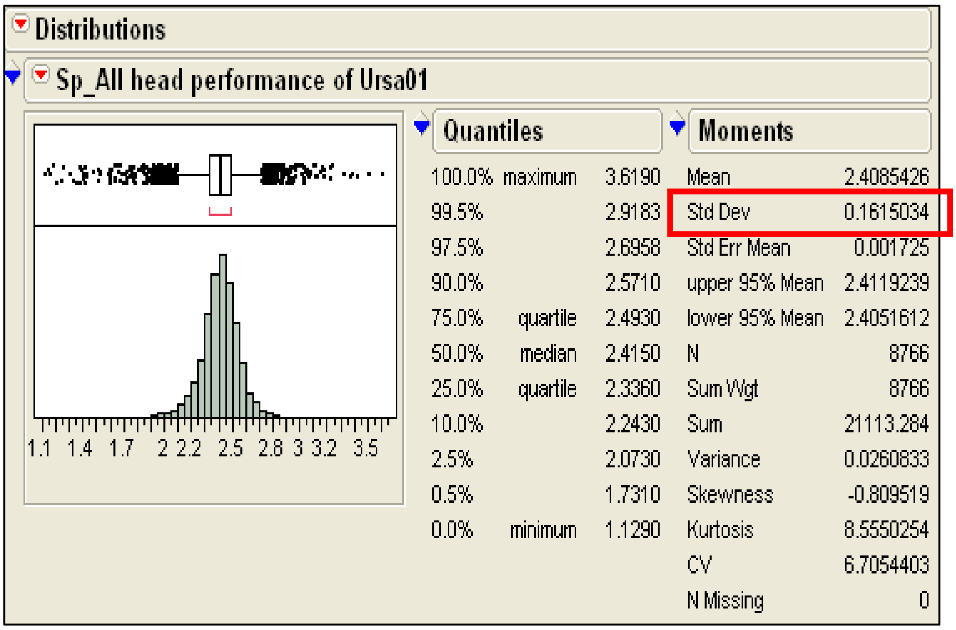
Quantiles

100.0%	maximum	1.911
99.5%		1.880
97.5%		1.467
90.0%		1.034
75.0%	quartile	0.625
50.0%	median	0.222
25.0%	quartile	-0.090
10.0%		-0.371
2.5%		-0.803
0.5%		-1.076
0.0%	minimum	-1.124

Moments

Mean	0.2747463
Std Dev	0.5549143
Std Err Mean	0.0297465
upper 95% Mean	0.3332525
lower 95% Mean	0.2162401
N	348
Sum Wgt	348
Sum	95.6117
Variance	0.3079299
Skewness	0.2635505
Kurtosis	0.0924984
CV	201.97338
N Missing	0

Figure 6 Assembly variation of Hp parameter.



Distributions

Sp_All head performance of Ursa01

Quantiles

100.0%	maximum	3.6190
99.5%		2.9183
97.5%		2.6958
90.0%		2.5710
75.0%	quartile	2.4930
50.0%	median	2.4150
25.0%	quartile	2.3360
10.0%		2.2430
2.5%		2.0730
0.5%		1.7310
0.0%	minimum	1.1290

Moments

Mean	2.4085426
Std Dev	0.1615034
Std Err Mean	0.001725
upper 95% Mean	2.4119239
lower 95% Mean	2.4051612
N	8766
Sum Wgt	8766
Sum	21113.284
Variance	0.0260833
Skewness	-0.809519
Kurtosis	8.5550254
CV	6.7054403
N Missing	0

Figure 7 Assembly variation of Sp parameter.

Our analysis tool uses Visual Basic Application (VBA) to interface between Crystal Ball and Microsoft Excel. We apply system application design concept shown in Figure 8. Each of the steps in Figure 8 is described in detail below.

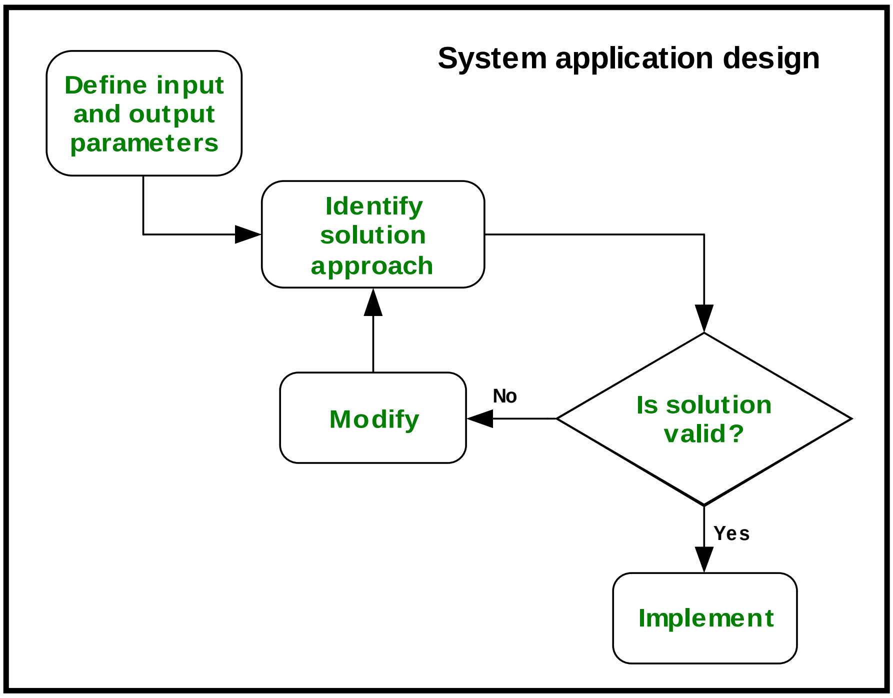


Figure 8 The system application design concept.
Source: Kamlesh and Daniel (1994)

- Define input and output parameters.

This step defines key input parameters that have impacted on critical product performance and define relationship between key input parameters and critical product performance.

- Collect data.

We collect key input parameter.

- Develop a simulation model and run a simulation experiment.

The system is modeled with simulation. Once a simulation model of the problem has been implemented, a simulation experiment is run to estimate performance measures of interest.

- Validate and Implement the solution

After get the result from the simulation model, it is extremely important to validate the solution to make sure that the solution can be describing the variation contribution of system and can be implemented.

- Modify the Model

If during the validation step, the solution cannot be implemented, the additional constraints those were omitted during the original model formulation or may be some of the original constraints were incorrect and need to be modified. In this case, return to the model formulation step and carefully make the appropriate modifications to describe more accurately the real system should be done.

RESULTS AND DISCUSSION

1. Define input and output parameters

The simulation model that used in our analysis tool needs Key Parameter Inputs (KPIs) which represents random input process. We input these values into the transfer function that we get from the design team of our company to predict Key Parameter Outputs (KPOs).

Head pitch (Hp) and spring force (Sp) have high impacts on quality of our customers' product; therefore, they are KPOs. The KPIs are selected from the factors that are related to Hp and Sp (See Table 3)

Our company measures product quality of incoming parts from supplier and finished product before sending to customers (See Figure 3). From the past experience, we realize the head installation and bearing installation processes are the main points that cause variation in the Ursa01 production.

We have to know how the assembly process impact the variation of KPOs, but currently we do not have a measurement tool to measure Hp and Sp after the head installation process. We have to develop a measurement that can take measurements of Hp and Sp at each process (See Figure 9).

Table 3 Key Parameter Inputs list.

Process step / Part	Parameter	Remark
Incoming head	Hp	Hp parameter from incoming head
	Sp	Sp parameter from incoming head
Incoming leg	Leg height	Height of leg on Sections 1 and 2
	Leg pitch	Pitch of leg on Sections 1 referenced from 2
Bearing	Pivot shaft run out	Run out on bearing shaft that place on datum bearing
	Bearing height bearing to leg datum	Difference in height between datum bearing and leg
Ursa01 key dimensions	Dimension parameters	Dimension of Ursa01 that impacts on critical parameters
Head installation effect	Process effect	Head assembly process that impacts on critical parameters
Part shipping	Error term	Product assembly process that impacts on critical parameters

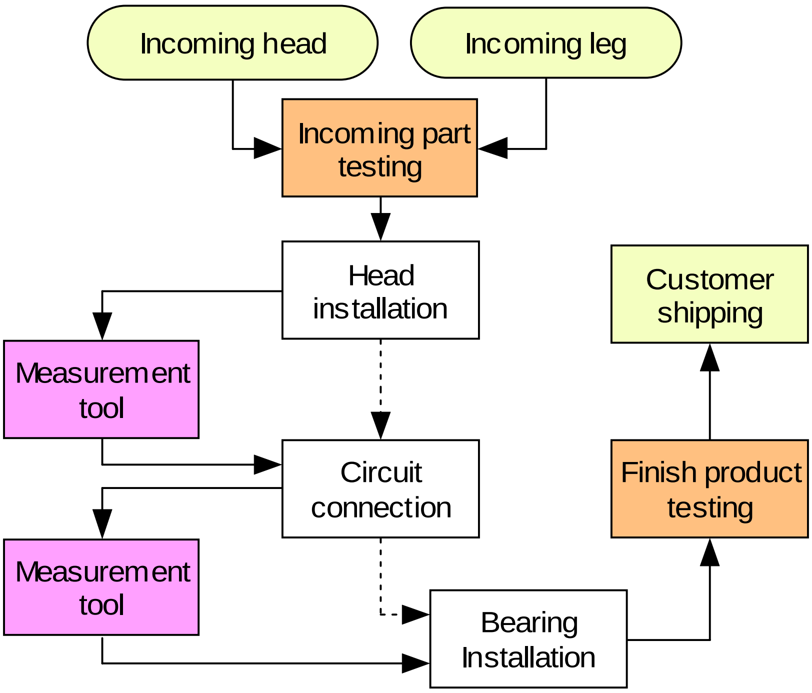


Figure 9 Process assessment flow chart.

We use the measurement tool that are available in our company to develop it, but the measurement tool are not capable to measure Hp and Sp directly. Therefore, we have to find other parameters that can predict Hp and Sp. From the Geometric drawing study, we can select KPIs for predicting Hp and Sp (See Figure 10). The transfer functions from drawing analyses are:

Head pitch transfer functions:
for head up: Hp = $C_1 + A_1 * Hp(incoming) - (B_1 * Leg\_Ht)$
for head down: Hp = $C_2 + A_2 * Hp(incoming) + (B_2 * Leg\_Ht)$

Spring force transfer functions:
For head up: Sp = $G_1 + D_1 * Sp(incoming) + (E_1 * Leg\_Ht) + (F_1 * Leg\_P)$
For head down: Sp = $G_1 + D_2 * Sp(incoming) - (E_2 * Leg\_Ht) - (F_2 * Leg\_P)$

Where
Hp = Head pitch of finish products (degree).
Hp(incoming) = Head pitch of incoming parts (degree).
Sp = Spring force of finish products (gram).
Sp (incoming) = Spring force of incoming parts (gram).
Leg _Ht = Leg height that measure at Section 3 (inch).
Leg_P = Leg pitch that measure from Section 3 and 4 (degree).

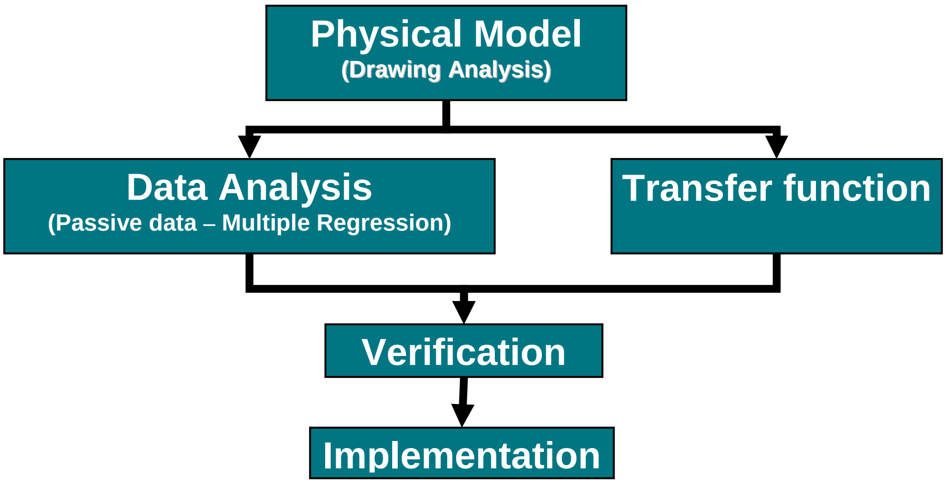


Figure 10 Transfer function development.

We estimate regression parameters (e.g., Ai, Bi, ..., Gi) from historical data of Ursa01. To reduce variation, we control factors such as incoming parts all come from one supplier are produced with the same machine and used only one fixture. The results of regression data analysis is shown in below and Appendix A.

Head pitch transfer function:

For head up:
$$Hp = -0.069 + (0.767 * Hp(incoming)) - (237.289 * Leg\_Ht), \; R^2_{adj} = 0.851 \tag{1.1}$$

For head down:
$$Hp = -0.123 + (0.988 * Hp(incoming)) + (241.643 * Leg\_Ht), \; R^2_{adj} = 0.871 \tag{1.2}$$

Spring force transfer function:

For head up:
$$Sp = 0.663 + (0.779 * Sp(incoming)) + (14.855 * Leg\_Ht) + (0.066 * Leg\_P), \; R^2_{adj} = 0.881 \tag{1.3}$$

For head down:
$$Sp = 0.417 + (0.793 * Sp(incoming)) - (10.234 * Leg\_Ht) - (0.049 * Leg\_P), \; R^2_{adj} = 0.942 \tag{1.4}$$

Layfield (2003) states that "R^2 is a statistic that will give some information about the goodness of fit of a model. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates the real data points. An R^2 of 1.0 indicates that the regression line perfectly fits the data." In some (but not all) instances where R^2 is used, the predictors are calculated by ordinary least-squares regression: that is, by minimizing SSE. In this case R^2 increases as we increase the number of variables in the model (R^2 will not decrease). This illustrates a drawback to one possible use of R^2, where one might try to include more variables in the model until "there is no more improvement." This leads to the alternative approach of looking at the adjusted R^2. $R^2_{(adj)}$ is a modification of R^2 that adjusts for the number of explanatory terms in a model. Unlike R^2, the $R^2_{(adj)}$ increases only if the new term improves the model more than would be expected by chance. The adjusted R^2 can be negative, and will always be less than or equal to R^2.

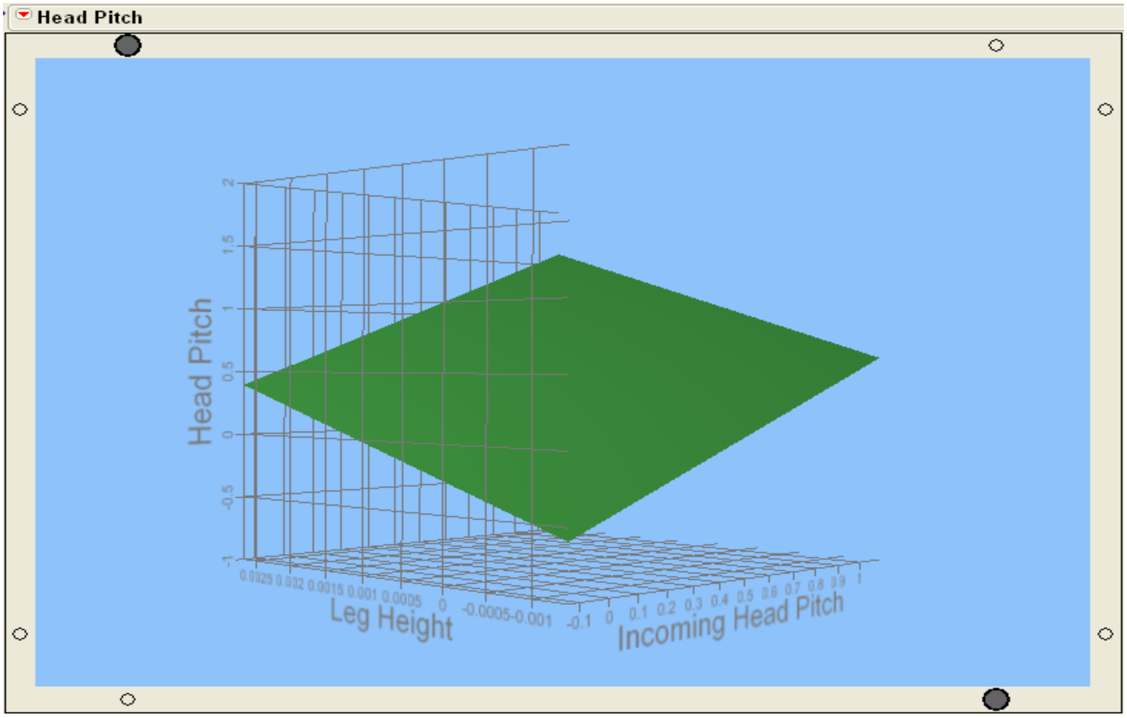
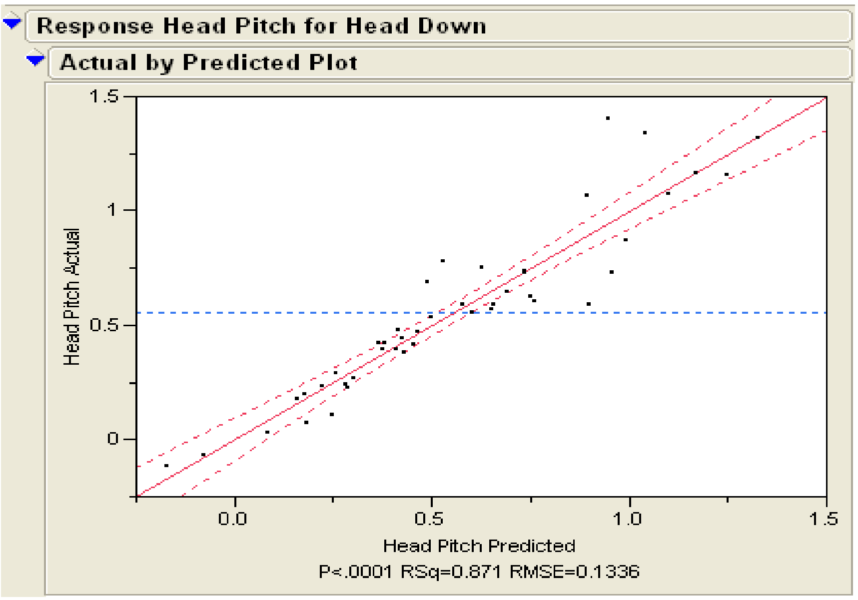


Figure 11 Surface plot of Hp parameter for head down.



P<.0001 RSq=0.871 RMSE=0.1336

Figure 12 Actual by predicted plot of Hp parameter for head down.

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The Equation (1.1)–(1.4) can explain more than 85% variations in Hp and Sp parameters. Figure 11 and 12 show the example of Hp parameter for head down. We use these transfer functions in the simulation model where we create variability in Hp and Sp through a normally distributed error terms.

2. Collect Data

To assess the variability in the process, we must have the data for Hp and Sp. Currently, there are no measurement tools available. Therefore, we have to develop a new measurement system. The measurement tools are limited in that we cannot measure Hp and Sp directly, but measure Leg_H and Leg_P parameters which are then used to predict Hp and Sp.

2.1. Measurement systems

In order to develop measurement system, we use *SWOT* analysis to select measurement tool system in our company (See Table 4). Focusing only on internal factors, we ignore *Opportunities* and *Threats* in the SWOT analysis. We have 4 types of measurement tools. We use 2 types of reference plane (*Datum*). For measurement type A, B and D, We use actuator datum (datum C) as a reference plane, but measurement type C uses bearing datum (datum B).

We select measurement type D for the following reasons: Firstly, measuring area is highly sensitive to measure Hp and Sp. Measurement type A cannot measure it without causing part damage because of contact measurement. Secondly, Measurement type B is not viable in terms of cost and time; it takes a long time to measure, and it needs a special fixture to support parts. Thirdly, Measurement types C and D use the same methodology, but Measurement type C is hard to modify; it requires measuring parts that must have bearing.

Table 4 SWOT analysis.

Measurement Type	**Strength**	**Weakness**
A	- High accuracy	- Outside clean room
	- Flexibility to set measured positions	- Taking a long time to measure
		- Probe can damage part at sensitive area
		- Only 1 machine available.
B	- Very high accuracy	- Only 1 machine available.
	- More data analysis and 3D presentation of results.	- Hard to use and take a very long time to measure
	- Optical test, so it does not cause damages to products.	- Require a specific fixture to set it
C	- More accurate than Measurement type D	- Hard to modify a fixture and machine code.
	- Take only a short time to measure	- Measuring part has to have bearing to measure
	- More than 10 machines are available.	- Most of limitation come from "shadow Cast" technology
	- Optical test is not damaging part at sensitive area	
D	- Easy to use modify program	- Low accuracy compare with another optical measurement
	- Take only a short time to measure	- Most of limitation come from "shadow Cast" technology
	- More than 10 machines are available	
	- Optical test is not damaging part at sensitive area	

2.2. Machine development

Originally, Measurement type D is used to measure actuator on each leg without head readers and writers at sections 1 and 2 from drawing, (See Figure 13) but we develop it to measure on leg of actuator with a head at Sections 3 and 4 (See Figure 14).

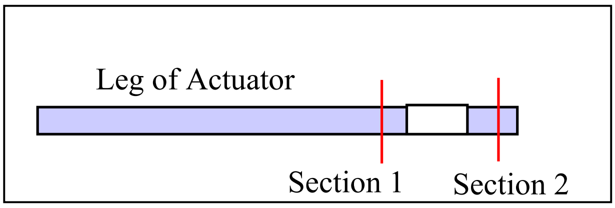


Figure 13 Location of sections 1 and 2 on leg of actuator.

The difference of distant on the horizontal axis between Sections 3 and 4 is 0.34 inch that number is requirement from the Design team to calculate Leg_P. We calculate Leg_P parameter by using difference height (Leg_Ht) of Sections 3 and 4. We use Leg_Ht of Section 3 as a reference plane. If Leg_Ht of Section 4 is less than Section 3, the value of Leg_P is going to be negative. On another hand, Leg_P is going to be positive. In Equations (2.1) and (2.2), we apply Trigonometry theory to calculate Leg_P (See Figure 14).

$$\text{For head up:}\quad Leg\_P = -\{180/\pi * \tan^{-1}[(Leg\_Ht(S4) - Leg\_Ht(S3))/0.34]\} \tag{2.1}$$

$$\text{For head down:}\quad Leg\_P = \{180/\pi * \tan^{-1}[(Leg\_Ht(S4) - Leg\_Ht(S3))/0.34]\} \tag{2.2}$$

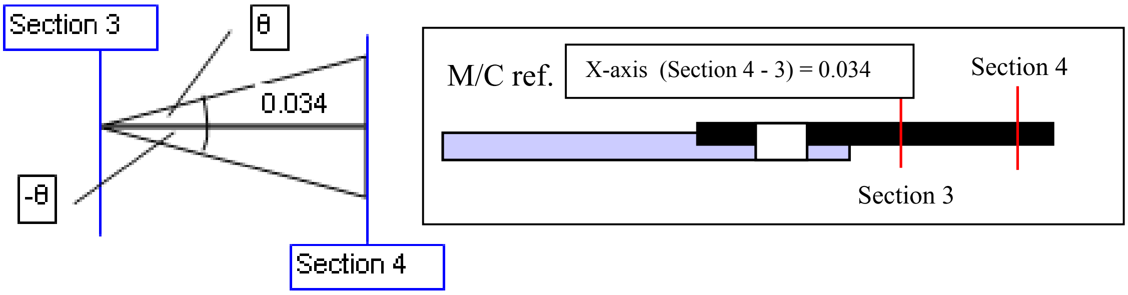


Figure 14 Leg pitch calculation.

In order to find the location that appropriate to measure, we use the single-factor experiment design to conduct the experiment. Five steps of design of experiment are: (Pande, *el at*., 2000)

2.2.1. Plan

We select Response factor, Decision factor and Block factor (See table 5). The reason that we use only 4 locations for this experiment because the number of lines limitation in machine code that allows us to put only 4 locations.

Table 5 Single factor experiment.

Parameter	Description (unit)	Number of levels	1	2	3	4
Response	Difference of height between measurement Type D reading and final tester reading (Inch)					
Factor	Location to measure on the horizontal from center of bearing hole (inch)	4	0.94	0.955	0.965	0.98
Block	Head position (-)	4	0	1	2	3

2.2.2. Design

We use the full-factorial experiment using the factor levels that are selected from the previous step. For each experiment, we use Minitab software to calculate. Setting the type-I error (α) = 0.05, the difference value = 0.0004 (From design team) and the power of the test = 0.9, we select the sample size equal to 30 sample.

2.2.3. Run

We take a measurement at 4 positions on 4 head positions (See Figure 15). Measuring on the location of the horizontal, we have to develop a machine code to control machine.

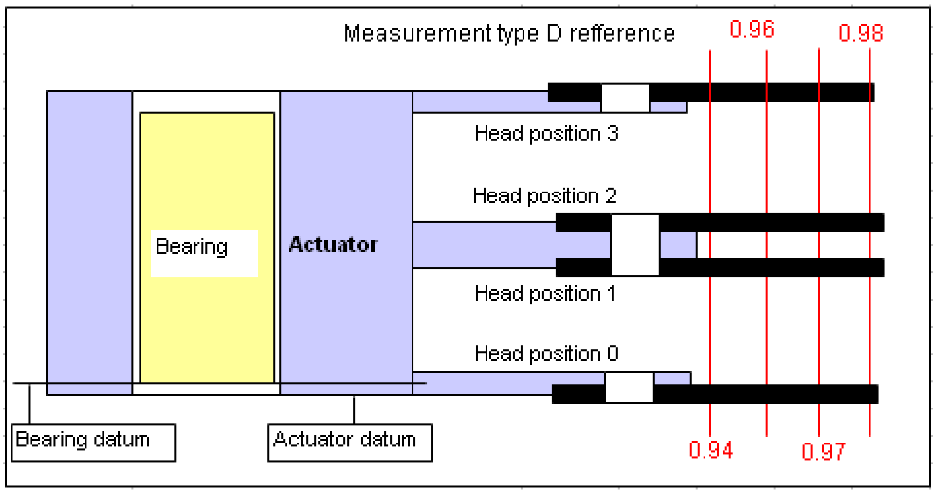


Figure 15 Measuring position on Ursa01.

2.2.4. Analysis

The ANOVA results are shown in Table 6 (difference between measurement type D and final tester readings) at the significance level 95%. (See Appendix C)

Table 6 ANOVA .

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	P-value
Measuring Position	3	0.00000346	1.16E-06	2.9048	0.0344
Head position	3	0.00106465	0.000355	892.5787	<.0001
Error	473	0.00018806	3.98E-07		
Total	479	0.00125618			

2.2.5. Act

Multiple comparisons are a method that allows us to perform some follow-up test to isolate the specific differences. We select Fisher's LSD method to find the position that minimizes the response.

The four location measurement averages are:

Position 1 = 0.0011056 Position 2 = 0.0015257
Position 3 = 0.0015636 Position 4 = 0.0017831

Each treatment average use Block = 4 levels and we use $\alpha = 0.05$ so $t_{0.025,\,474}$ = 2.24856. Therefore the value of the LSD is

$$\begin{aligned} \text{LSD} &= t_{0.025,\,474} * \text{SQRT(2*Mean square error / Block level)} \\ &= 2.24856 * \text{SQRT(2* 3.98E-07 / 4)} \\ &= 0.001 \end{aligned}$$

Any pair of treatment averages that differ by 0.001 indicates that this pair of treatment means is significantly different. The comparisons are shown below:

Table 7 Comparison averages of treatment pairs.

Comparisons positions	Mean different		LSD
4 vs 1	0.0006775	<	0.001
4 vs 2	0.0002574	<	0.001
4 vs 3	0.0002195	<	0.001
3 vs 1	0.000458	<	0.001
3 vs 2	0.000458	<	0.001
2 vs 1	0.0004201	<	0.001

They are not different significantly, however we want to get the minimum response. We select position 1 (0.94) to use to measure on actuators.

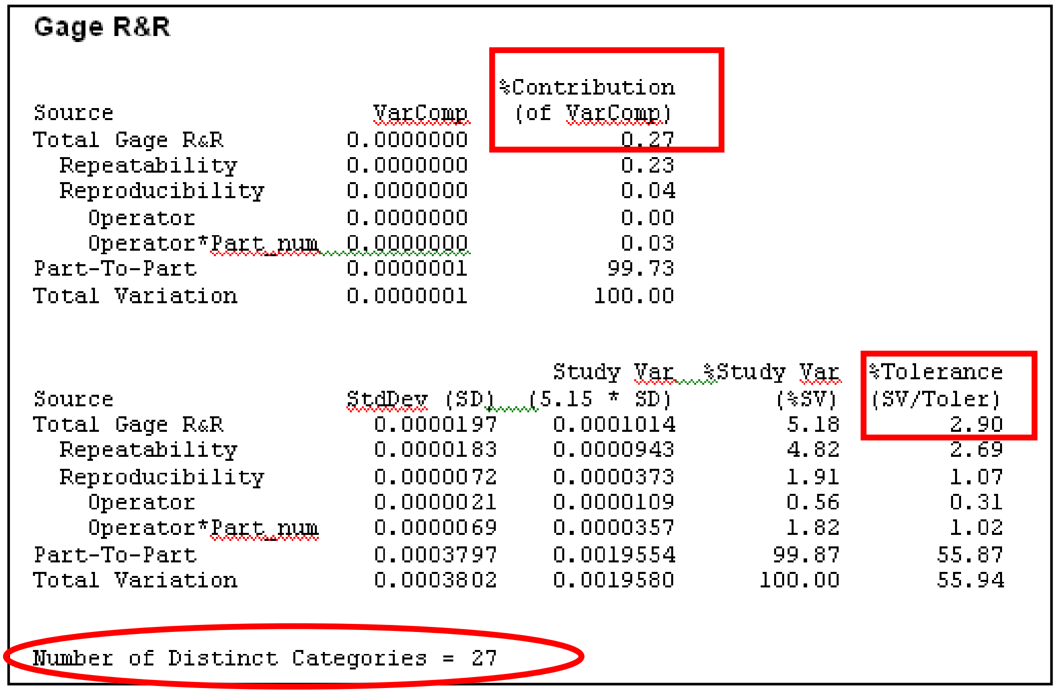
2.3. Tester stability test

After we select the location to measure at Sections 3 and 4, we develop machine codes to control measuring devices, and we test with Gage Repeatability and Reproducibility (GR&R) from our company procedure.

GR&R

- Select 10 sample parts, which uniformly cover the acceptable range of process outputs or process variation.
- Select two or three operators who normally perform measurements with the equipment being evaluated and refer to the operators as A, B and C.
- Arrange the parts in random order and let operator A measure the 10 parts. Record the result. Let operator B and then C measure the same 10 parts without seeing operator A's readings, and record the result.
- Repeat the cycle for two or three times, using different random order of measurements. Record the data.
- After complete measurement of samples, analyze numerical results by Minitab or other statistical software.

The results from Minitab are going to give us, for example, in Figure 16



```
Gage R&R

                                       %Contribution
Source                    VarComp       (of VarComp)
Total Gage R&R          0.0000000               0.27
  Repeatability         0.0000000               0.23
  Reproducibility       0.0000000               0.04
    Operator            0.0000000               0.00
    Operator*Part_num   0.0000000               0.03
Part-To-Part            0.0000001              99.73
Total Variation         0.0000001             100.00


                                     Study Var  %Study Var  %Tolerance
Source                  StdDev (SD)  (5.15 * SD)     (%SV)  (SV/Toler)
Total Gage R&R            0.0000197    0.0001014      5.18        2.90
  Repeatability           0.0000183    0.0000943      4.82        2.69
  Reproducibility         0.0000072    0.0000373      1.91        1.07
    Operator              0.0000021    0.0000109      0.56        0.31
    Operator*Part_num     0.0000069    0.0000357      1.82        1.02
Part-To-Part              0.0003797    0.0019554     99.87       55.87
Total Variation           0.0003802    0.0019580    100.00       55.94


Number of Distinct Categories = 27
```

Figure 16 GR&R result from Minitab.

Tester should pass all of below rules. The example on Figure 16 passes the entire rule on Table 8. The percent contribution of variation component is 0.27. It means the tester machine are added the variation into measurement readings 0.27% of total variation. The percent tolerance for GR&R is 2.90. It means the six times of variation is 2.9% compare with tolerance (Our company procedure allows us to use 5.15 instead of 6 times of variation). The number of distinct categories is 27. This number represents the 27 number of non-overlapping confidence intervals that will span the range of product variation.

Table 8 Qualified tester condition from our company procedure.

Decision Rules	%Contribution	Number of Distinct Categories	% Tolerance
Reject	> 10 %	< 5	> 35%
Acceptable	3 - 10 %	5-10	10 - 35 %
Excellent	0 - 3.0 %	> 10	0 - 10 %

The result has shown that the GR&R are very good (See table 9 and Appendix B for more information). It passes the entire of qualified tester from company procedure.

Table 9 Result of GR&R of Leg_ht parameter at Section 3 on measurement type D.

Head	%Contribution	Number of Distinct Categories	% Tolerance
0	0.2	31	2.18
1	0.1	45	3.09
2	0.27	27	2.09
3	0.36	23	3.21

2.4. Tester correlation

In order to compare the measurement type D and final tester, we have to determine their correlation. We apply multiple linear regressions to find a transfer function for converting Leg_Ht and Leg_P that we get from Measurement type D to the reading from the final product tester.

We conduct experiments to find the relationship between both testers. To Reduce the effect of bearing installation and material variations, the control factors are: Using the same supplier of incoming heads, actuators and bearings and using the same operators to install bearings

The sample size of this experiment is 30, and the measurement after the circuit connection process (See Figure 17)

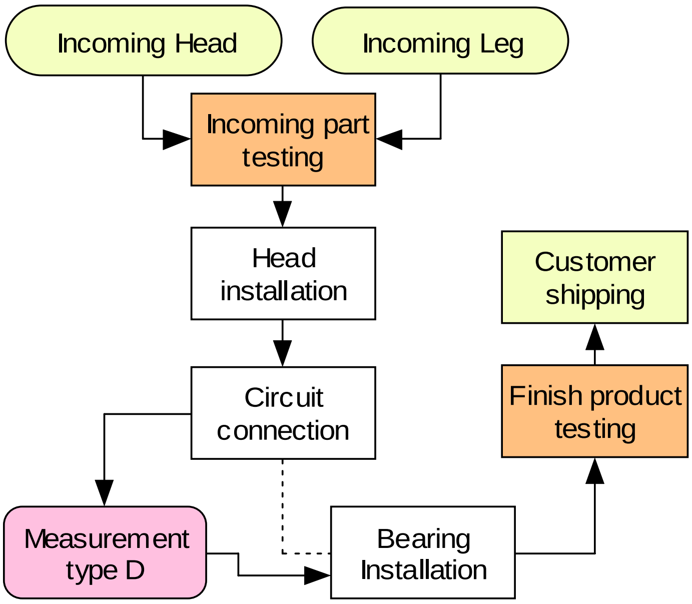


Figure 17 Experiment flow chart.

After we get a result from the experiment, we correlate both testers. Leg_Ht parameters use Equations (2.3) – (2.6).

$$\text{Leg\_Ht 0} = 0.000968 + (1.0766103 * \text{Leg\_Ht0(type D)} + (0.99415 * \text{BRG\_Ht}) + (0.015213 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.72 \quad (2.3)$$

$$\text{Leg\_Ht 1} = -0.00121 + (1.1048829 * \text{Leg\_Ht0(type D)} + (0.864153 * \text{BRG\_Ht}) + (0.013387 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.89 \quad (2.4)$$

$$\text{Leg\_Ht 2} = 0.00139 + (1.4136581 * \text{Leg\_Ht0(type D)} + (0.853857 * \text{BRG\_Ht}) + (0.013177 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.84 \quad (2.5)$$

$$\text{Leg\_Ht 3} = -0.00149 + (0.9999921 * \text{Leg\_Ht0(type D)} + (0.731824 * \text{BRG\_Ht}) + (0.014066 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.90 \quad (2.6)$$

For Leg_P parameters use Equations (2.7) – (2.10).

$$\text{Leg\_P 0} = -0.01447 + (0.9771862 * \text{Leg\_Ht0(type D)}\ ,\ R^2_{adj} = 0.95 \quad (2.7)$$

$$\text{Leg\_P 1} = -0.04319 + (1.0805112 * \text{Leg\_Ht0(type D)} + (0.67652 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.96 \quad (2.8)$$

$$\text{Leg\_P 2} = -0.04098 + (0.9354471 * \text{Leg\_Ht0(type D))}\ ,\ R^2_{adj} = 0.92 \quad (2.9)$$

$$\text{Leg\_P 3} = 0.085701 + (1.0575324 * \text{Leg\_Ht0(type D)} + (-1.247 * \text{BRG\_P})\ ,\ R^2_{adj} = 0.92 \quad (2.10)$$

Where

Leg _Ht = Leg height that is measurement reading from final tester (inch).
Leg_P = Leg pitch that is measurement reading from final tester (degree).
Leg _Ht(type D) = Leg height that is measurement reading from final tester (inch).
Leg_P(type D) = Leg pitch that is measurement reading from final tester (degree).
BRG_Ht = Bearing height (inch).
BRG_P = Bearing pitch (degree).

The $R^2_{(adj)}$ is very good. It can explain nearly 90 percent of variability in Leg_Ht and Leg_Ht. (See more on Appendix C).

Measurement type D passes the tester qualification. Our company can use the developed Measurement type D to assess the process variability.

2.5. Process assessment

Based on the experience of our company, the head installation process is cause variability to critical parameters. Using the Measurement type D to measure Leg_Ht and Leg_P after the head installation process, the Hp and Sp variation on Ursa01 is increased. We use the result of this experiment as an input (called "Assembly added") to the analysis tool in term of "Assembly Added." After Head installation, mean of Hp added up about 0.186 degrees for head up, but Hp of head down does not change. Sp is changing about 0.9 gram for head up and down.

Table 10 Ursa01's summary input parameters.

Inputs	value
HSA Assembly added Hp(deg)	0.11
HSA Assembly added Sp(g)	0.178
Hp Sensitivity to bas plate height (deg/in)	241.64
Hp Sensitivity to base plate pitch (deg/deg)	0
Sp Sensitivity to base plate height(g/in)	10.23
Sp Sensitivity to base plate pitch (g/deg)	0.04

3. Develop a simulation model

Section 3 consists of 2 sections. Section3.1 describes assumptions of our simulation model. VBA interface between Crystal Ball and Excel is in Section 3.2.

3.1. Assumptions of simulation model

Most of input parameters are from Ursa01 drawings, and some of them are from the experiment in "Collect data" part (Section2). To run the Crystal Ball, we need to define probability distributions of random parameters. The model assumptions of model are mostly from experts' opinions. To get the accurate result, we added an error factor to compensate the errors that occur in model and the unknown factors. Part shipping is an error term. We start from Sigma Commitment Roadmap model (See Figure 1) to find the assumption for our model. We put all of the assumptions in our model and relationship between input parameters and critical product performances on Table 11 through 13.

To select the appropriate value for Part shipping, trial and error is the method. Our company have margin of product performance variation that can add up into their product.

Table 11 Ursa01's an assumption input of parameters.

Input Parameters	**Assumption**	**Value1**	**Value2**
Pivot OD Tolerance	Normal	0	
Actuator Bore Diameter Tolerance	Normal	0	
Actuator Bore Perpendicular(uin)	Normal	0	
Actuator Bore Perpendicular rot angle relative to head(deg)	Uniform	-135	225
Pivot Shaft Run out(uIn)	Uniform	-225	225
Pivot Shaft 1 sigma height(B-C) err(uin) Means as close point to C	Normal	0	
Shaft Close Point Angle relative to head @ install	Uniform	-225	135
Shaft Close Point Angle relative to head @ glue	Uniform	-45	315
Leg Tip 0 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 1 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 2 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 3 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 4 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 5 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 6 Height Err to Actuator 'C'(uin)	Normal	0	200
Leg Tip 0 Pitch(udeg)	Normal	0	114500
Leg Tip 1 Pitch(udeg)	Normal	0	114500
Leg Tip 2 Pitch(udeg)	Normal	0	114500
Leg Tip 3 Pitch(udeg)	Normal	0	114500
Leg Tip 4 Pitch(udeg)	Normal	0	114500
Leg Tip 5 Pitch(udeg)	Normal	0	114500
Leg Tip 6 Pitch(udeg)	Normal	0	114500
Head installation design induced Outer Head mean Hp (deg)	Normal	0	0.0000001
Head installation design induced up Fly mean Hp (deg)	Normal	0.125	0.14
Head installation design induced Down Fly mean Hp (deg)	Normal	-0.125	0.14

Table 11 (Continued).

Input Parameters	Assumption	Value1	Value2
Head installation design induced Outer Head mean Sp (g)	Normal	0	0.0000001
Head installation design induced Up Fly mean Sp (g)	Normal	0.05	0.0000001
Head installation design induced Down Fly mean Sp (g)	Normal	-0.05	0.0000001

Table 12 Ursa01's an assumption input of incoming head parameters.

Input Parameters	Assumption	Value1	Value2
Incoming head 0 Hp(udeg)	Normal	0	350000
Incoming head 1 Hp(udeg)	Normal	0	350000
Incoming head 2 Hp(udeg)	Normal	0	350000
Incoming head 3 Hp(udeg)	Normal	0	350000
Incoming head 4 Hp(udeg)	Normal	0	350000
Incoming head 5 Hp(udeg)	Normal	0	350000
Incoming head 6 Hp(udeg)	Normal	0	350000
Incoming head 7 Hp(udeg)	Normal	0	350000
Incoming head 8 Hp(udeg)	Normal	0	350000
Incoming head 9 Hp(udeg)	Normal	0	350000
Incoming head 10 Hp(udeg)	Normal	0	350000
Incoming head 11 Hp(udeg)	Normal	0	350000
Incoming head 0 Sp (g)	Normal	0	0.065
Incoming head 1 Sp (g)	Normal	0	0.065
Incoming head 2 Sp (g)	Normal	0	0.065
Incoming head 3 Sp (g)	Normal	0	0.065
Incoming head 4 Sp (g)	Normal	0	0.065
Incoming head 5 Sp (g)	Normal	0	0.065
Incoming head 6 Sp (g)	Normal	0	0.065
Incoming head 7 Sp (g)	Normal	0	0.065
Incoming head 8 Sp (g)	Normal	0	0.065
Incoming head 9 Sp (g)	Normal	0	0.065
Incoming head 10 Sp (g)	Normal	0	0.065
Incoming head 11 Sp (g)	Normal	0	0.065

Table 13 Ursa01's an assumption input of process parameters.

Input Parameters	Assumption	Value1	Value2	Value3	Value4
Baseplate to Tip 0 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 1 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 2 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 3 Gap(uin)	Beta	0	1	2	3

Baseplate to Tip 4 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 5 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 6 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 7 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 8 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 9 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 10 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 11 Gap(uin)	Beta	0	1	2	3
Baseplate to Tip 0 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 1 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 2 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 3 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 4 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 5 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 6 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 7 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 8 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 9 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 10 Pitch(udeg)	Normal	0	0.33		
Baseplate to Tip 11 Pitch(udeg)	Normal	0	0.33		
Ursa01 Assy Induced Head 0 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 1 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 2 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 3 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 4 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 5 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 6 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 7 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 8 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 9 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 10 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 11 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Head 11 Hp(udeg)	Normal	0	140000		
Ursa01 Assy Induced Sp Head 0	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 1	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 2	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 3	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 4	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 5	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 6	Normal	0	0.052		

Table 13 (Continued)

Input Parameters	**Assumption**	**Value1**	**Value2**	**Value3**	**Value4**
Ursa01 Assy Induced Sp Head 7	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 8	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 9	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 10	Normal	0	0.052		
Ursa01 Assy Induced Sp Head 11	Normal	0	0.052		
Ursa01 Ship Induced Head 0 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 1 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 2 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 3 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 4 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 5 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 6 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 7 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 8 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 9 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 10 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Head 11 Hp(udeg)	Normal	0	0.333		
Ursa01 Ship Induced Sp Head 0	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 1	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 2	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 3	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 4	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 5	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 6	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 7	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 8	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 9	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 10	Normal	0	0.0001		
Ursa01 Ship Induced Sp Head 11	Normal	0	0.0001		

3.2. VBA functions in our simulation model

Analysis tool that we develop have 2 modules as follows;

3.2.1. Main Program

This module connects between Crystal Ball and Excel. It calls simulation engine in Crystal Ball, set configurations to run simulation, and collect data from simulation results. Users are not allowed to modify. It has 9 sub routines to control a simulation model and graphically present the simulation result into graph.

3.2.1.1. RunApplication() controls the sequence of sub routines in main program module and assigns the value of global variables.

3.2.1.2. Delgraph() deletes graphs form Excel sheets.

3.2.1.3. PrepareSheet() clears data in data sheets and creates a head column for data sheets.

3.2.1.4. RunDistributions() assigns configurations of simulation runs and run the simulation.

3.2.1.5. ImportData() imports data from the simulation result.

3.2.1.6. RearrangeData() puts data from temporary data location into data source location and rearrange data for convert data from ranking of correlation to the percent contributions of variation.

3.2.1.7. ConvertData() converts the rank of correlation data from simulation to the percent contributions of variation in Ursa01 model.

3.2.1.8. Abs_Value() converts data from data source to absolute value.

3.2.1.9. CreateGraphAndPivot() summarize data from simulation into graphs and pivot tables.

3.2.2. Support Program

Supporting Program module is an interface between users and simulation engine. It allows user to set type of assumption and the parameters associated with of assumptions.

4. Validate and Implement the Solution

4.1. Validating data and model

Validating can be separated into 2 sections. Section4.1.1 is raw data. Model verification is in section4.1.2.

4.1.1. Raw data

The data that gathered from real world situation should have to have a tolerance for any error. Moreover, it is necessary that the data should have verified the accuracy; precision and reliable before uses it.

For the production data that we use to do the regression analysis, it is necessary to verify this type of data. Because our company has many suppliers, many configurations of product and many experiment data which are combine together in database. We have to filter the production data and keep only one supplier and one configuration that we are interested and exclude all of experiment data from our raw data. So it can use for determine and analyze the solution accurately.

For our experiment data, it is not necessary to verify this type of data. Because we control the environment of experiment and also factors that could be impact to our experiment.

4.1.2. Model validation and implementation

In order to define the appropriate assumption for Part shipping, Trial and Error is the method to find the assumption of error term. Our company have margin of product performance variation that can add up into their product. We use variation margin, supplier variation commitment and customer request as a condition boundary to verify model.

4.2. Implementing solution

For input of Head installation effect and Coefficient of parameters, we construct confident interval for those parameters that show on table 14 and 15.

Table 14 Sensitivity for Regression coefficient.

	Parameters	Head	Coefficient	Standard error	$t_{0.025,\infty}$	Lower	Upper
Hp	Leg_Ht	Down	241.64	21.384	1.96	199.73	283.56
	Leg_Ht	Up	237.29	22.093	1.96	193.99	280.59
	Leg_Ht	All				193.99	283.56
Sp	Leg_Ht	Down	10.23	0.985	1.96	8.30	12.16
	Leg_Ht	Up	14.86	1.058	1.96	12.78	16.93
	Leg_Ht	All				8.30	16.93
	Leg_P	Down	0.05	0.0052	1.96	0.04	0.06
	Leg_P	Up	0.07	0.0064	1.96	0.05	0.08
	Leg_P	All				0.04	0.08

Table 15_ Sensitivity for Head installation effect.

	STDev	n	$\chi^2_{99,579.0}$	$\chi^2_{0.025,99}$	Lower	Upper
Hp	0.112	100	73.361081	128.422	0.098337	0.130108
Sp	0.178	100	73.361081	128.422	0.156285	0.206778

We conduct DOE using 3^k design for input of Hp and Sp parameters that we got from sensitivity analysis. The design of experiment is on table 16.

Table 16 3^k Design for experiment.

	Parameters	Low level	Mid level	High level
Hp	Head installation	0.098	0.112	0.13
	Leg_Ht	193.99	239.47	283.56
SP	Head installation	0.156	0.178	0.207
	Leg_Ht	8.3	12.54	16.93
	Leg_P	0.04	0.06	0.08

From the result of experiment, the percents contribution of variation of each experiment is the same. For Hp parameter (See Table 17), the incoming Hp and Leg height (incoming actuator) are contributing about 75 percents of model. They are incoming part from our supplier. The error term (Shipping part) is about 5 percents. 20 percents is for process factors. The main variation of our model is from incoming part.

Table 17 Percents variation contributions of Hp after put new process inputs.

Priority	Parameters	% Contributions of variation
1	Incoming Hp	48.48
2	Leg height	24.60
3	Pivot Shaft height error	7.78
4	Head install design induced up Fly	6.05
5	Part shipping	5.45
6	Pivot Shaft Run out	5.05
7	Part assembly	1.07
8	Actuator Bore Perpendicular	0.61
9	Leg pitch	0.39
10	Actuator Bore Diameter Tolerance	0.04
	Total	99.51

For Sp parameter (See Table 18), the incoming Sp is about 62 percents and error term is 24 percents. The main effect of Sp is incoming Sp, but only from incoming head.

Comparing between before and after put new process factors (See Table 19 and 20), Hp parameter can reduce the percents variation contribution of error term from 16.89

to 5.45 percents, but the new process inputs Sp parameter cannot explain the error term on Sp parameter. It is still the same percents variation contribution (About 27 percents).

Table 18 Percents variation contributions of Sp after put new process inputs.

Priority	Parameters	% Contributions of variation
1	Incoming Sp	62.89
2	Part shipping	27.02
3	Part assembly	7.94
4	Leg height	0.80
5	Pivot Shaft height error	0.41
6	Pivot Shaft Run out	0.21
7	Head install design induced up Fly	0.12
8	Actuator Bore Perpendicular	0.05
9	Leg pitch	0.02
10	Actuator Bore Diameter Tolerance	0.01
	Total	99.47

Table 19 Percents variation contributions of Hp before put new process inputs.

Priority	Parameters	% Contributions of variation
1	Incoming Hp	72.07
2	Part shipping	16.89
3	Head install design induced up Fly	8.17
4	Part assembly	1.33
5	Leg pitch	0.05
	Total	98.50

Table 20 Percents variation contributions of Sp before put new process inputs.

Priority	Parameters	% Contributions of variation
1	Incoming Sp	62.51
2	Part shipping	27.07
3	Part assembly	9.03
4	Pivot Shaft height error	0.05
5	Head install design induced up Fly	0.03
	Total	98.69

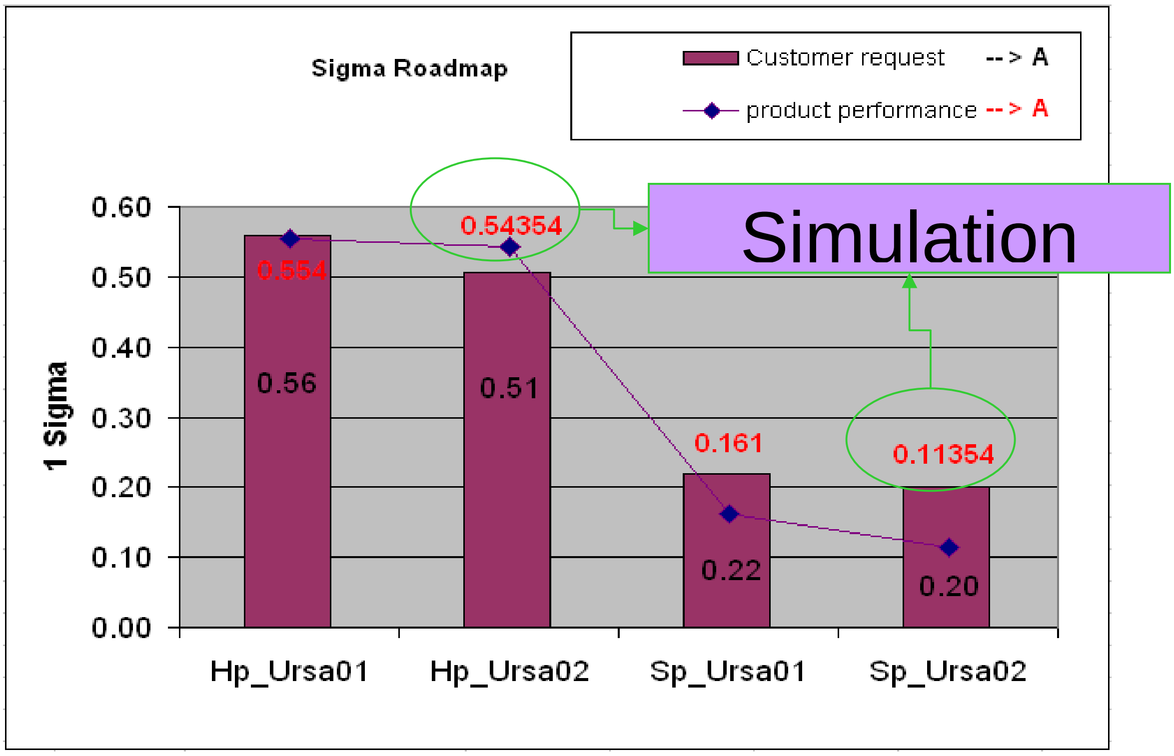


Figure 18 The result of Ursa02 simulation.

For Ursa02, we assign incoming Hp and Sp are on target with 0.33 degree and 0.8 gram. The simulation result is 0.54 degree for Hp standard deviation and 0.11 gram for Spring force standard deviation. Comparing with customer requirement of Ursa02, Hp is 0.51 degrees and Sp is 0.2 gram. Our company has to reduce variation for head pitch that exceeded from customer requirement. Spring force standard deviation is less than customer requirement.

Table21 Summary result of simulation

Parameters	Product	Customer request	Source of data	
			Actual data	Simulation data
Head pitch (degrees)	Ursa01	0.56	0.554	-
	Ursa02	0.51	-	0.54354
Spring force (grams)	Ursa01	0.22	0.161	-
	Ursa02	0.2	-	0.11354

CONCLUSIONS

The objective of this study was to develop the interface software program between Crystal Ball and Excel to predict product performance of the next product generation, do what if analysis and generate percent contribution of variation for each factor in our model. To develop more accurate model and reduce error term, measurement type D is developed to measure new input parameter that impacted to critical parameters. Following the constructive the Analysis tool, Visual Basic for Application language was chosen to develop the interface Excel and Crystal Ball.

Our case study is Ursa01. We focus on standard deviation of new product Ursa02, which is developed from Ursa01. Since they have almost the same configuration, we applied data from Ursa01 to predict Ursa02 performance.

We can summarize the result below.

1. In addition to measuring height of actuator, measurement type D can also measure the height of base plate of HGA. The measurement location that get the lowest error is 0.94 inch from machine reference.
2. Our proposed transfer function can reduce the contribution variation of Hp's error term from 16.89% to 5.45%, but it cannot reduce Sp's error term. It is still about 27 %.
3. The Hp and Sp of incoming head are critical to variations of Hp and Sp of HSA (about 50 to 65 % contributions).

Our study considers process factors and geometry of product. For future work, other important factors can be added to the system, and other product type also be considered.

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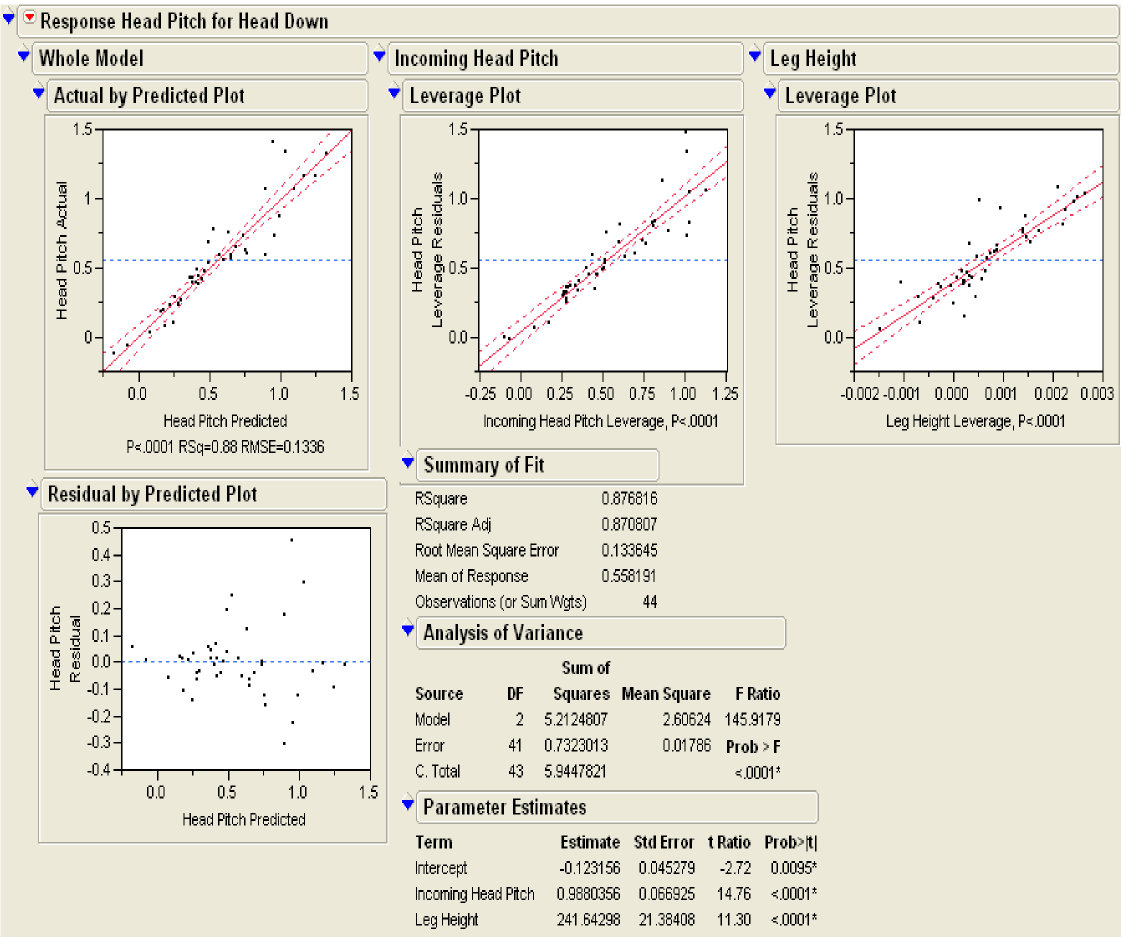
APPENDICES

Appendix A

Regression Analysis



Summary of Fit

RSquare	0.876816
RSquare Adj	0.870807
Root Mean Square Error	0.133645
Mean of Response	0.558191
Observations (or Sum Wgts)	44

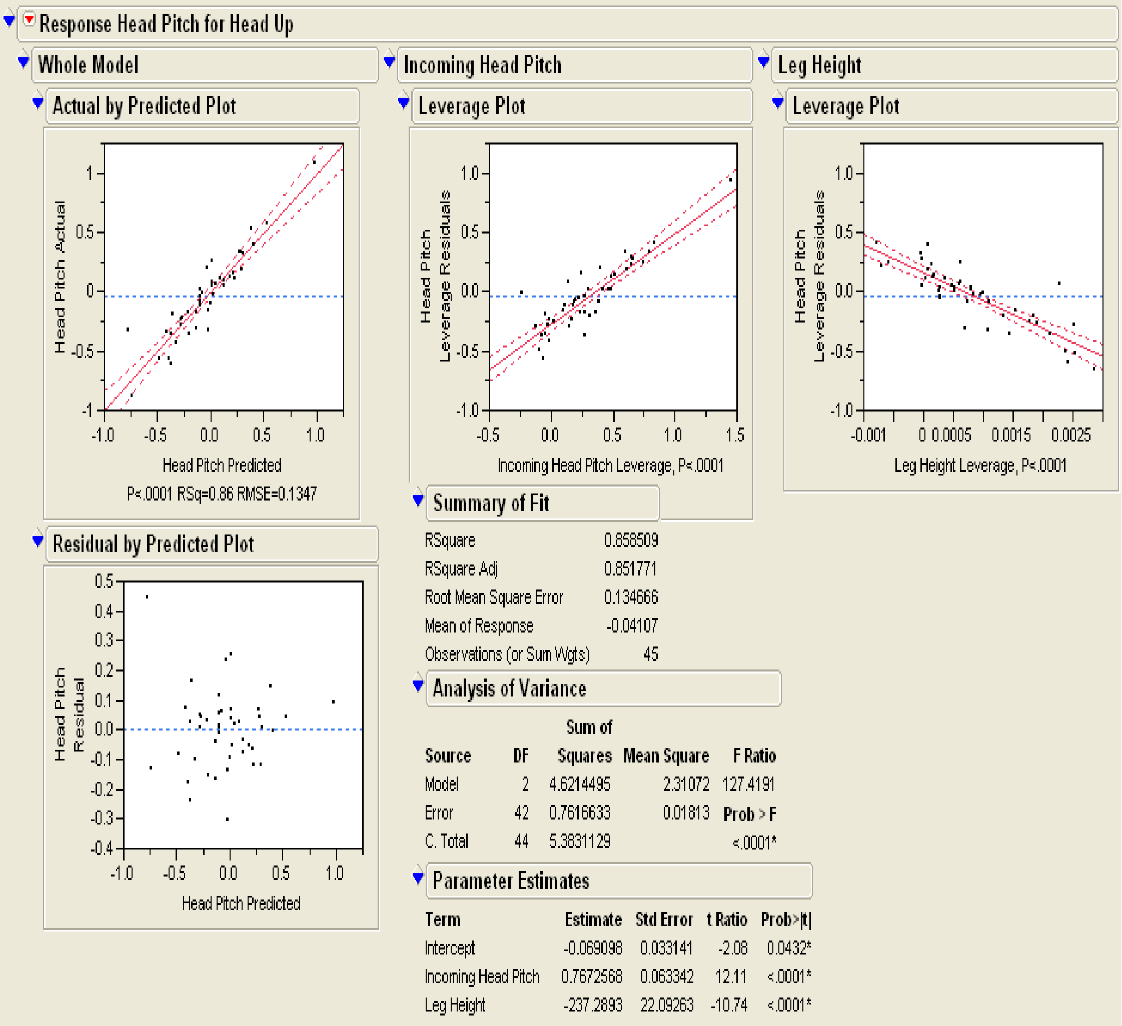
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	5.2124807	2.60624	145.9179
Error	41	0.7323013	0.01786	Prob > F
C. Total	43	5.9447821		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.123156	0.045279	-2.72	0.0095*
Incoming Head Pitch	0.9880356	0.066925	14.76	<.0001*
Leg Height	241.64298	21.38408	11.30	<.0001*

Appendix Figure A1 Regression analysis of Hp for head down.



Summary of Fit

RSquare	0.858509
RSquare Adj	0.851771
Root Mean Square Error	0.134666
Mean of Response	-0.04107
Observations (or Sum Wgts)	45

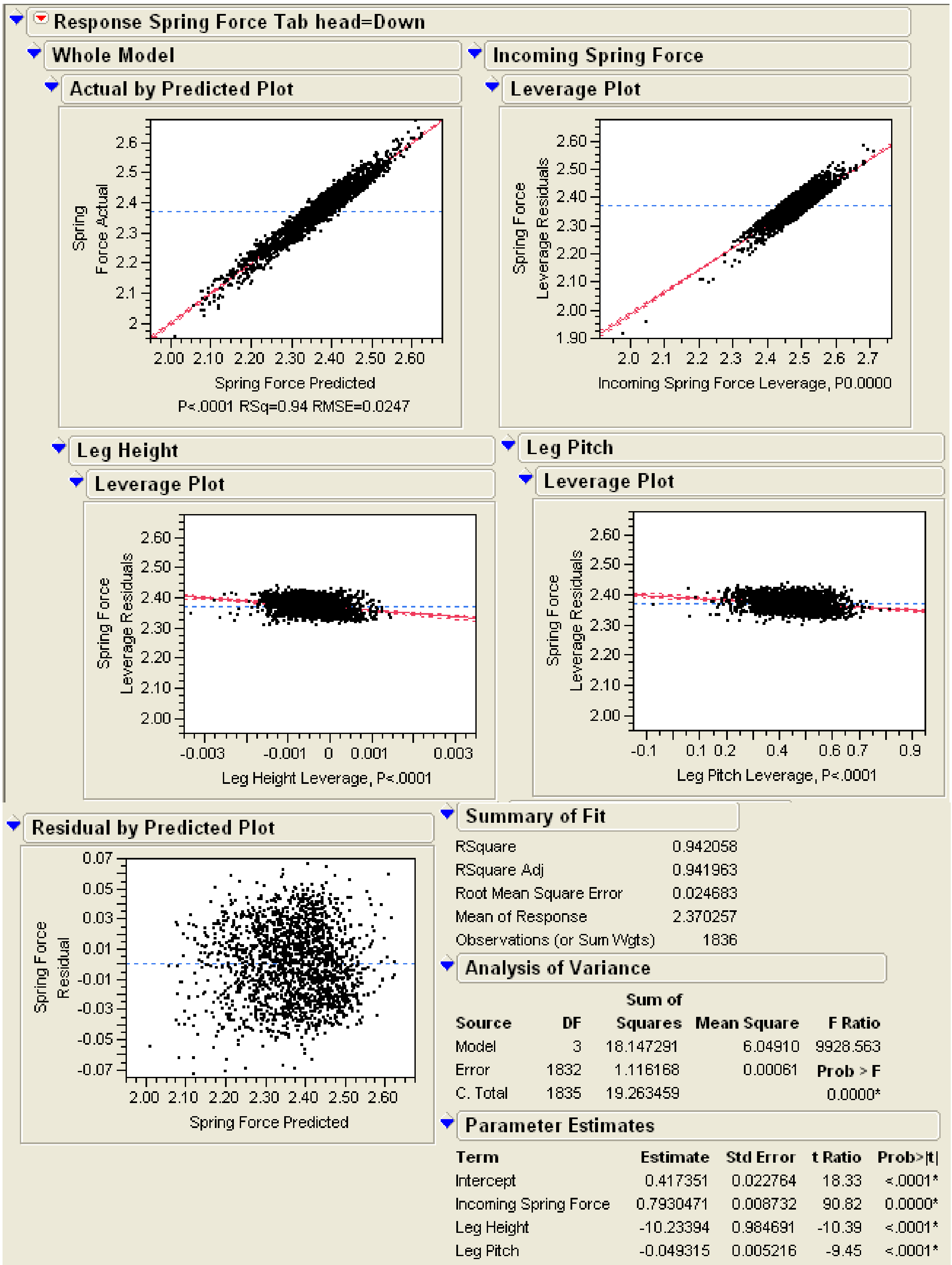
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	4.6214495	2.31072	127.4191
Error	42	0.7616633	0.01813	Prob > F
C. Total	44	5.3831129		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.069098	0.033141	-2.08	0.0432*
Incoming Head Pitch	0.7672568	0.063342	12.11	<.0001*
Leg Height	-237.2893	22.09263	-10.74	<.0001*

Appendix Figure A2 Regression analysis of Hp for head up



Summary of Fit

RSquare	0.942058
RSquare Adj	0.941963
Root Mean Square Error	0.024683
Mean of Response	2.370257
Observations (or Sum Wgts)	1836

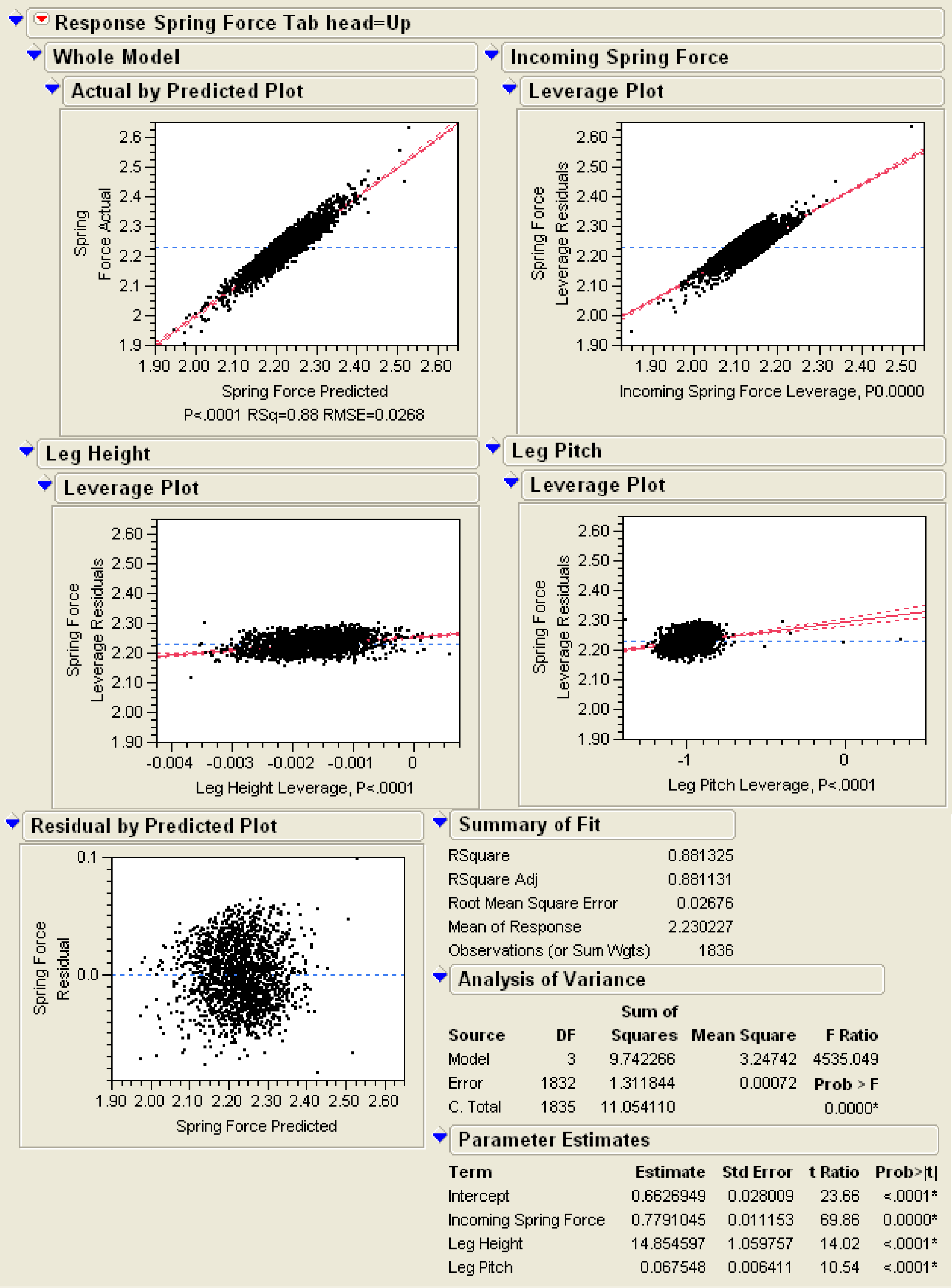
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	18.147291	6.04910	9928.563
Error	1832	1.116168	0.00061	**Prob > F**
C. Total	1835	19.263459		0.0000*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.417351	0.022764	18.33	<.0001*
Incoming Spring Force	0.7930471	0.008732	90.82	0.0000*
Leg Height	-10.23394	0.984691	-10.39	<.0001*
Leg Pitch	-0.049315	0.005216	-9.45	<.0001*

Appendix Figure A3 Regression analysis of Sp for head down.



Summary of Fit

RSquare	0.881325
RSquare Adj	0.881131
Root Mean Square Error	0.02676
Mean of Response	2.230227
Observations (or Sum Wgts)	1836

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	9.742266	3.24742	4535.049
Error	1832	1.311844	0.00072	**Prob > F**
C. Total	1835	11.054110		0.0000*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.6626949	0.028009	23.66	<.0001*
Incoming Spring Force	0.7791045	0.011153	69.86	0.0000*
Leg Height	14.854597	1.059757	14.02	<.0001*
Leg Pitch	0.067548	0.006411	10.54	<.0001*

Appendix Figure A4 Regression analysis of Sp for head up.

Appendix B

Gage Repeatability and Reproducibility (GR&R)

Appendix B1 GR&R of Leg Tip height head 0

Gage R&R Study - ANOVA Method

```
Gage R&R for 1EXBP H0

Gage name:       Head 0
Date of study:   31/07/2007
Reported by:     Niti Kittisatien
Tolerance:       0.0035
Misc:
```

Two-Way ANOVA Table With Interaction

```
Source             DF         SS         MS        F      P
Part_num            8  0.0000054  0.0000007  6112.06  0.000
Operator            1  0.0000000  0.0000000     1.68  0.231
Part_num * Operator  8  0.0000000  0.0000000     0.45  0.882
Repeatability      36  0.0000000  0.0000000
Total              53  0.0000054
```

Two-Way ANOVA Table Without Interaction

```
Source         DF         SS         MS        F      P
Part_num        8  0.0000054  0.0000007  3060.71  0.000
Operator        1  0.0000000  0.0000000     0.84  0.364
Repeatability  44  0.0000000  0.0000000
Total          53  0.0000054
```

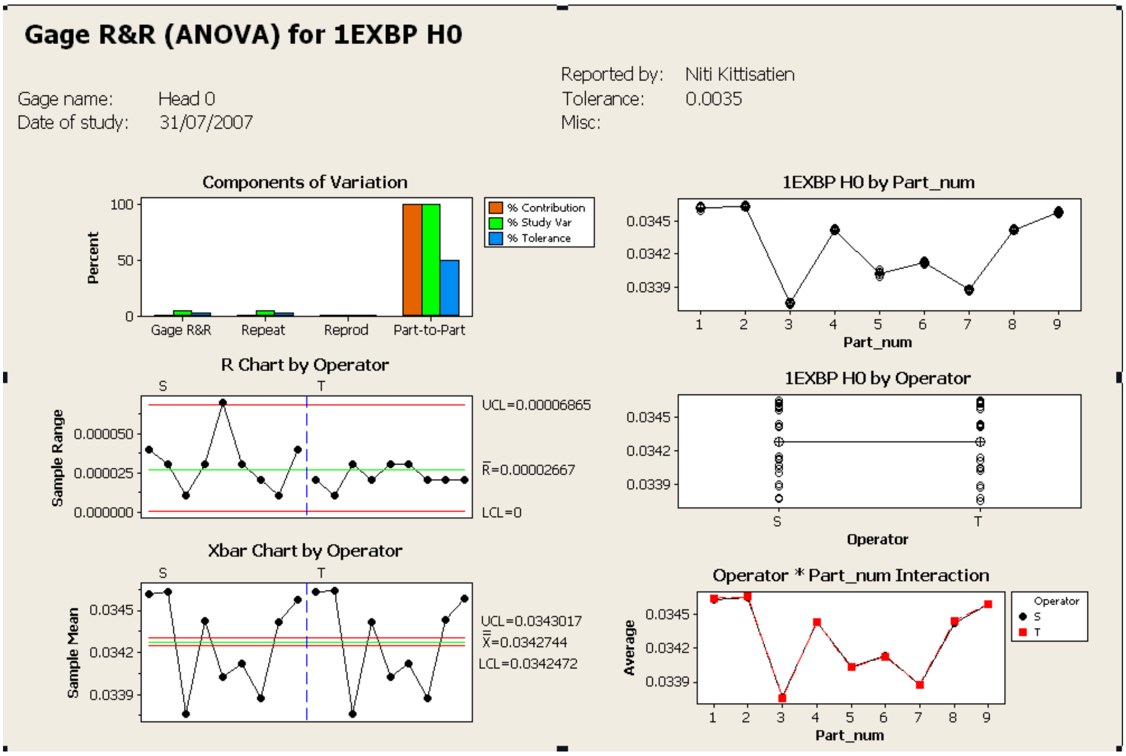
Gage R&R

```
                              %Contribution
Source               VarComp  (of VarComp)
Total Gage R&R     0.0000000          0.20
  Repeatability    0.0000000          0.20
  Reproducibility  0.0000000          0.00
    Operator       0.0000000          0.00
Part-To-Part       0.0000001         99.80
Total Variation    0.0000001        100.00


                                 Study Var  %Study Var  %Tolerance
Source             StdDev (SD)  (5.15 * SD)       (%SV)  (SV/Toler)
Total Gage R&R       0.0000148    0.0000764        4.42        2.18
  Repeatability      0.0000148    0.0000764        4.42        2.18
  Reproducibility    0.0000000    0.0000000        0.00        0.00
    Operator         0.0000000    0.0000000        0.00        0.00
Part-To-Part         0.0003350    0.0017251       99.90       49.29
Total Variation      0.0003353    0.0017268      100.00       49.34


Number of Distinct Categories = 31
```

Gage R&R for 1EXBP H0



Gage R&R (ANOVA) for 1EXBP H0

Gage name: Head 0
Date of study: 31/07/2007

Reported by: Niti Kittisatien
Tolerance: 0.0035
Misc:

Appendix Figure B1 GR&R of Tip height head 0.

Appendix B2 GR&R of Leg Tip height head 1

Gage R&R Study - ANOVA Method

```
Gage R&R for 1EXBP H1

Gage name:       Head 1
Date of study:   31/07/2007
Reported by:     Niti Kittisatien
Tolerance:       0.0035
Misc:
```

Two-Way ANOVA Table With Interaction

```
Source              DF         SS         MS        F      P
Part_num             8  0.0000219  0.0000027  3865.57  0.000
Operator             1  0.0000000  0.0000000     0.67  0.437
Part_num * Operator  8  0.0000000  0.0000000     2.29  0.043
Repeatability       36  0.0000000  0.0000000
Total               53  0.0000219
```

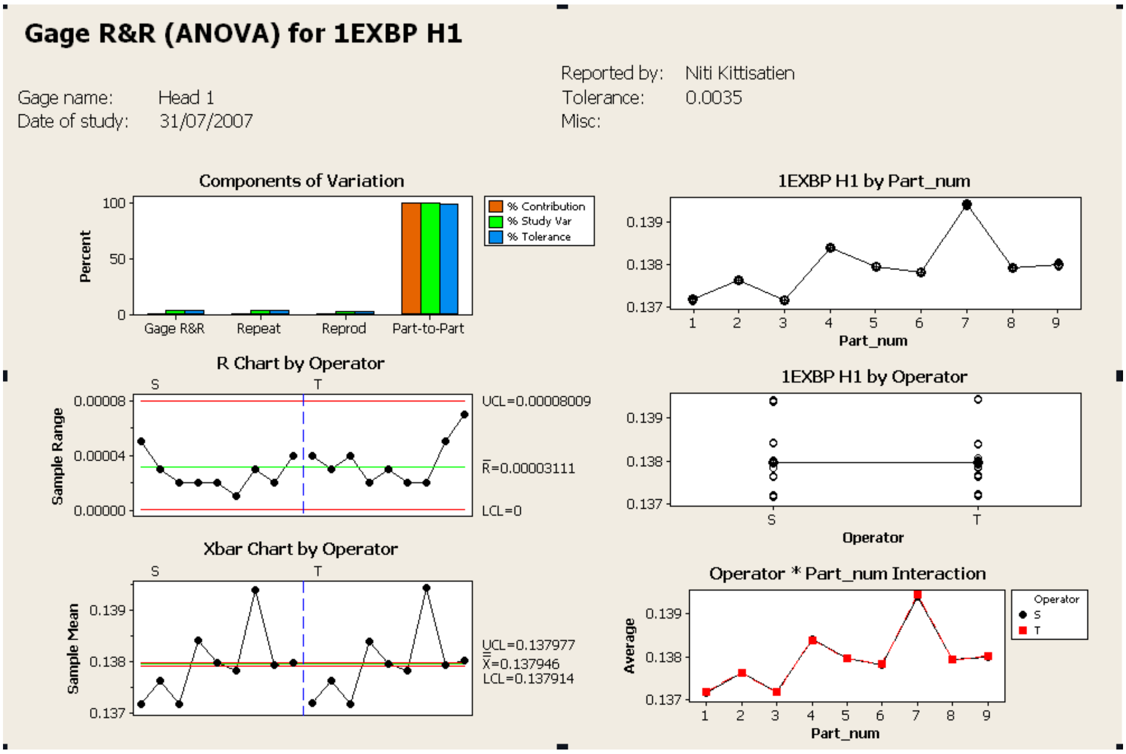
Gage R&R

```
                                  %Contribution
Source                  VarComp   (of VarComp)
Total Gage R&R        0.0000000           0.10
  Repeatability       0.0000000           0.07
  Reproducibility     0.0000000           0.03
    Operator          0.0000000           0.00
    Operator*Part_num 0.0000000           0.03
Part-To-Part          0.0000005          99.90
Total Variation       0.0000005         100.00


                                     Study Var  %Study Var  %Tolerance
Source                StdDev (SD)  (5.15 * SD)       (%SV)  (SV/Toler)
Total Gage R&R          0.0000210    0.0001083        3.11        3.09
  Repeatability         0.0000176    0.0000906        2.60        2.59
  Reproducibility       0.0000115    0.0000593        1.71        1.70
    Operator            0.0000000    0.0000000        0.00        0.00
    Operator*Part_num   0.0000115    0.0000593        1.71        1.70
Part-To-Part            0.0006750    0.0034763       99.95       99.32
Total Variation         0.0006753    0.0034780      100.00       99.37


Number of Distinct Categories = 45
```

Gage R&R for 1EXBP H1



Gage R&R (ANOVA) for 1EXBP H1

Reported by: Niti Kittisatien
Tolerance: 0.0035
Misc:

Gage name: Head 1
Date of study: 31/07/2007

Appendix Figure B2 GR&R of Tip height head 1.

Appendix B3 GR&R of Leg Tip height head 2

Gage R&R Study - ANOVA Method

```
Gage R&R for 1EXBP H2

Gage name:       Head 2
Date of study:   31/07/2007
Reported by:     Niti Kittisatien
Tolerance:       0.0035
Misc:
```

Two-Way ANOVA Table With Interaction

```
Source              DF         SS         MS        F      P
Part_num             8  0.0000069  0.0000009  1806.21  0.000
Operator             1  0.0000000  0.0000000     1.25  0.296
Part_num * Operator  8  0.0000000  0.0000000     1.43  0.218
Repeatability       36  0.0000000  0.0000000
Total               53  0.0000069
```

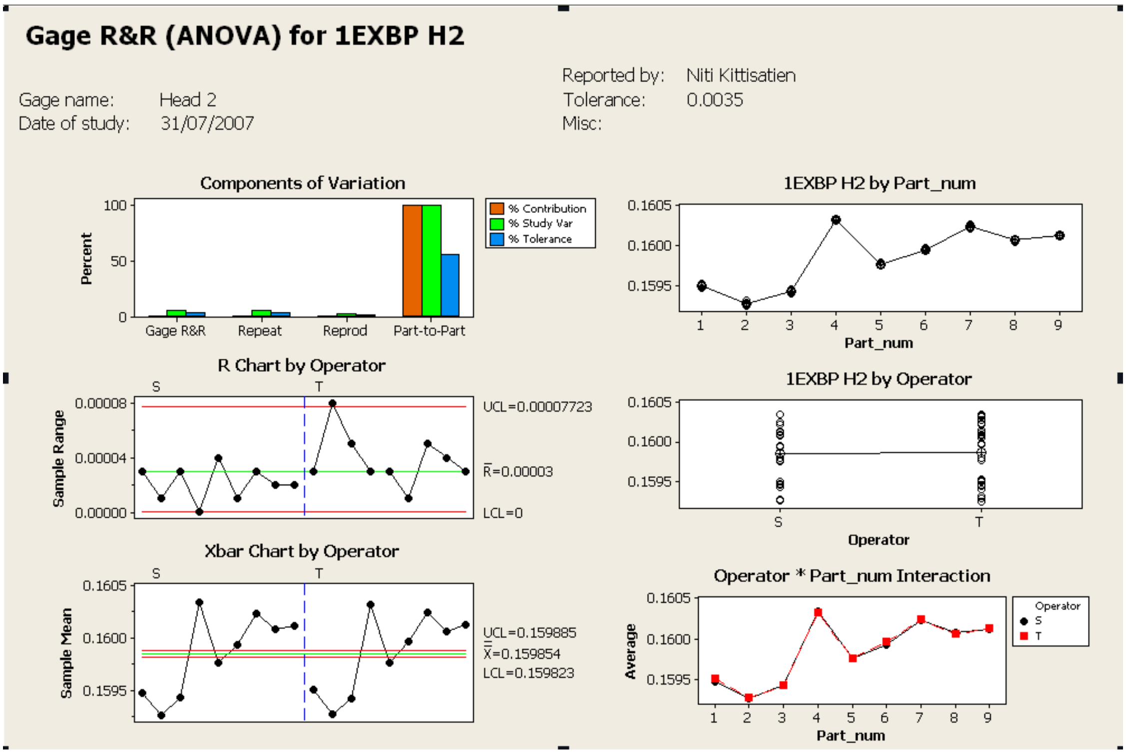
Gage R&R

```
                                 %Contribution
Source                 VarComp   (of VarComp)
Total Gage R&R       0.0000000           0.27
  Repeatability      0.0000000           0.23
  Reproducibility    0.0000000           0.04
    Operator         0.0000000           0.00
    Operator*Part_num  0.0000000         0.03
Part-To-Part         0.0000001          99.73
Total Variation      0.0000001         100.00


                                  Study Var  %Study Var  %Tolerance
Source               StdDev (SD)  (5.15 * SD)     (%SV)  (SV/Toler)
Total Gage R&R         0.0000197  0.0001014        5.18        2.90
  Repeatability        0.0000183  0.0000943        4.82        2.69
  Reproducibility      0.0000072  0.0000373        1.91        1.07
    Operator           0.0000021  0.0000109        0.56        0.31
    Operator*Part_num  0.0000069  0.0000357        1.82        1.02
Part-To-Part           0.0003797  0.0019554       99.87       55.87
Total Variation        0.0003802  0.0019580      100.00       55.94


Number of Distinct Categories = 27
```

Gage R&R for 1EXBP H2



Gage R&R (ANOVA) for 1EXBP H2

Gage name: Head 2
Date of study: 31/07/2007

Reported by: Niti Kittisatien
Tolerance: 0.0035
Misc:

Appendix Figure B3 GR&R of Tip height head 2.

Appendix B4 GR&R of Leg Tip height head 3

Gage R&R Study - ANOVA Method

```
Gage R&R for 1EXBP H3

Gage name:       Head 3
Date of study:   31/07/2007
Reported by:     Niti Kittisatien
Tolerance:       0.0035
Misc:
```

Two-Way ANOVA Table With Interaction

```
Source              DF         SS         MS        F      P
Part_num             8  0.0000064  0.0000008  1672.65  0.000
Operator             1  0.0000000  0.0000000     4.25  0.073
Part_num * Operator  8  0.0000000  0.0000000     1.18  0.340
Repeatability       36  0.0000000  0.0000000
Total               53  0.0000064
```

Two-Way ANOVA Table Without Interaction

```
Source         DF         SS         MS        F      P
Part_num        8  0.0000064  0.0000008  1906.82  0.000
Operator        1  0.0000000  0.0000000     4.84  0.033
Repeatability  44  0.0000000  0.0000000
Total          53  0.0000064
```

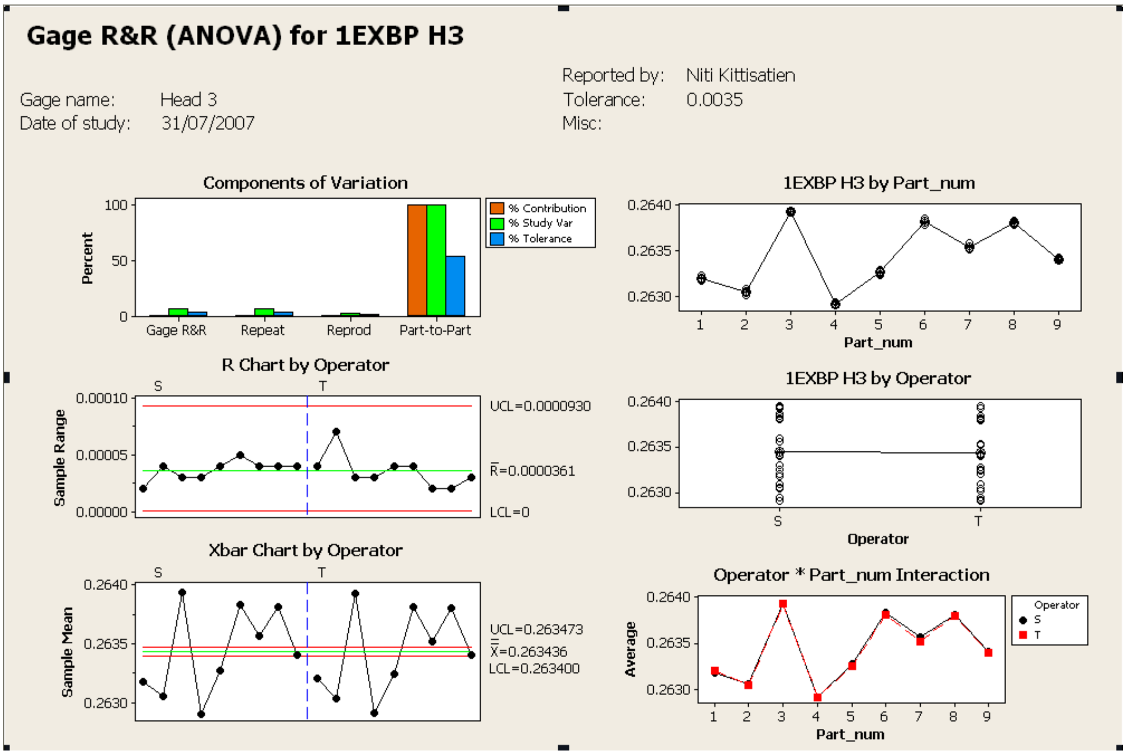
Gage R&R

```
                              %Contribution
Source               VarComp   (of VarComp)
Total Gage R&R     0.0000000           0.36
  Repeatability    0.0000000           0.31
  Reproducibility  0.0000000           0.04
    Operator       0.0000000           0.04
Part-To-Part       0.0000001          99.64
Total Variation    0.0000001         100.00


                                 Study Var  %Study Var  %Tolerance
Source             StdDev (SD)  (5.15 * SD)       (%SV)  (SV/Toler)
Total Gage R&R       0.0000218    0.0001124        5.99        3.21
  Repeatability      0.0000204    0.0001051        5.60        3.00
  Reproducibility    0.0000077    0.0000396        2.11        1.13
    Operator         0.0000077    0.0000396        2.11        1.13
Part-To-Part         0.0003638    0.0018736       99.82       53.53
Total Variation      0.0003645    0.0018769      100.00       53.63


Number of Distinct Categories = 23
```

Gage R&R for 1EXBP H3



Gage R&R (ANOVA) for 1EXBP H3

Gage name: Head 3
Date of study: 31/07/2007

Reported by: Niti Kittisatien
Tolerance: 0.0035
Misc:

Appendix Figure B4 GR&R of Tip height head 3.

Appendix C

Machine Correlation Transfer Function

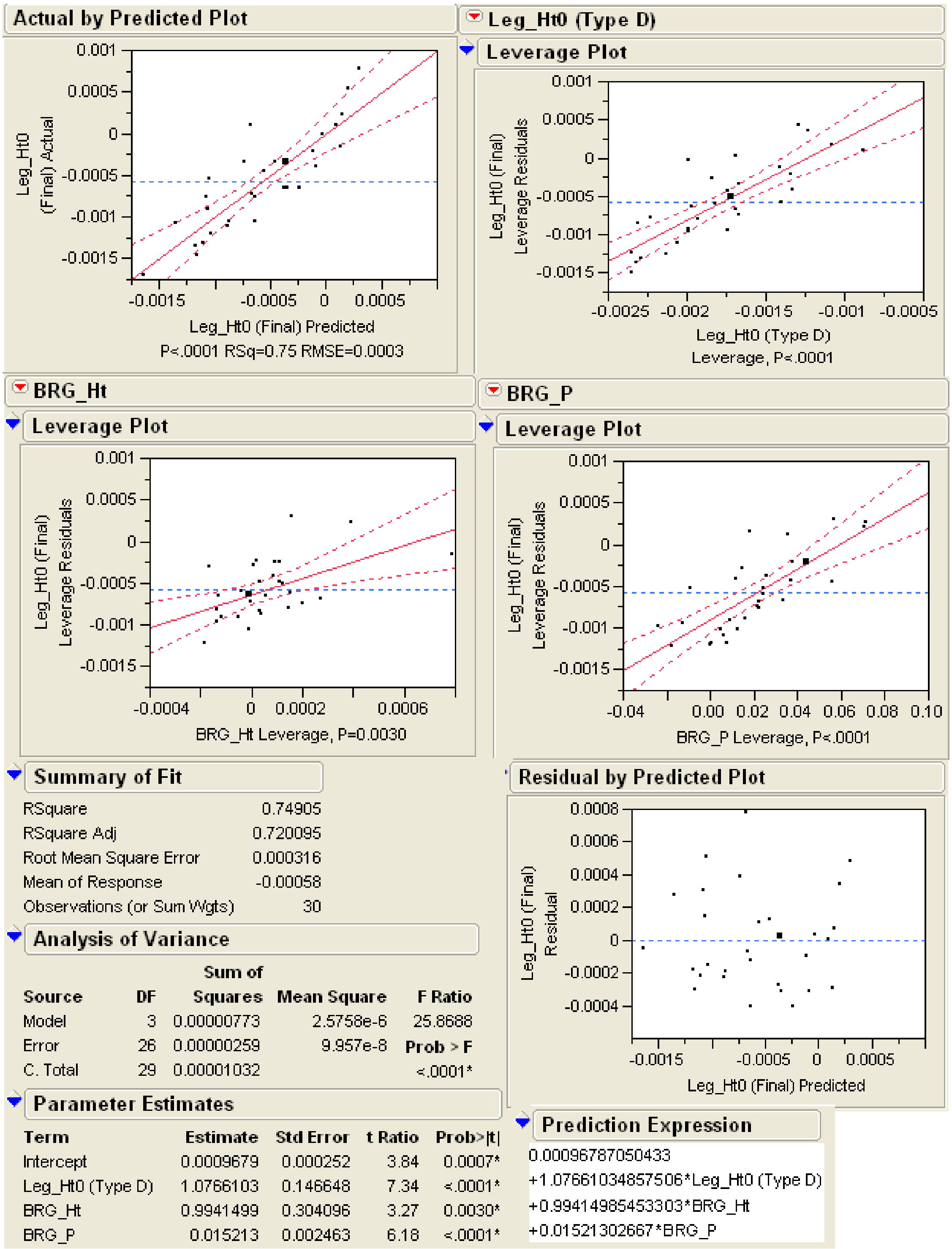
Appendix C1 Summary machine correlation transfer function

Head position	Mean	Number
H0	-0.00178	120
H1	0.00105	120
H2	-0.00167	120
H3	0.00143	120

Appendix Table1 Mean of head position.

<table>
<tr><th colspan="7">Means and Std Deviations of Error By Measuring All Position Head position</th></tr>
<tr><td>Measuring location</td><td>Number</td><td>Mean</td><td>Std Dev</td><td>Std Err Mean</td><td>Lower 95%</td><td>Upper 95%</td></tr>
<tr><td>0.94</td><td>30</td><td>-0.00126</td><td>0.000642</td><td>0.00012</td><td>-0.0015</td><td>-0.001</td></tr>
<tr><td>0.955</td><td>30</td><td>-0.00186</td><td>0.000613</td><td>0.00011</td><td>-0.0021</td><td>-0.0016</td></tr>
<tr><td>0.965</td><td>30</td><td>-0.00198</td><td>0.000608</td><td>0.00011</td><td>-0.0022</td><td>-0.0018</td></tr>
<tr><td>0.98</td><td>30</td><td>-0.00203</td><td>0.000582</td><td>0.00011</td><td>-0.0022</td><td>-0.0018</td></tr>
<tr><th colspan="7">Means and Std Deviations of Error By Measuring Position Head position=H0</th></tr>
<tr><td>Measuring location</td><td>Number</td><td>Mean</td><td>Std Dev</td><td>Std Err Mean</td><td>Lower 95%</td><td>Upper 95%</td></tr>
<tr><td>0.94</td><td>30</td><td>-0.00126</td><td>0.000642</td><td>0.00012</td><td>-0.0015</td><td>-0.001</td></tr>
<tr><td>0.955</td><td>30</td><td>-0.00186</td><td>0.000613</td><td>0.00011</td><td>-0.0021</td><td>-0.0016</td></tr>
<tr><td>0.965</td><td>30</td><td>-0.00198</td><td>0.000608</td><td>0.00011</td><td>-0.0022</td><td>-0.0018</td></tr>
<tr><td>0.98</td><td>30</td><td>-0.00203</td><td>0.000582</td><td>0.00011</td><td>-0.0022</td><td>-0.0018</td></tr>
<tr><th colspan="7">Means and Std Deviations of Error By Measuring Position Head position=H1</th></tr>
<tr><td>Measuring location</td><td>Number</td><td>Mean</td><td>Std Dev</td><td>Std Err Mean</td><td>Lower 95%</td><td>Upper 95%</td></tr>
<tr><td>0.94</td><td>30</td><td>0.000783</td><td>0.000563</td><td>0.0001</td><td>0.00057</td><td>0.00099</td></tr>
<tr><td>0.955</td><td>30</td><td>0.001059</td><td>0.000566</td><td>0.0001</td><td>0.00085</td><td>0.00127</td></tr>
<tr><td>0.965</td><td>30</td><td>0.000975</td><td>0.000635</td><td>0.00012</td><td>0.00074</td><td>0.00121</td></tr>
<tr><td>0.98</td><td>30</td><td>0.001371</td><td>0.000617</td><td>0.00011</td><td>0.00114</td><td>0.0016</td></tr>
<tr><th colspan="7">Means and Std Deviations of Error By Measuring Position Head position=H2</th></tr>
<tr><td>Measuring location</td><td>Number</td><td>Mean</td><td>Std Dev</td><td>Std Err Mean</td><td>Lower 95%</td><td>Upper 95%</td></tr>
<tr><td>0.94</td><td>30</td><td>-0.00121</td><td>0.00055</td><td>0.0001</td><td>-0.0014</td><td>-0.001</td></tr>
<tr><td>0.955</td><td>30</td><td>-0.00174</td><td>0.000564</td><td>0.0001</td><td>-0.002</td><td>-0.0015</td></tr>
<tr><td>0.965</td><td>30</td><td>-0.00184</td><td>0.000562</td><td>0.0001</td><td>-0.002</td><td>-0.0016</td></tr>
<tr><td>0.98</td><td>30</td><td>-0.00191</td><td>0.000548</td><td>0.0001</td><td>-0.0021</td><td>-0.0017</td></tr>
<tr><th colspan="7">Means and Std Deviations of Error By Measuring Position Head position=H3</th></tr>
<tr><td>Measuring location</td><td>Number</td><td>Mean</td><td>Std Dev</td><td>Std Err Mean</td><td>Lower 95%</td><td>Upper 95%</td></tr>
<tr><td>0.94</td><td>30</td><td>0.001101</td><td>0.00055</td><td>0.0001</td><td>0.0009</td><td>0.00131</td></tr>
<tr><td>0.955</td><td>30</td><td>0.001415</td><td>0.000554</td><td>0.0001</td><td>0.00121</td><td>0.00162</td></tr>
<tr><td>0.965</td><td>30</td><td>0.001381</td><td>0.000591</td><td>0.00011</td><td>0.00116</td><td>0.0016</td></tr>
<tr><td>0.98</td><td>30</td><td>0.001811</td><td>0.000573</td><td>0.0001</td><td>0.0016</td><td>0.00202</td></tr>
</table>

Appendix Table2 The result of experiment.



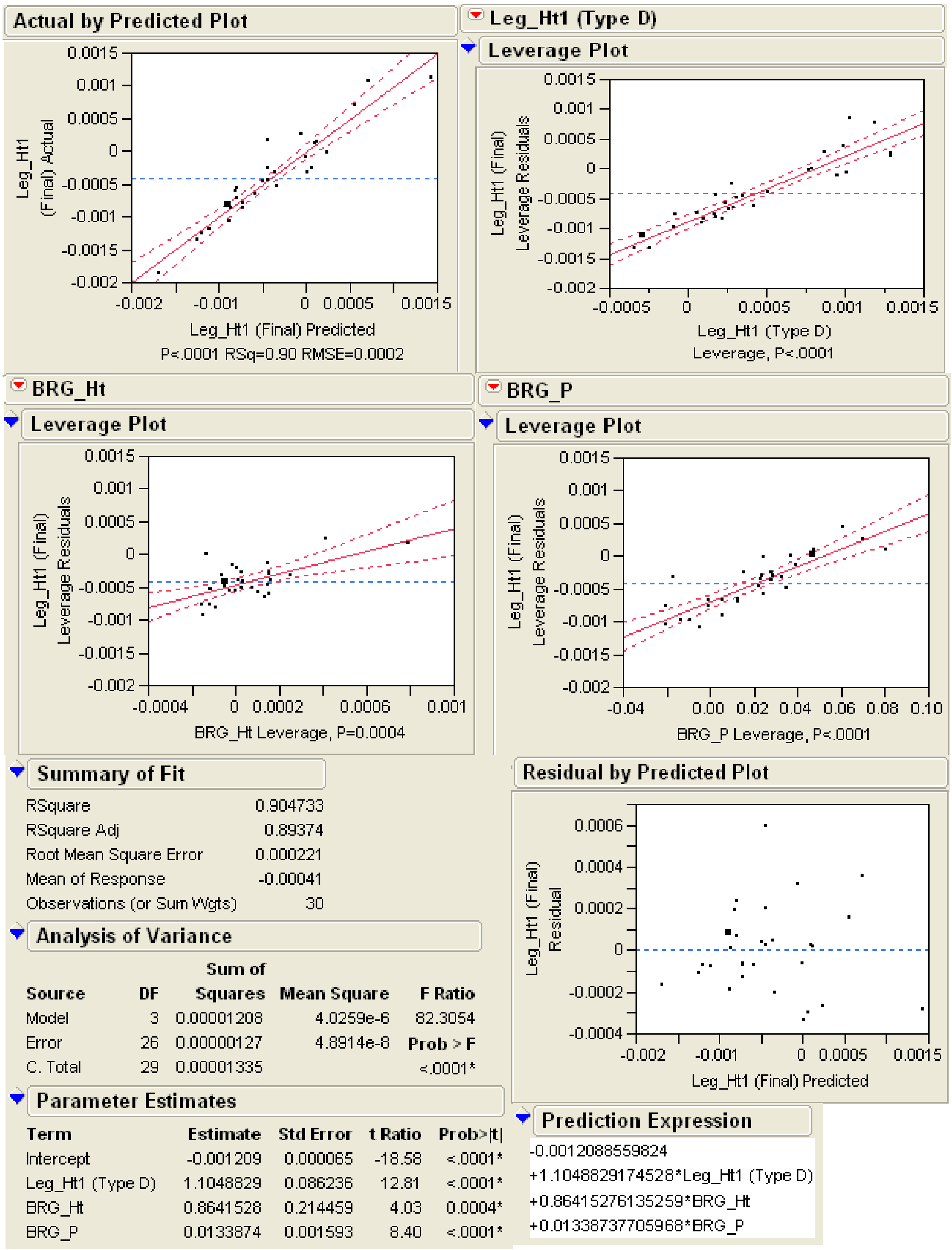
```
RSquare                          0.74905
RSquare Adj                      0.720095
Root Mean Square Error           0.000316
Mean of Response                -0.00058
Observations (or Sum Wgts)            30
```

```
                       Sum of
Source      DF        Squares   Mean Square    F Ratio
Model        3    0.00000773    2.5758e-6     25.8688
Error       26    0.00000259    9.957e-8      Prob > F
C. Total    29    0.00001032                  <.0001*
```

```
Term              Estimate    Std Error   t Ratio   Prob>|t|
Intercept         0.0009679   0.000252     3.84     0.0007*
Leg_Ht0 (Type D)  1.0766103   0.146648     7.34     <.0001*
BRG_Ht            0.9941499   0.304096     3.27     0.0030*
BRG_P             0.015213    0.002463     6.18     <.0001*
```

```
0.00096787050433
+1.07661034857506*Leg_Ht0 (Type D)
+0.99414985453303*BRG_Ht
+0.01521302667*BRG_P
```

Appendix Figure C1 Linear regression of Leg_Ht 0.



Summary of Fit

RSquare	0.904733
RSquare Adj	0.89374
Root Mean Square Error	0.000221
Mean of Response	-0.00041
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.00001208	4.0259e-6	82.3054
Error	26	0.00000127	4.8914e-8	**Prob > F**
C. Total	29	0.00001335		<.0001*

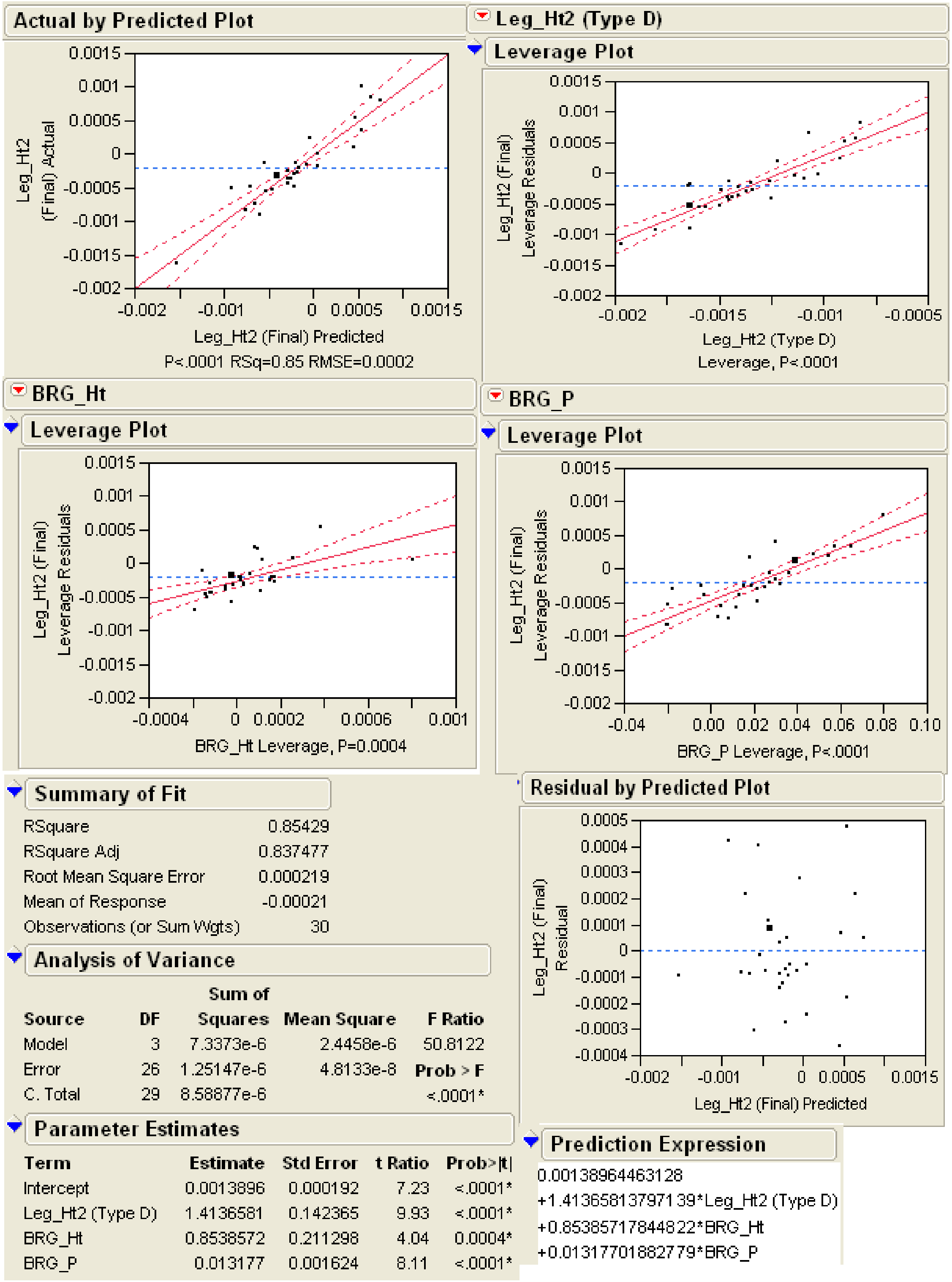
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.001209	0.000065	-18.58	<.0001*
Leg_Ht1 (Type D)	1.1048829	0.086236	12.81	<.0001*
BRG_Ht	0.8641528	0.214459	4.03	0.0004*
BRG_P	0.0133874	0.001593	8.40	<.0001*

Prediction Expression

-0.0012088559824
+1.1048829174528*Leg_Ht1 (Type D)
+0.86415276135259*BRG_Ht
+0.01338737705968*BRG_P

Appendix Figure C2 Linear regression of Leg_Ht 1



Summary of Fit

RSquare	0.85429
RSquare Adj	0.837477
Root Mean Square Error	0.000219
Mean of Response	-0.00021
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	7.3373e-6	2.4458e-6	50.8122
Error	26	1.25147e-6	4.8133e-8	**Prob > F**
C. Total	29	8.58877e-6		<.0001*

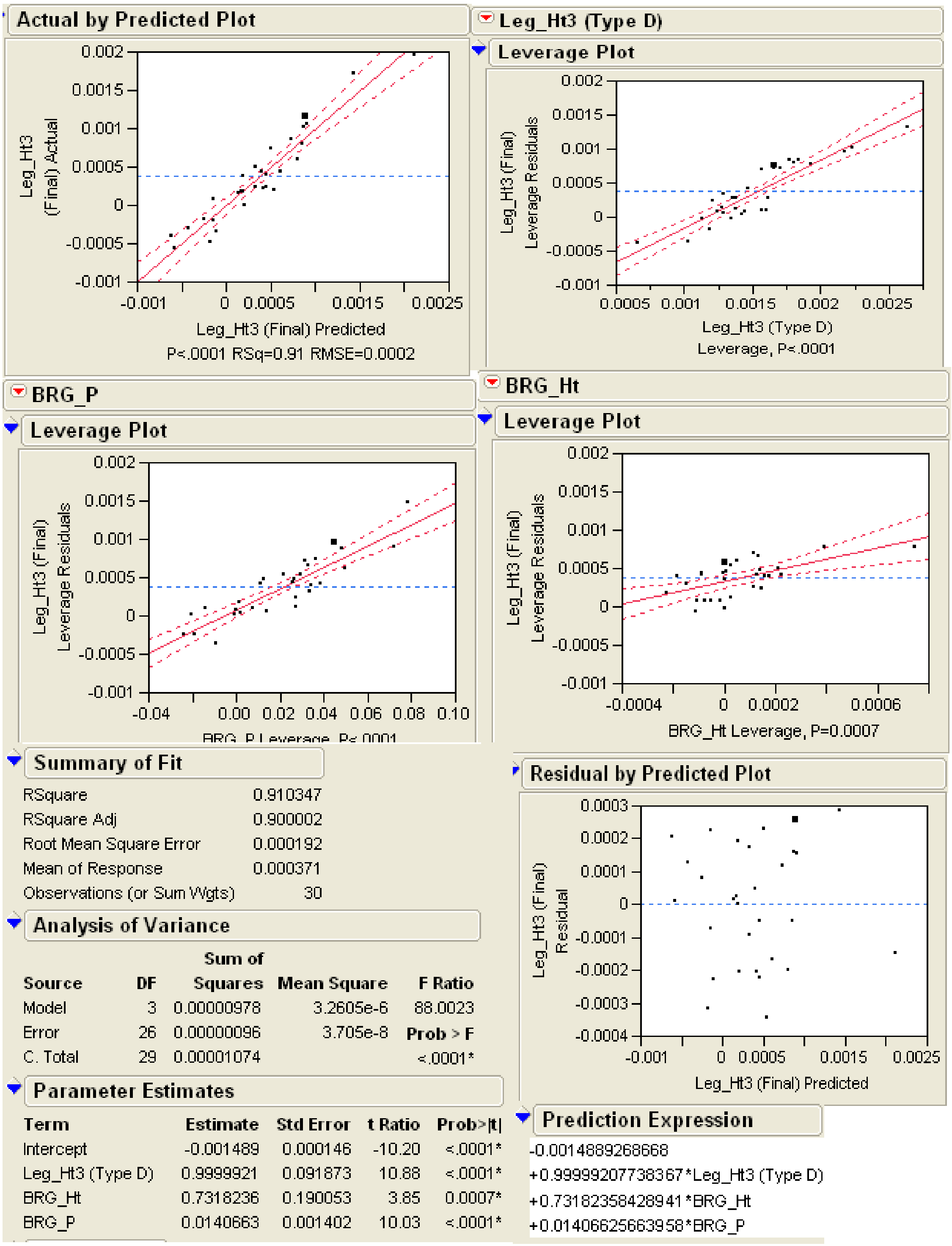
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.0013896	0.000192	7.23	<.0001*
Leg_Ht2 (Type D)	1.4136581	0.142365	9.93	<.0001*
BRG_Ht	0.8538572	0.211298	4.04	0.0004*
BRG_P	0.013177	0.001624	8.11	<.0001*

Prediction Expression

0.00138964463128
+1.41365813797139*Leg_Ht2 (Type D)
+0.85385717844822*BRG_Ht
+0.01317701882779*BRG_P

Appendix Figure C3 Linear regression of Leg_Ht 2.



Summary of Fit

RSquare	0.910347
RSquare Adj	0.900002
Root Mean Square Error	0.000192
Mean of Response	0.000371
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.00000978	3.2605e-6	88.0023
Error	26	0.00000096	3.705e-8	Prob > F
C. Total	29	0.00001074		<.0001*

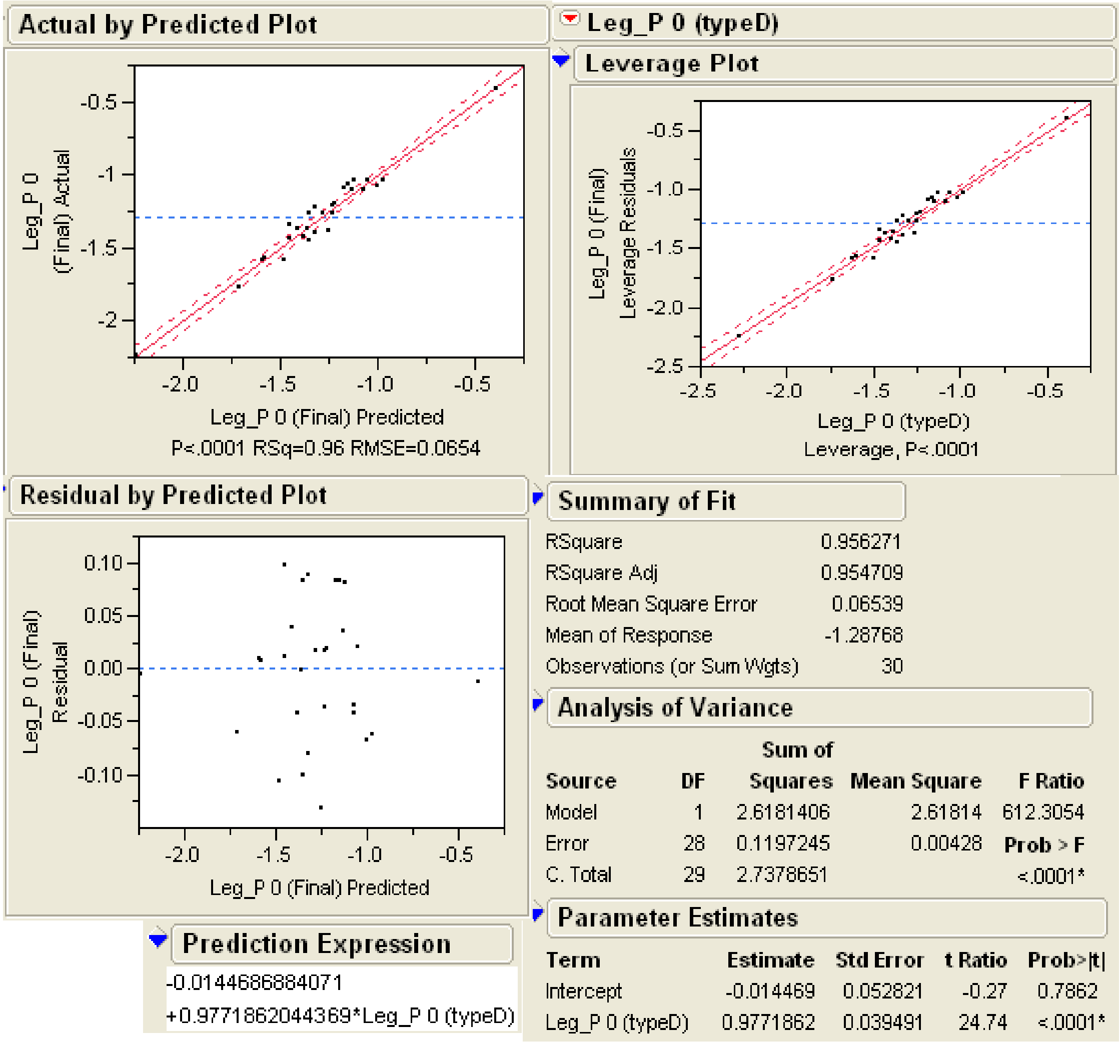
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.001489	0.000146	-10.20	<.0001*
Leg_Ht3 (Type D)	0.9999921	0.091873	10.88	<.0001*
BRG_Ht	0.7318236	0.190053	3.85	0.0007*
BRG_P	0.0140663	0.001402	10.03	<.0001*

Prediction Expression

-0.0014889268668
+0.99999207738367*Leg_Ht3 (Type D)
+0.73182358428941*BRG_Ht
+0.01406625663958*BRG_P

Appendix Figure C4 Linear regression of Leg_Ht 3.



Prediction Expression

-0.0144686884071
+0.9771862044369*Leg_P 0 (typeD)

Summary of Fit

RSquare	0.956271
RSquare Adj	0.954709
Root Mean Square Error	0.06539
Mean of Response	-1.28768
Observations (or Sum Wgts)	30

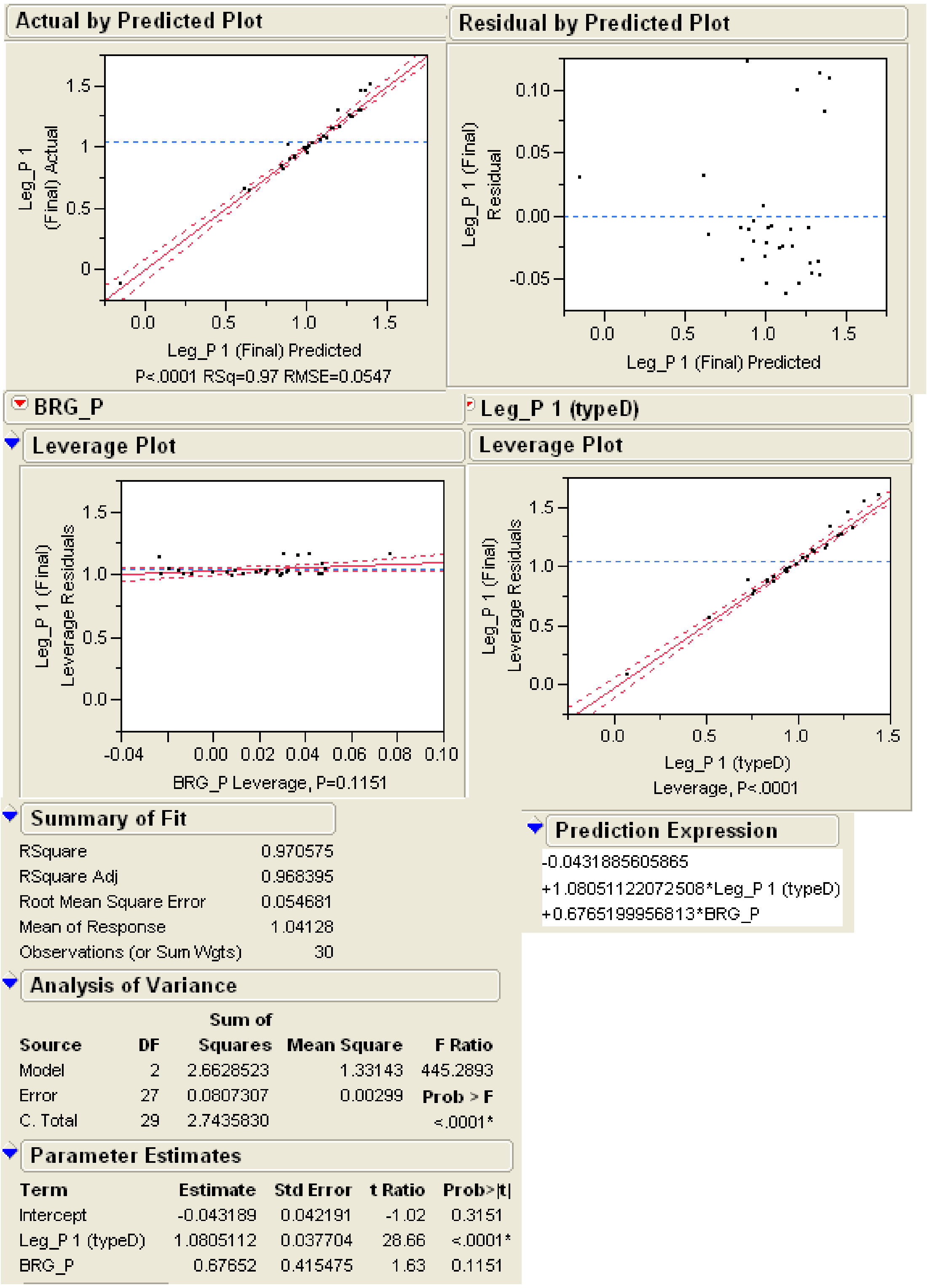
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	2.6181406	2.61814	612.3054
Error	28	0.1197245	0.00428	**Prob > F**
C. Total	29	2.7378651		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.014469	0.052821	-0.27	0.7862
Leg_P 0 (typeD)	0.9771862	0.039491	24.74	<.0001*

Appendix Figure C5 Linear regression of Leg_P 0.



Summary of Fit

RSquare	0.970575
RSquare Adj	0.968395
Root Mean Square Error	0.054681
Mean of Response	1.04128
Observations (or Sum Wgts)	30

Prediction Expression

-0.0431885605865
+1.08051122072508*Leg_P 1 (typeD)
+0.6765199956813*BRG_P

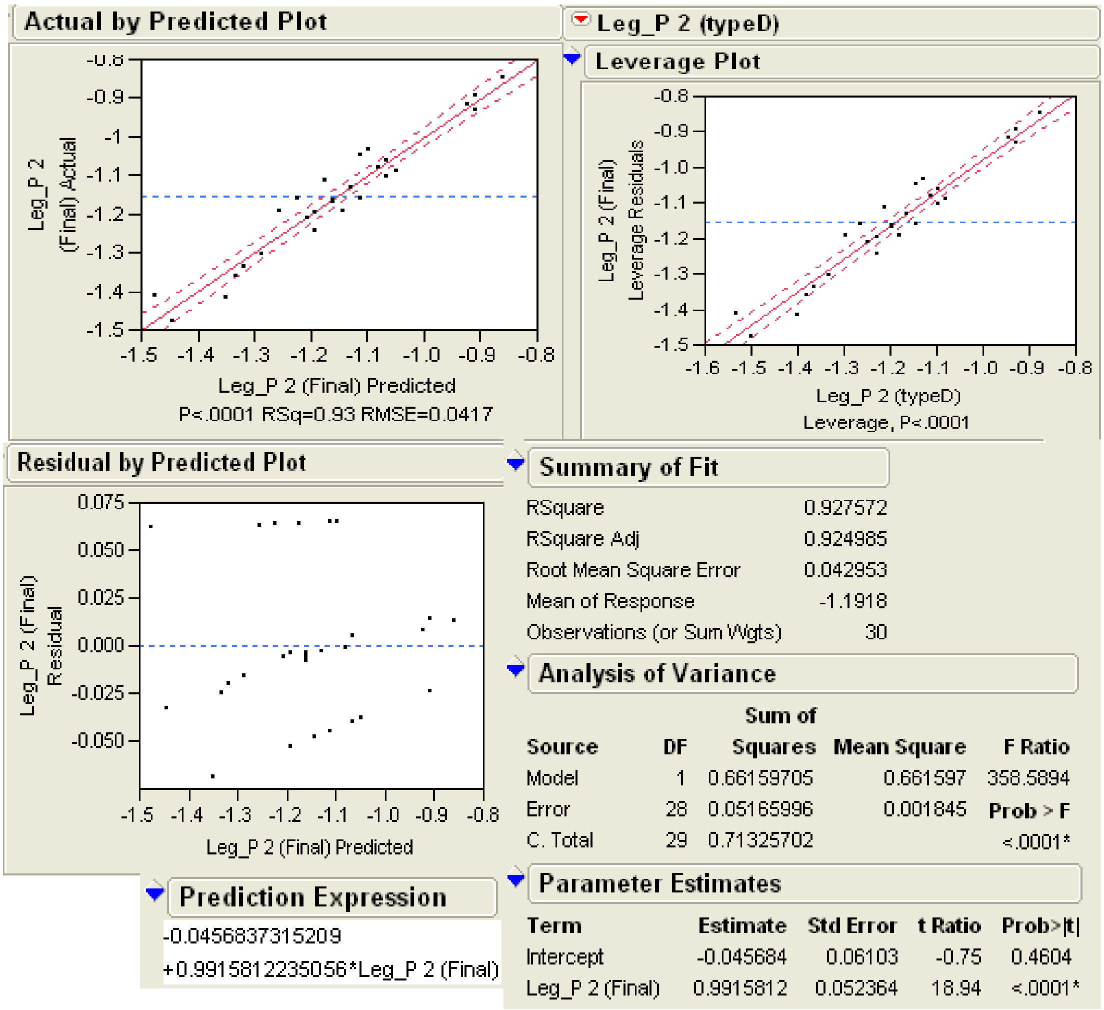
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	2.6628523	1.33143	445.2893
Error	27	0.0807307	0.00299	**Prob > F**
C. Total	29	2.7435830		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.043189	0.042191	-1.02	0.3151
Leg_P 1 (typeD)	1.0805112	0.037704	28.66	<.0001*
BRG_P	0.67652	0.415475	1.63	0.1151

Appendix Figure C6 Linear regression of Leg_P 1.



Summary of Fit

RSquare	0.927572
RSquare Adj	0.924985
Root Mean Square Error	0.042953
Mean of Response	-1.1918
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.66159705	0.661597	358.5894
Error	28	0.05165996	0.001845	**Prob > F**
C. Total	29	0.71325702		<.0001*

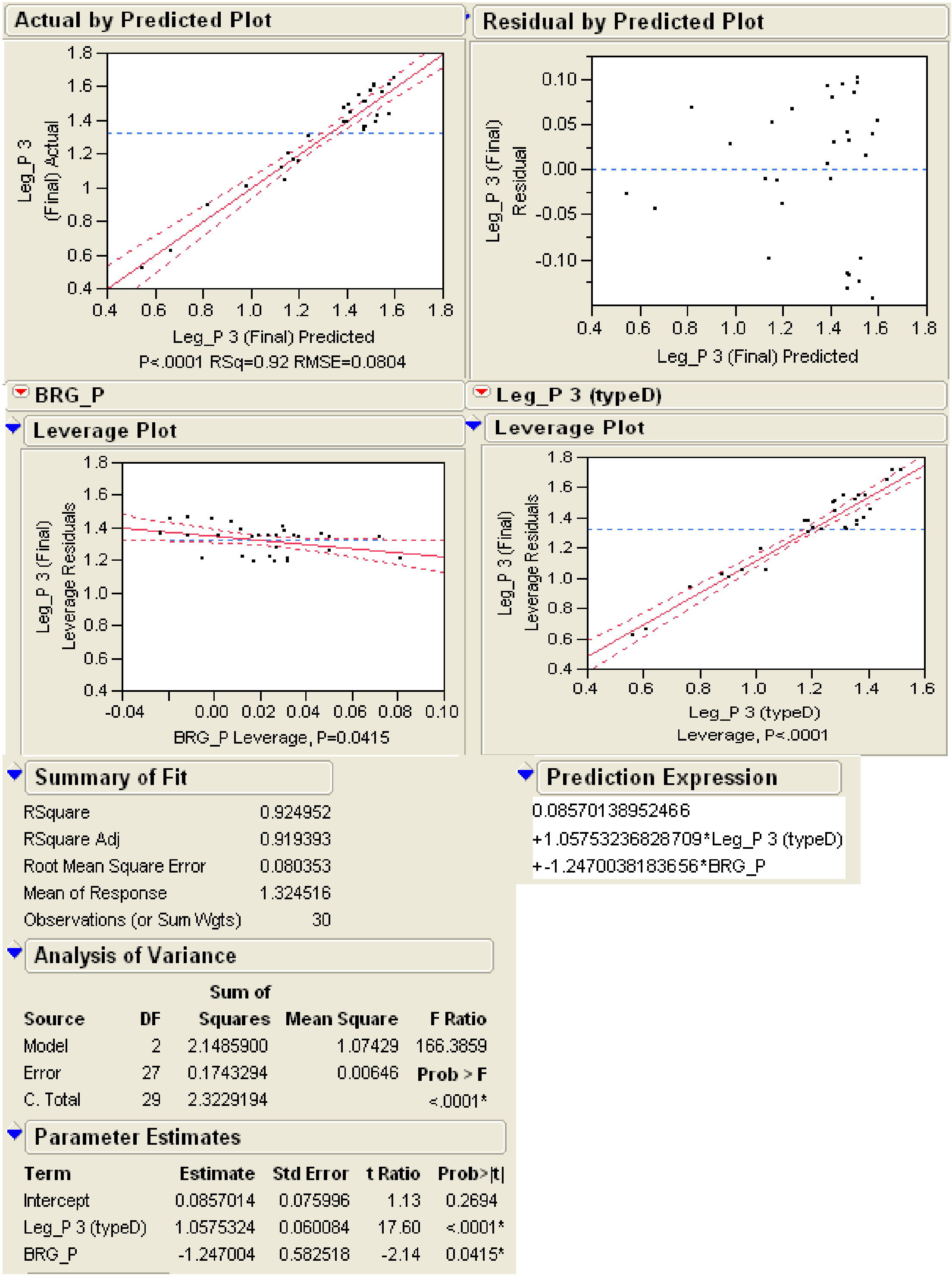
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.045684	0.06103	-0.75	0.4604
Leg_P 2 (Final)	0.9915812	0.052364	18.94	<.0001*

Prediction Expression

-0.0456837315209
+0.9915812235056*Leg_P 2 (Final)

Appendix Figure C7 Linear regression of Leg_P 2.



Summary of Fit

RSquare	0.924952
RSquare Adj	0.919393
Root Mean Square Error	0.080353
Mean of Response	1.324516
Observations (or Sum Wgts)	30

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	2.1485900	1.07429	166.3859
Error	27	0.1743294	0.00646	**Prob > F**
C. Total	29	2.3229194		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.0857014	0.075996	1.13	0.2694
Leg_P 3 (typeD)	1.0575324	0.060084	17.60	<.0001*
BRG_P	-1.247004	0.582518	-2.14	0.0415*

Prediction Expression

0.08570138952466
+1.05753236828709*Leg_P 3 (typeD)
+-1.2470038183656*BRG_P

Appendix Figure C8 regression of Leg_P 3.