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The Dosimetry Award Program at Rocky Flats

by

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ABSTRACT

A primary goal of the Department of Energy and its contractor organizations is to limit the amount of radiation any one employee can obtain. Recently, the administration at Rocky Flats designed a new limit stating that an employee could attain no more than 2 REM during any one year. As a result, DOE officials and Rocky Flats administrators organized an incentive plan in which Rocky Flats would receive payment for those REM reductions which were the result of increased safety measures. At first it was thought that a simple vertical scale, much like that on a thermometer, would sufficiently model this program. This model, however, is very limiting in that it does not consider the production level of the plant at given times. For example, for clean up purposes last winter, production in one of the buildings at R.F. was halted. Correspondingly, the attained REM count for all employees at R.F. was significantly lower during this period. Should DOE be forced to pay for this type of reduction as a vertical scale model would state? Obviously not, as the apparent REM reduction was not the result of increased safety measures but from a decrease in production. With this in mind, a proposal has been put forward to use regression to predict exposures for a given time period as a function of the level of production during the period. This thesis will explore the use of regression toward the Dosimetry Award Program at three distinct levels, the micro, the macro, and the plant. A major result of this thesis will be the recommendation of one of these levels.

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Introduction

Limiting radiation exposures to the lowest possible levels has long been an important part of the Heath Physics and radiation protection programs of the United States Department of Energy (DOE), its predecessor agencies and contractor organizations. The philosophy backing this concept is incorporated throughout DOE facilities by the ALARA program, an acronym which stands for limiting radiation dose levels to those that are: As Low As Reasonably Achievable.

Central to the ALARA philosophy is the belief that, "limiting personnel and environment radiation exposures to the lowest levels corresponds with sound economic and social considerations."[1] This idea presupposes that no radiation exposure should occur without a positive net benefit whether it be of a technological, economic or social nature. In addition, assumed in this philosophy is that any radiation, however small, carries with it some sort of risk or a certain probability of risk which should be countered with benefits of equal or greater measure. This, unmistakably, is the essence of the ALARA philosophy and implies, "that one should not stop looking for ways to incur less dose for a given output of work, as long as the cost does not exceed the possible equivalent cost of potential dose saving."[2]

Structurally, ALARA is based on the linear nonthreshold hypothesis, which is the assumption that damage from radiation is directly proportional to the dose incurred. Further, no threshold or dose exists below which there is no detriment. As stated in the Health Physics Manual for Reducing Radiation Exposure Levels to those that are As Low As Reasonably Achievable, " [at present] ... there is considerable controversy about the uncertainty of detriment, if any, from low levels of radiation dose and about which the dose-response curve is correct. The linear nonthreshold hypothesis appears to best satisfy the need for a practical yet conservative approach to this controversy."[3]

Although the ALARA program is relatively new, its roots date back to the beginning of the Atomic Age. As early as 1946, the ALARA philosophy was introduced into the radiation safety manual for the laboratory that would later become known as Oak Ridge National Laboratory. During the 1950's, the Nuclear Age became an increasing and alarming reality in the United States and other first world nations. Consequently, the necessity for radiation safety for individuals as well as for the environment was stronger than ever. By 1960, the recently created Atomic Energy Commission (AEC) formally adopted the ALARA philosophy by stating in its orders "...human exposure to ionizing radiation shall be kept as low as practicable."[4] In 1975, requirements for keeping radiation as low as practicable were introduced in the manual of the Energy Research and Development Administration (ERDA). Finally, in 1981, these requirements were included into the most recent DOE order to its contractor organizations. These requirements represent the formulation of the ALARA philosophy by the Department of Energy and its many contractors.

As stated above, the most recent DOE order (5480.11) titled, "Radiation Protection for Occupational Workers," was initiated in 1981 and updated in 1988. The overall purpose of this order is to establish radiation protection standards and program requirements for the Department of Energy and DOE contractor operations with respect to the protection of the individual worker from ionizing radiation.

The Policies listed in this order include:

a.) It is the policy of DOE to implement radiation protection standards that are consistent with the Presidential approved guidance to Federal Agencies promulgated by the Environmental Protection Agency (EPA) and based on the recommendations by authoritative organizations, e.g., the National Council on Radiation Protection and Measurements (NCRP), and the International Commission on Radiological Protection (ICRP).

b.) It is the policy of DOE to operate its facilities and conduct its activities so that radiation exposures are maintained within the limits promulgated by this order and as far below this order as reasonably achievable. This policy applies to annual, committed, and cumulative dose equivalents.[5]

Figure 1 summarizes the radiation exposure limits as posted by the Department of Energy.

Stochastic Effects	5 rem (annual effective dose equivalent)
Non-Stochastic Effects	
Lens of eye	15 rem (annual dose equivalent)
Extremity	50 rem (annual dose equivalent)
Skin of whole body	50 rem (annual dose equivalent)
Organ or tissue	50 rem (annual dose equivalent)
Unborn Child	
Entire gestation period	0.5 rem (annual dose equivalent)

Figure 1 Radiation Protection Standards

Stochastic Effects can be defined as the limiting value of annual effective dose equivalent from both internal and external sources received in any year by an occupational worker. As seen in Figure 1, the Department of Energy has set this limit at 5 rem per year. Through concern over these stochastic effects, Rocky Flats administration began, in 1978, a policy of cutting the posted DOE annual rem equivalent limit in half. In other words, the exposure to radiation a Rocky Flats worker can attain is limited to 2.5 rem in any one year. Within the last year, Rocky Flats administrators decided to obtain an even more stringent policy concerning stochastic effects. Consequently, the limit was reduced to 2.0 rem that any one Rocky Flats worker may acquire in a single year.

In a coordinated effort, Department of Energy officials and Rocky Flats administrators organized incentive programs in an attempt to achieve this new limit at Rocky Flats. One such program, and one which this thesis is concerned with, is the Dosimetry Award Program (GAO-89-1). This program was designed to encompass six six-month periods (Figure 2), with the attained rem count for a given period being the target for the next six-month period. The incentive for this program is as follows: Rocky Flats would receive from DOE payment for each rem under 95% of the target for the first six-month period. For example, the initial target for the first six-month period was 208 rem total plant exposure, five percent below this is 198 rem, and anything below this would result in Rocky Flats receiving payment per rem.

TIMELINE FOR THE DOSIMETRY AWARD PROGRAM

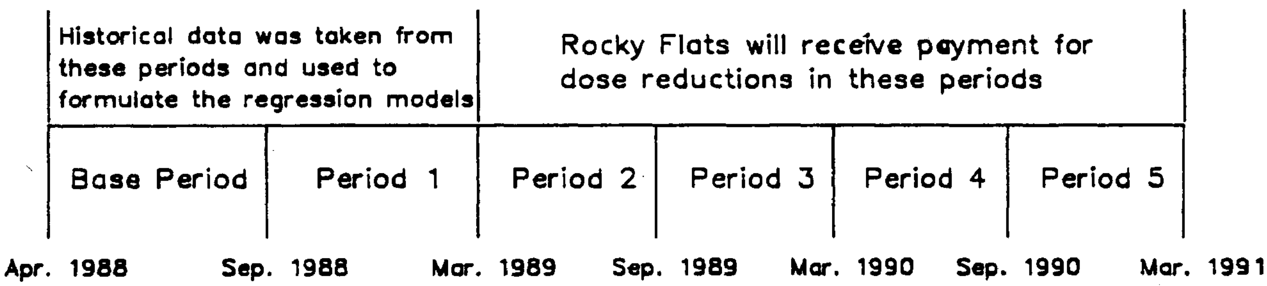

Figure 2 Timeline For The Dosimetry Award Program

One of the requirements DOE had concerning this program is that only rem reductions from the result of new efforts to reduce exposure by Rocky Flats personnel would be reimbursed. For example, a building manager who organizes safer and more efficient methods for his employees to handle radioactive wastes in his building would be a legitimate rem reduction for which the Department of Energy would pay. It is because of this reason that only 95% of the rem reduction was compensated for in the first six-month period with the belief that reductions would occur simply from knowledge of this program by Rocky Flats employees.

Originally, it was thought that a simple vertical scale would sufficiently model this program as shown in Figure 3. This model is, however, limited as it does not consider the production level of the plant at given times. For example, for clean up purposes during the winter of 1989, production in one of the buildings at R.F. was halted. Correspondingly, the attained rem count for this period was significantly lower. Should DOE be forced to pay R.F. for this huge rem reduction? Obviously not as the apparent reduction was not the result of increased safety measures but from a decrease in production. With this in mind, a proposal has been put forward to use regression to predict expected exposures for a given time period as a function of the level of production during the period. These predicted exposures would provide the adjusted baseline targets for the respective time periods which compose the Dose Reduction Program. This procedure will be much more beneficial in that it will allow the Dosimetry Award Program to serve its designed purpose; to

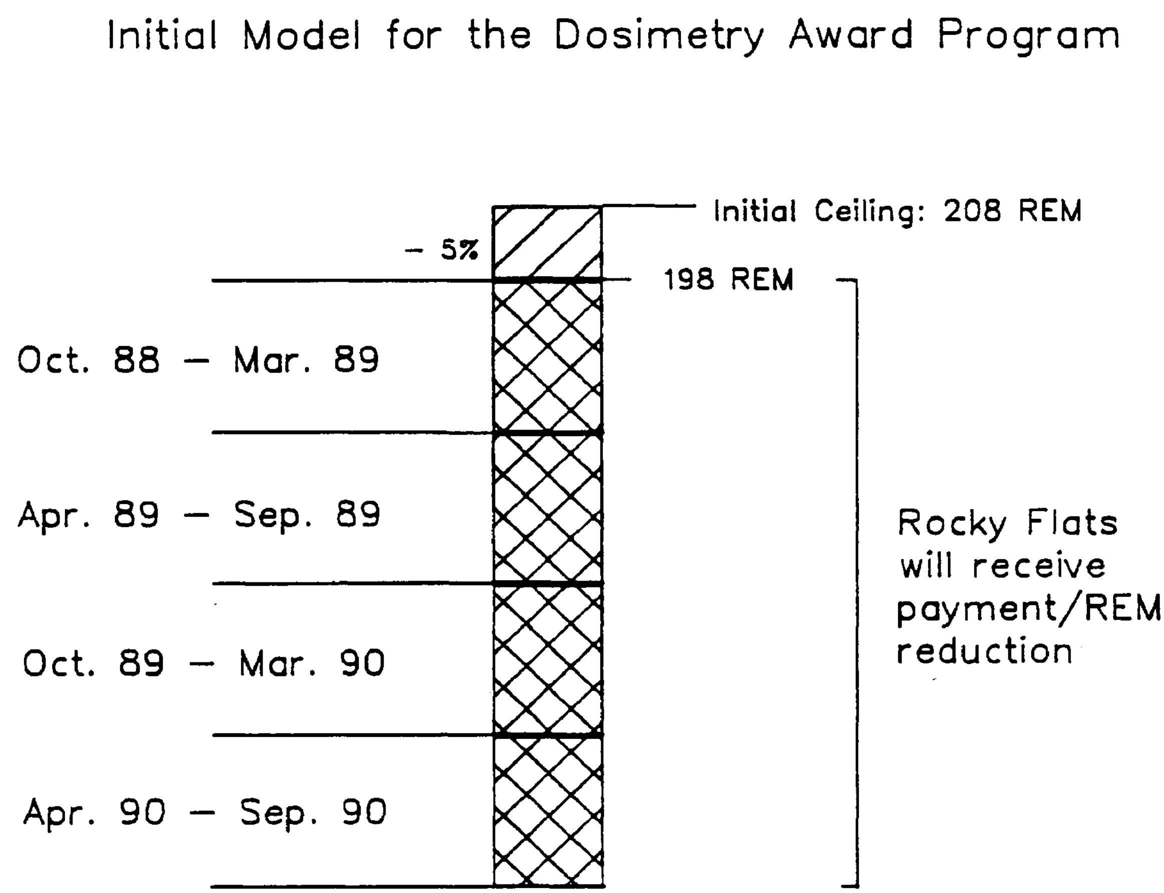

Figure 3 Initial Model for the Dosimetry Award Program

promote increases in safety so that R.F. will become a better environment for its employees and the surrounding communities.

At Rocky Flats, it has been determined that there are presently 19 separate groups (Table 1) which are significant contributors to the plant exposure total. These groups include organizations which are involved with the handling of incoming material, hands-on production, and the treatment of wastes generated by production.

The purpose of this thesis is to explore the regression approach to the Dosimetry Award Program. This approach is investigated at three distinct levels; the group level (micro)in which all 19 trend groups will be separately analyzed, the building level (macro) where the trend groups are combined into three distinct building compounds, and finally the plant level where all groups are combined together. The micro level is discussed in depth in chapters 1 and 2 of this thesis. The macro and plant levels are analyzed in chapter 3. The major result of this thesis will be the recommendation of which one of the levels to be implemented.

Table 1

The Groups Involved With The

Dosimetry Award Program

Group Name	Building Number	Organization Code
Special Assembly	777	18310
Maintenance	771	29100
Mass Spec	559	32210
Pu Chemistry	559	32220
Pu Spec	559	32230
Pu Ops Supp Lab	771	32420
Quality Acceptance	707	33130
NDT	707	33220
Prod Control	707	53200
Foundry	707	56310
Assembly	707	56321
Machining	707	56330
Process Ops	776	61120
Hydride Ops	779	61130
NDA & MC	371	61310
NDA & MC	771	61310
Process Ops	771	61520
Liquid Waste Ops	774	64200
Solid Waste Trtmnt	776	64300

Chapter 1

The Micro Approach

Earlier this year, an Individual Group Goals Worksheet was distributed to the respective supervisors of each of the 19 groups listed in Table 1. This worksheet consists of various sections, all of which were to be completed by the supervisors. The first section deals with the goals the supervisors wanted their group to fulfill over the lifetime of the Dosimetry Award Program. In the next section of the worksheet, the supervisors were to document the methods they and their employees would use to achieve their predetermined goals. The third section is titled, "Workload that Corresponds to Groups' Exposure." Here, the supervisors were asked to document the activities during which their employees were exposed to radiation. The information provided in this area corresponds with the production index (indices) for the group. As will be later be explained, this index (indices) will be the independent or random variables in the various regression equations. In the final section of this worksheet, the supervisors were to obtain as much historical data from previous fiscal years associated to their production index(s) as was possible.

Figure 4 is an example of the Individual Group Goals Worksheet from the supervisor of NDA & MC (Non-Destructible Assay & Material Control) in building 371. As seen in this figure, the goal desired by this supervisor are to reduce accumulative exposure attained by his group by 11%.

GAO 88-1
INDIVIDUAL GROUP GOALS WORK SHEET

PAGE 1 OF 2

BUILDING 371 GROUP NAME NDA & MC

ORGANIZATION CODE 61310

SUPERVISOR Bruce Springsteen EXT. 4210 PAGE 0-096

REPRESENTATIVE Jimmy Buffet EXT. 7644 PAGE

EVALUATION PERIOD 4/89 THRU 9/30

GOALS

1. REDUCE ACCUMULATIVE EXPOSURE FOR THE GROUP BY 11 % OF THE BASELINE.

2. Reduce individual exposure through better utilization of personnel, thorough job preparation and planning and increased use of radiation shielding.

3.

4.

METHODS TO REACH GOALS AND PERSON RESPONSIBLE

1. Improve coordination between inter-active support groups to minimize delays for personnel operating in radiation areas.

2. Improve communications between shift supervisors to more evenly distribute the group workload and improve efficiency.

3. Request surveys within storage vaults to pin point high radiation areas. Transfer sources of high radiation to low traffic areas.

4. Expidite completion of new repack glovebox which was designed to improve efficiency of repack operations that will minimize operator handling time of special nuclear material.

Group Manager

USE ADDITIONAL SHEETS AS NECESSARY.

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(continued)

Figure 4 Individual Group Goals Work Sheet

GAO 88-1
INDIVIDUAL GROUP GOALS WORK SHEET

WORKLOAD THAT CORRESPONDS TO GROUP'S EXPOSURE

Workload: Average manhours spent handling / counting SPECIAL NUCLEAR MATERIAL based on staffing and operational equipment.

PREVIOUS WORKLOAD BY MONTH, QUARTER, OR 6 MONTH PERIOD FOR THE PAST THREE YEARS

FY-89

OCT	2205		
NOV	[illegible]		
DEC	1785	6090	
JAN	[illegible]		
FEB	[illegible]		
MAR	1980	5620	[illegible]
APR			
MAY			
JUN			
JUL			
AUG			
SEP			

FY-88

OCT	2205		
NOV	[illegible]		
DEC	1785	5090	
JAN	2100		
FEB	2205		
MAR	2310	5615	[illegible]
APR	[illegible]		
MAY	2310		
JUN	2205	6720	
JUL	2100		
AUG	2415		
SEP	2205	6720	[illegible]

FY-87

OCT			
NOV			
DEC			
JAN			
FEB			
MAR			
APR			
MAY			
JUN			
JUL			
AUG			
SEP			

FY-86

OCT			
NOV			
DEC			
JAN			
FEB			
MAR			
APR			
MAY			
JUN			
JUL			
AUG			
SEP			

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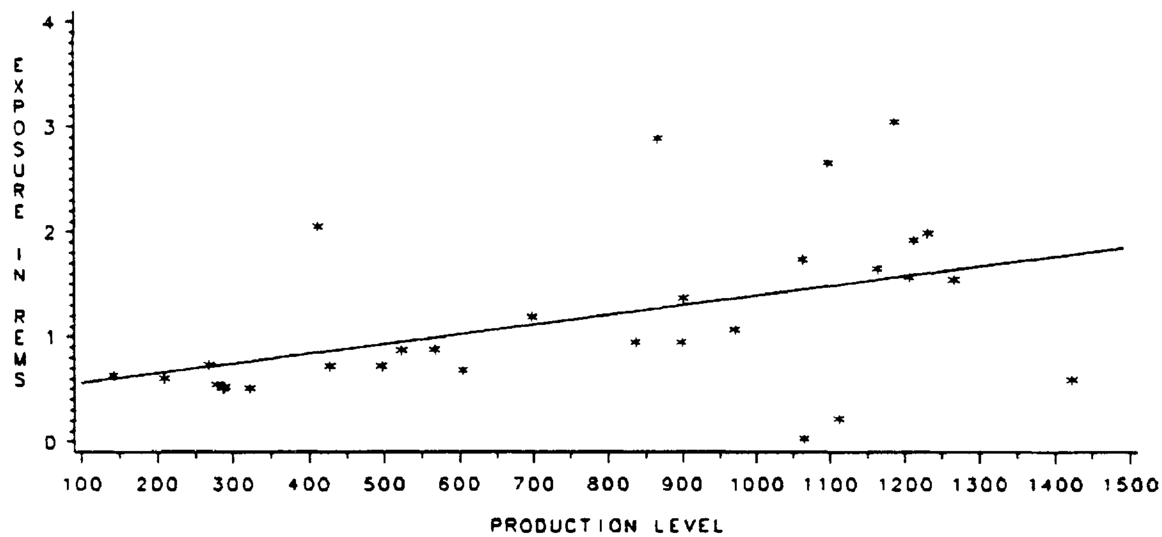
Figure 4 (continued)

Further; this supervisor states that this goal will be reached by better utilization of his employees through job preparation, planning, and increased use of radiation shielding. On the second page of Figure 4, the supervisor detailed that his employees became exposed to radiation by the number of hours they handled and counted special nuclear materials.

Upon receiving all of the 19 trend group supervisors' completed worksheets, regression models using the provided historical production indices were fitted for each group. The results of this initial model fitting are shown in table 2. With this information, it was possible to begin to examine how, when and where Rocky Flats personnel were receiving ionizing radiation.

As an example, consider the trend group, Solid Waste Treatment (organization code = 64300) at the bottom of Table 2. The production index provided by the the supervisor of this group is the number of drums processed through a Size Reduction Vault per month. In other words, the supervisor of Solid Waste Treatment believed that his employees became exposed to radiation through the number of drums of radioactive waste they processed each month. A scatter plot with this data is contained in Figure 5. Once again, on Table 2, under the intercept column for Solid Waste Treatment is the number 467.8. This number represents that if there were no drums processed during a given month, one would expect this groups' exposure total to be equal to 467.8 person-millirem. The slope for this group indicates that for each drum processed, an additional .926 person-millirem is expected.



Month	Year	Index1	Exposure
10	86	1266	1.55000
11	86	1206	1.57000
12	86	1423	0.59000
1	87	1065	0.03000
2	87	1112	0.22000
3	87	1188	3.05000
4	87	1164	1.65000
5	87	901	1.37000
6	87	1098	2.66000
7	87	1231	1.99000
8	87	1212	1.92000
9	87	867	2.89000
10	87	1063	1.74000
11	87	971	1.07000
12	87	697	1.19000
1	88	836	0.95000
2	88	142	0.63000
3	88	523	0.87000
4	88	496	0.72000
5	88	411	2.05000
6	88	899	0.95000
7	88	567	0.88000
8	88	269	0.73000
9	88	604	0.68000
10	88	428	0.72000
11	88	322	0.51000
12	88	279	0.54000
1	89	289	0.52000
2	89	286	0.51000
3	89	209	0.60000

Figure 5 Scatterplot for Solid Waste Treatment

Table 2

Regression Results for Models Containing Production Data Only

Name	Intercept	Slope	R-square	p-value
771 Special Assembly	115.6	0.293	.69	.0005
771 Maintenance	-740.5	0.258	.36	.0031
559 Mass Spec	745.8	0.0*	.00	.9044
559 Pu Chemistry	691.7	0.0*	.03	.1896
559 Pu Spec	600.8	0.0*	.19	.1318
771 Pu Ops Supp Lab	1134.7	-0.157 -3.684 0.0013	.62	.0001
707 Qual Acceptance	648.3	0.0*	.08	.7656
707 NDT	571.7	0.0*	.08	.2566
707 Prod Control	1351.7	0.0**	--	--
707 Foundry	***	***	.57	.0001
707 Assembly	-326.8	18.501 25.850	.79	.0198
707 Machining	450.7	0.433	.30	.0348
776 Process Ops	***	***	.34	.0022
779 Hydride Ops	124.0	0.012	.50	.0001
371 NDA & MC	-3762.2	2.756	.42	.0035
771 NDA & MC	-1478.7	2.145	.68	.0001
771 Process Ops	7663.2	24.11	.45	.0001

(continued)

Table 2 (continued)

Name	Intercept	Slope	R-square	p-value
Liquid Waste Ops	11.0	5.858	.66	.0013
Solid Waste Trtmnt	467.8	0.926	.21	.0099

* Flat regression line used due to lack of correlation.

** Flat regression line assumed and used due to unavailable data.

*** Omitted for classification reasons.

For this particular group, the regression equation takes the form:

$$Y = \beta_0 + \beta_1(\text{production index})$$

where Y is the exposure in millirems and β_0 and β_1 are estimated to be 467.8 and 0.926, respectively.

Thus,

$$\text{Exposure} = 467.8 + .926(\text{Number of Barrels Processed})$$

This equation corresponds to the regression line and is the solid line on Figure 5.

With the regression models found on Table 2, predictions using the models were computed for the two subsequent six-month periods, April '88 - September '88 and October '88 - March '89. These predictions can be found in Table 3. The index column on this table corresponds to the production index for that specific group. Continuing with the Solid Waste Treatment example, the index for this group is 3246. This number represents that there were a total of 3246 barrels of radioactive waste processed by Solid Waste Treatment employees during the six-month period, Apr. '88 - Sept. '88. A monthly rate of one sixth this number was used in the regression model to predict a monthly exposure. That exposure was multiplied by six for the six month period resulting in a prediction for that production level of 5.8 rem. Note that the actual exposure for this group during this six month period was 6.0 rem.

The total exposure for the entire plant during the months April '88 through September '88 was 208 rem. For the same period, the regression models predicted a total of 196.8 rem. Similarly, the actual attained exposure for the entire plant for the following period, October '88 - March '89, was 129.2 rem. Predictions from the regression models for this same period reveal a total of 168.2 rem.

Why do there exist such discrepancies between the totals of the actual attained dosage and the regression predictions? The answer lies with the regression models themselves, as many of these models are quite poor, showing little or no correlation between the attained dosage and the given production index. This signifies that further study of the regression models is in order. One method which this thesis incorporates, to study the regression models in more detail is through use of Anaysis of Variance (ANOVA) tables.

Table 3

Observed vs Predicted Six-Month
Exposure Levels (in person-rem)

Organization	Apr88 to Sep88 Index	Pred	Observed	Oct '88 to Mar89 Index	Pred	Observed
771 Spec Assm	1730	1.2	1.4	1390	1.1	1.3
771 Maint	53866	9.5	9.5	37576	5.3	3.4
559 Mass Spec	*	4.5	4.4	*	4.5	4.6
559 Pu Chem	*	4.2	4.3	*	4.2	4.0
559 Pu Spec	*	3.6	4.1	*	3.6	3.1
771 Pu Ops	35173 1369	8.1	6.4	11085 1120	3.6	4.1
707 Qual Accpt	*	3.9	4.5	*	3.9	3.2
707 NDT	*	3.4	3.4	*	3.4	3.4
707 Prod Cont	*	8.1	8.6	*	8.1	7.6
707 Foundry	**	25.5	27.9	**	22.2	19.0
707 Assembly	419 112	8.7	10.6	443 184	11.0	11.3
707 Mach	12982	8.3	8.4	12387	7.4	7.5
776 Proc Ops	**	10.2	14.6	**	14.2	11.6
779 Hydr Ops	90544	1.8	1.4	68677	1.6	1.3
371 NDA & MC	13440	14.5	12.9	11760	9.8	9.1
771 NDA & MC	8599	9.6	8.6	6623	5.3	5.2
771 Proc Ops	707	63.0	68.1	276	52.6	24.8

(continued)

Table 3 (continued)

Organization	Apr88 to Sep88 Index	Pred	Observed	Oct '88 to Mar89 Index	Pred	Observed
Liq Wast Ops	491	2.9	2.9	200	1.2	1.3
Solid WstTrt	3246	5.8	6.0	1813	4.5	3.4
Totals		196.8	208.0		168.2	129.2

* Production information not used due to flat regression lines.

** Omitted for classification reasons.

An ANOVA table contains a vast amount of valuable information for analyzing regression models. An ANOVA table for the trend group, Solid Waste Treatment is contained in Figure 6. As stated in Neter, Wasserman, and Kunter (NWK), "the analysis of variance approach is based on the partitioning of sums of squares and degrees of freedom associated with the response variable Y."[6] In the case of this thesis, the response variable is the radiation dose incurred. By examining the upper portion of Figure 6, in the sum of squares column, one can see the numbers:

3.77809090
13.80732577
17.58541667 .

The first number corresponds to the regression sum of squares which is denoted as SSR. The following number represents the error sum of squares (SSE). The sum of these two numbers is the total sum of squares (SSTO) which is the third number listed.

Organization Code # 64300: Building 776 Solid Waste Treatment

Analysis of Variance

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	1	3.77809090	3.77809090	7.662	0.0099
Error	28	13.80732577	0.49311878		
Total	29	17.58541667			

R-square : 0.2148 Root MSE : 0.7022242
Adjusted R-square : 0.1868

Parameter Estimates

Variable	df	Parameter Estimate	Standard Error	T for H0: Parameter=0	Probability of a greater T
Intercep	1	0.46783033	0.28692507	1.630	0.1142
Index1	1	0.000925857	0.000334490	2.768	0.0099

Index1 = the production index1 for Solid Waste Treatment which is the number of drums processed each month.

Figure 6 Analysis of the historical data for Solid Waste Treatment

The variation of the i^{th} observation is conventionally measured in terms of the deviations:

$$Y_i - \bar{Y}$$

[As shown in Figure 7a.]

The SSTO is the sum of these deviations squared (ie., SSTO = $(\Sigma Y_i - \bar{Y})^2$). The greater the SSTO, the greater is the variation among the Y observations.

When using regression, the variation reflecting the uncertainty in the data is that of the Y observations around the regression line:

$$Y_i - \hat{Y}_i$$

where $\hat{Y}_i$ is the fitted value for the i^{th} observation.

These types of deviations correspond to the SSE and are shown in Figure 7b. The larger the SSE, the greater is the variation of the Y observations around the regression line. The SSE is also known as the unexplained variation.

The SSR, like the SSE, is a sum of squared deviations. However, the deviations for this measure resemble:

$$\hat{Y}_i - \bar{Y}$$

where $\bar{Y}$ is the mean of the fitted values.

This type of deviation is shown in Figure 7c. Each deviation is simply the difference between the fitted value on the regression line and the mean of the fitted values Y. The SSR can be considered to be a measure of the variation of the Y observation associated with the regression line.

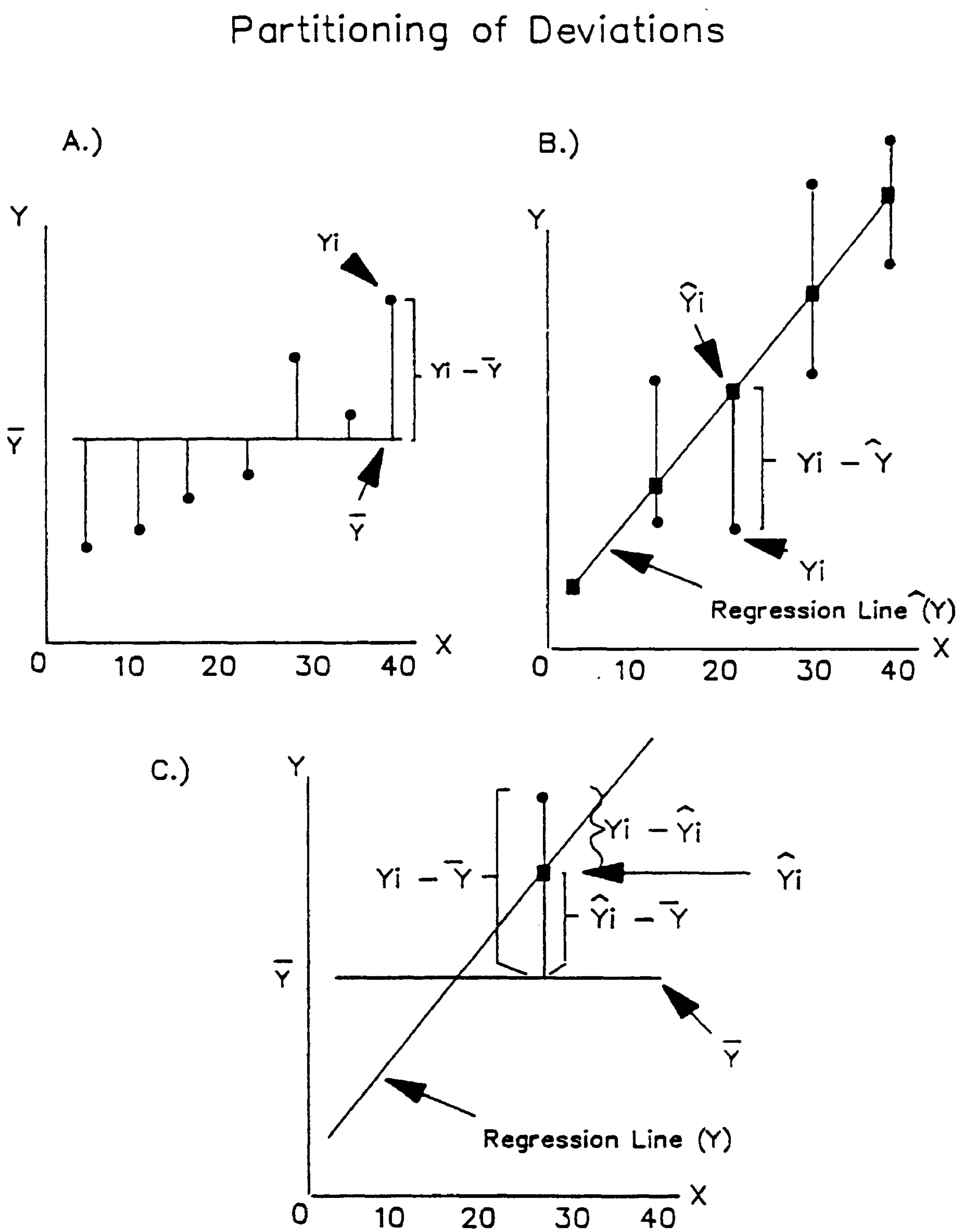


Figure 7 Partitioning of Deviations

The larger the SSR in relation to the SSTO, the greater the effect of the regression relation in accounting for the total variation in the Y observations. The SSR can also be defined as the explained variation.

For our example, Solid Waste Treatment (Figure 6):

$$SSR = SSTO - SSE = 17.58541667 - 13.80732577 = 3.77809090$$

This indicates that a very small amount of the total variability in the attained exposure total for Solid Waste Treatment employees is accounted for by the relation between the number of barrels processed and the group's exposure total. In other words, the measure of the number of waste barrels processed, alone, does not account for most of the exposure this group's employees received.

Also listed on an ANOVA table are measures which test a regression relationship. Tests which can state whether or not a relationship exists between a response variable and an independent variable(s). More specifically, in the ANOVA table in Figure 6, these tests will reveal if there is a relation between the total amount of radiation obtained by Solid Waste Treatment employees and the number of radioactive waste barrels they process each month.

Under the column Mean Square, two numbers are listed:

3.77809090
0.49311878 .

These two numbers correspond to the regression mean square (MSR) and the mean square error (MSE). It is important to consider these two numbers when analyzing a regression model because through observation of these two numbers alone, one can state whether or not there is a statistical relationship between the response and the independent variables. As NWK states, "...For testing whether or not $\beta_1 = 0$ (whether or not a relationship exists between the response variable and the independent variable(s)), a comparison of the MSR and the MSE suggests itself. If the MSE and the MSR are of the same order of magnitude, this would suggest that $\beta_1 = 0$. On the other hand, if the MSR is substantially greater than the MSE, this would suggest that β_1 does not equal 0 (a relation does exist). This, indeed, is the basic idea underlying the Analysis of Variance test."[7] In accordance with this rule, there obviously does exist a relationship between the exposure received by Solid Waste Treatment employees and the number of barrels of waste they process as the MSR ≈ 3.77 while the MSE ≈ 0.49.

Another test which verifies regression relations is also provided in an ANOVA table is the F-test and is defined:

$$F^* = \frac{MSR}{MSE}$$

For our example, $F^* = \frac{3.77809090}{0.49311870} = 7.662$

The decision rule for the F-Test as stated by NWK is as follows:

If $F^* \leq F(1 - \alpha; 1, n - 2)$ then conclude H_o

If $F^* > F(1 - \alpha; 1, n - 2)$ then conclude H_a

where $H_o : \beta_1 = 0$
$H_a : \beta_1$ does not $= 0$

For our example,

$$F^* > F(1 - \alpha; 1, n - 2)$$

$$7.662 > F(.95; 1, n - 2)$$

$$7.662 > 4.26$$

This test again verifies that there is definitely a relationship present between the attained radiation Solid Waste Treatment employees attained and the number of barrels of radioactive waste they process each month.

The probability of obtaining a greater F-value than the one already found in the F-test is called the p-value. Large p-values support H_o while small p-values support H_a. A test can be carried out by comparing the p-value with a specified risk α.

$$\text{If } p \geq \alpha \text{, then } H_o \text{ is concluded}$$

$$\text{If } p < \alpha \text{, then } H_a \text{ is concluded}$$

For this thesis and most industrial applications, the specified risk, α, is equal to 0.05. As seen in Figure 6,

$$.0099 < 0.05$$

and therefore, H_a is concluded.

Not only does an ANOVA table tell an analyst that there are regression relations present, but it also contains information concerning the significance of these regression relations. The principal statistics used in this thesis to determine the worth of a regression model, were the R^2 and adjusted R^2 statistics.

Listed on the ANOVA table in Figure 6:

$$R^2 = 0.2148$$
$$\text{Adjusted } R^2 = 0.1868$$

In any industrial application as well as the Dosimetry Award Program, these are small R^2 statistics. An $R^2 = 0.2148$ states that only 21% of the variation in the radiation exposure observations was attributable to the number of barrels of radioactive waste Solid Waste Treatment employees processed.

The Root Mean Square Error (Root MSE) is another vital statistic which can be used to reveal the significance of a regression model. Again on Figure 6:

Root Mean Square Error = .7022242

This states that for the regression model comparing the attained exposure of Solid Waste Treatment employees and the number of barrels of radioactive waste processed, approximately 70% of the variation in the historical exposure observations is left unexplained by the use of this model. In other words, by the use of the Root MSE, one can see that the regression model is quite poor because only a small fraction of the variation among the exposure observations is explained.

Chapter 2

Improving The Micro Level Regression Models

Fortunately, there are many techniques which are incorporated into this thesis which remedy the situation encountered in the previous chapter: poor fitting regression models for the majority of the 19 trend groups. The primary reason for these poor fitting regression models is that many of the trend group managers submitted production indicators which were poorly correlated to their groups' exposure totals. For example, initially, the supervisor of Solid Waste Treatment thought that his employees obtained most of their radiation through the processing of barrels of radioactive waste. However, after analyzing the ANOVA table for this group, it was concluded that this was not the case as the regression model only had an $R^2 = 0.2148$.

The first measure which was taken in order to improve the regression models for the 19 trend groups involved residual analysis. Analysis of the residuals proves to be extremely useful in the detection of outlying observations. Once these "outliers" are discovered and determined to be influential, they can be deleted leaving an improved regression model. To begin with, studentized residuals for each of the 19 trend groups were found. Studentized residuals were used rather than ordinary residuals because they have constant variance which allows for a more comparative analysis. Figure 8 is an example of a studentized residual plot for the trend group, Special Assembly in building 771. As can be seen on this plot, two of the observations, marked by pluses (+), appear to be

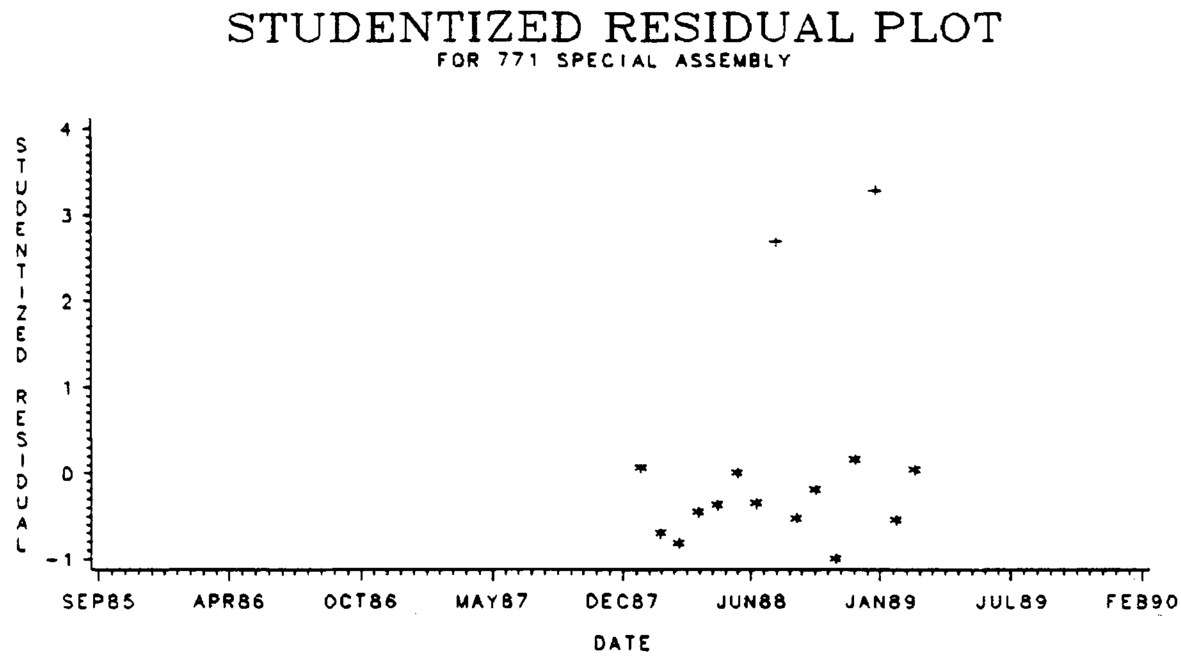


Figure 8 Studentized Residual Plot

outlying. However, observations such as these are not deleted on the basis of studentized residuals alone. Although the studentized residuals are good at "pointing out" or indicating that outlying observations might be present, there are other rigorous tests which show that speculative observations are indeed outlying and therefore affecting the regression model.

One such test was completed on the residuals for the trend group, 771 Special Assembly in Figure 9. This is a simple plot of the response variable (dose) vs. the independent variable (the production index). Specifically, the production index for this group corresponds to the time these employees performed site and surveillance activities. The solid line on Figure 9 is the fitted regression line and the dashed lines constitute a 95% prediction interval for the predicted values. Observations which are inside this perdiction band are shown as stars. Points outside the 95% prediction band are shown as pluses (+)'s. This plot backs the assumption signaled by the studentized residuals; that the two observations can be considered as outliers.

As stated in NWK, "After identifying outlying observations, . . . the next step is to ascertain whether or not they are influential in affecting the fit of the regression function, leading to serious distortion effects."[8] The Cook's Distance measure is an overall measurement of the impact of the i^{th} observation on the estimated regression coefficients. Figure 10 is a plot of the Cook's Distances for the same trend group, 771 Special Assembly. Again, the two observations, which were signaled in

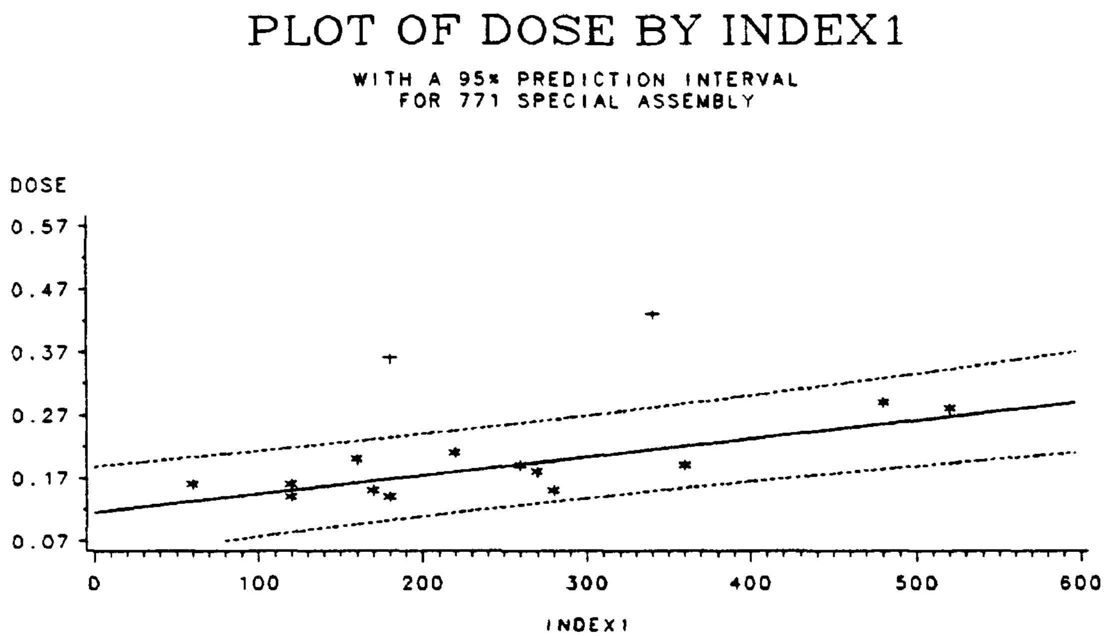


Figure 9 Plot of Dose by the Production Index

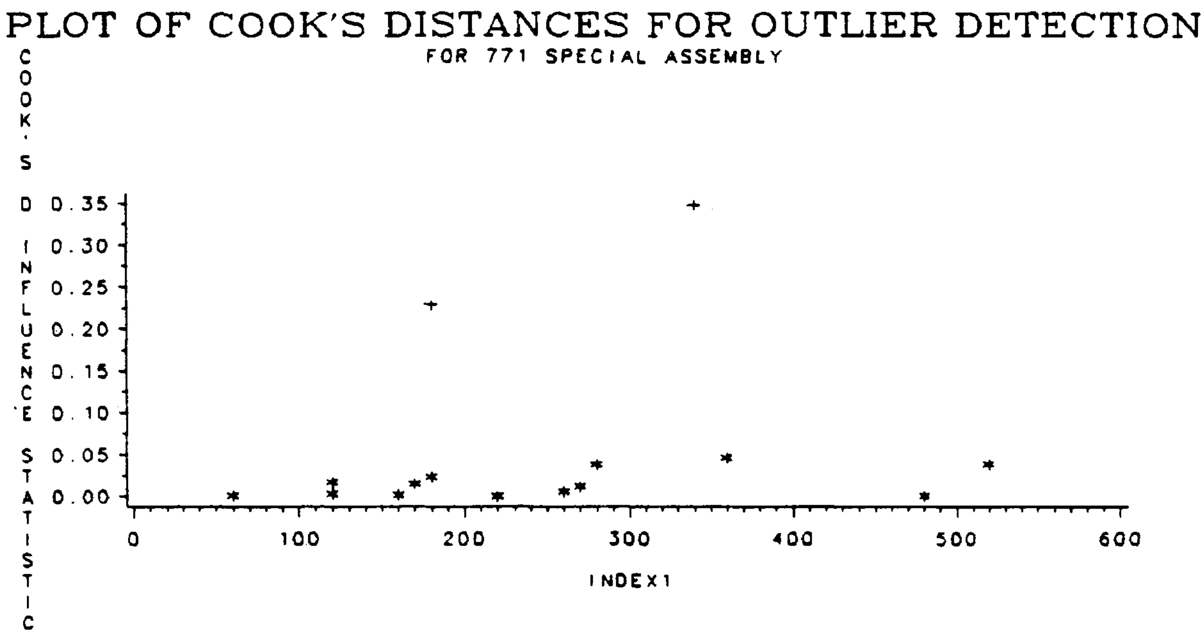


Figure 10 Cook's Distance Plot

Figures 8 & 9, are also being flagged in the Cook's Distance plot.

Even though these observations are clearly being signaled as outliers from the above tests, one last test is performed to determine if they should be deleted or not. This test simply involves judgement by the analyst (ie., does it or does it not make sense to delete the observation(s)). In most cases, the points are deleted because they denoted observations which were on the high side. In other words, the recorded dose level is abnormally high during a month in which the production was low. For example, during a low production month, a group of production workers might be asked to complete a task which is out of the ordinary for production personnel, such as taking out an old glovebox and installing a new one. Even though they are not working on activities that are directly associated with production, more specifically, with their production index, they have received exposure to radiation, thus causing an outlying observation. Occurrences as these, when things happen out of the ordinary, cause points to be outliers and greatly affect regression relations. This was probably the case for the two observations signaled as outliers on Figures 8, 9 & 10. Consequently, these two observations were deleted.

Two ANOVA tables (Table 4 and Table 5) were computed for our example, 771 Special Assembly. Table 4 is the complete analysis with the two outliers included in the model. Table 5 is the same analysis with the exception that the two outliers were deleted. Through comparing these two tables, the intercept of the model decreased from .13589 to .11567 along

Table 4

771 Special Assembly

outliers included

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F-value	Probability of Greater F
Model	1	0.02488	0.02488	4.008	0.0666
Error	13	0.08070	0.00621		
Total	14	0.10557			

R-square = 0.2356 Root MSE = 0.07879
Adjusted R-square = 0.1768

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H_0: Parameter=0	Probability of greater t
Intercept	1	0.13589	0.04459	3.047	0.0093
Index1	1	0.00032	0.00016	2.002	0.0666

Table 5

771 Special Assembly

outliers deleted

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F-value	Probability of Greater F
Model	1	0.01963	0.01963	23.974	0.0005
Error	11	0.00901	0.00082		
Total	12	0.02863			

R-square = 0.6855   Root MSE = 0.02861
Adjusted R-square = 0.6569

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H_o: Parameter=0	Probability of greater t
Intercept	1	0.11568	0.01671	6.922	0.0001
Index1	1	0.00029	0.00006	4.896	0.0005

with the slope of the model which went from .0032 to .0029. This causes the fitted regression line to be a flatter line with a lower intercept. Other statistics on the ANOVA table in Table 5 which back up the deletion of the outlying observations are the R^2 and the p-value. The R^2 went up drastically to .6855 while a p-value of .0005 states that this new model is statistically significant.

Analysis of the residuals was completed for each of the 19 trend groups encompassed by this study. As a result, an indicator variable, stating whether or not the observation was an outlier was added to the database. Regression models stated in this thesis from this point forward have had outlying observations deleted.

Another technique which can be used to improve regression models is, simply, to obtain more data. Due to the number of poor regression models discussed in the first chapter, an extensive effort was initiated to gather more information. The information sought was generally that which would better quantify the production index initially given by the respective supervisors. With this type of information, hopefully, added insights would be discovered, resulting in greatly improved regression models.

For various accountability reasons, each employee at Rocky Flats must complete a timecard each week detailing the specific types of work he/she performed during that week. While this type of information is generally used by the accounting department, it has proved to be invaluable for the Dosimetry Award Program since the number of hours employees performed various production indices is also available. Upon receiving this data from the accounting department, it was broken down into three sections for each of the 19 trend groups. These sections are:

Hourly hours - Represents the total amount of time hourly employees were associated with the production index for a given group. For example, in 771 Process Ops, this corresponds to the total amount of time hourly employees worked on the Hydrofluorination process for a given month.

Salary hours - Represents the total amount of time salaried employees were involved with a production index for a specific group during a given month.

Sum hours - Represents the total number of hours salaried and hourly employees were involved with a production index for a specific month during a given month.

Once this data was incorporated into the database, stepwise regression was used to find new regression models. stepwise regression is an automatic search procedure that develops sequentially the subset of dependant X variables to be included in the regression model. As NWK state, "Essentially, this search method develops a sequence of regression models, at each step adding or deleting an X variable. The criterion for adding or deleting an X variable can be stated in terms of . . . the F^* statistic."[9]

$$F^* = \frac{MSR(X_i)}{MSE(X_i)}$$

The stepwise regression procedure first fits a simple regression model for each potential X variable. Then, for each simple regression model the F^* statistic is computed for testing whether or not the slope is equal to zero. The X variable with the largest F^* statistic is the first variable to be considered. If the F^* for this variable is greater than a predetermined value (0.1500 for the stepwise procedure in SAS), then the variable will be added to the regression model. Table 6 is an example of how stepwise regression was used to improve the regression model for one of the 19 trend groups. This group, building 707 Assembly, has five potential dependent variables which can be in the regression model. These are:

Index1	-	First production index.
Index2	-	Second production index.
Hourly hours	-	Number of hours 707 Assembly hourly employees performed above indices.
Salary hours	-	Number of hours 707 Assembly salaried employees performed above indices.
Sum hours	-	Salary hours + hourly hours.

In order for any of these variables to enter the regression model, it must first have an $F^* \geq 0.1500$. Hourly hours has the largest F^* statistic and is therefore is the first variable to be submitted into the model. This is what occurs in Step 1 of the regression procedure shown on Table 6. Index2 is the variable with the next largest statistic. Because the F^* statistic is greater than 0.1500, the stepwise regression procedure admitted Index2 into the model in Step 2, also in Table 6. The result of this step is significant as the R^2 value for the model went from 0.7452 in

Step 1 to 0.9607 in Step 2. It is important to notice that the resulting model in Step 2 has a very low p-value (.0078) revealing that the model is statistically significant. The other remaining variables (Indexl, Salary hours, and Sum hours) did not have an F^* statistic $\geq$ 0.1500 and could not be considered to enter the model. At this point the stepwise procedure stopped.

Table 6

Example of the SAS Stepwise Regression Procedure

Note: For a dependant variable to enter and stay in the model, it must have an $F^* \geq .15$

Step 1:

Variable Hourly Hours entered into the model

R^2 = 0.74524337

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	1	1.60133	1.60133	11.70	0.0268
Error	4	0.54740	0.13685		
Total	5	2.14873			

Variable	B Value	Standard Error	Type II Sum of Squares	F-value	Probability of a greater F
Intercept	0.65881				
Hourly Hours	0.00119	0.00035	1.60133	11.70	0.0268

(continued)

Table 6 (continued)

Step 2:

Variable Index2 entered into the model

$R^2 = 0.96071343$

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	2	2.06432	1.03216	36.68	0.0078
Error	4	0.08442	0.02814		
Total	5	2.14873			

Variable	B Value	Standard Error	Type II Sum of Squares	F-value	Probability of a greater F
Intercept	1.10108				
Index2	-0.02209	0.00545	0.46299	16.45	0.0270
Hourly Hours	0.00119	0.00016	1.93894	68.91	0.0037

NO OTHER VARIABLES MET THE 0.1500 SIGNIFICANCE LEVEL FOR ENTRY INTO THE MODEL

Listed in Table 7 are the groups which the addition of productive hours (ie., hourly hours, salary hours, and sum hours) proved beneficial to their regression models. As can be seen by this table, the regression models are greatly improved over those models which just used production index data. For example, in Table 2 in Chapter 1, the trend group, Liquid Waste Ops. had the regression model:

$$\text{Dose} = 11.0 + 5.858(\text{Index1})$$

The R^2 value for this model is 0.66 and the p-value is 0.0013. When productive hour information is added, the regression model for the same group resembles:

$$\text{Dose} = 1068.5 + 11.4(\text{Index1}) + .461(\text{Salary hours})$$

The corresponding R^2 value for this group is equal to 0.87 while significance is maintained with a p-value = 0.0163.

The use of productive hour information did not help the regression models of those groups which were not listed in Table 7. This is due to the lack of correlation between the productive hour variables and the attained radiation dose for that group. As a result, the stepwise regression procedure did not admit these variables into the regression model.

To relate the significance of incorporating the productive hours data into the regression models, Table 8 was assembled. This table lists the

Table 7

Alternative Models Obtained Using Productive Hours

(in person-millirem per month)

Name	Intercept	Variables in Model	Slope	R-square	P-value
707 Prod Control	-1003.1	Hlyhrs	1.01	.69	.0198
707 Foundry	984.5	Salhrs	2.44	.63	.0324
707 Assembly	1101.1	Index2 Hlyhrs	-22.09 1.35	.96	.0078
707 Machining	238.3	Sumhrs	0.933	.89	.0168
776 Process Ops	-708.8	Index1 Sumhrs	.00398 0.631	.95	.0026
371 NDA & MC	1520.4	Hlyhrs	3.41	.85	.0034
771 NDA & MC					
771 Process Ops	1709.6	Index1 Hlyhrs	.0209 .604	.96	.0015
Liquid Waste Ops	1068.5	Index1 Salhrs	11.4 .461	.87	.0163
Solid Waste Trtmnt	96.4	Hlyhrs	.099	.79	.0074

actual attained dosage for all of the 19 trend groups during the six-month period, April 89 - September 89. Also listed in this table are the predictions of the two regression models for the same six-month period. In those cases where the productive hour data proved to be insignificant to the groups' attained radiation dose, the regression model which incorporates only the production index data was used.

From Table 8, the actual attained dosage for all of the 19 trend groups is 124.1 rem for the above mentioned six-month period. The predictions resulting from the regression models which only incorporated production index data sum to 186.6 rem for the same six-month period. Strikingly, predictions resulting from regression models which incorporate both production index data and productive hours data sum to only 132.0 rem.

At this point it is important to note that Rocky Flats would receive significantly more money from the Department of Energy for reducing radiation exposure, if the regression models using production index data alone were used (ie., Rocky Flats would receive payment corresponding to a 186.6 - 124.1 = 62.5 rem reduction). However, it is the goal of this thesis to present the model, regardless of the monetary consequences, which best represents attained radiation dosage of personnel at Rocky Flats. Using regression models with both production index data and productive hours data included, Rocky Flats would only receive payment for a 132.0 - 124.1 = 7.9 rem reduction.

Table 8

Comparison of the Two Regresion Models

vs. Actual Results (in person-rem)

Organization	Predicted (prod. data only)	Actual	Predicted (hourly data inc.)
777 Special Assembly	1.1	0.1	-
771 Maintenance	6.5	3.7	-
559 Mass Spec	4.5	3.2	-
559 Pu Chemistry	3.6	3.3	-
559 Pu Spec	1.1	3.0	-
771 Pu Ops Supp Lab	4.3	4.3	-
707 Qual Acceptance	3.9	3.6	-
707 NDT	3.4	3.1	-
707 Prod Control	8.1	6.9	8.0
707 Foundry	21.6	19.8	17.1
707 Assembly	18.0	13.4	10.4
707 Machining	8.2	7.3	7.5
776 Process Ops	15.0	11.8	9.9
779 Hydride Ops	2.0	1.7	-
371 NDA & MC	11.5	8.1	
			13.1*
771 NDA & MC	12.1	4.9	
771 Process Ops	56.8	23.2	30.7
Liquid Waste Ops	1.7	0.8	1.5
Solid Waste Trtmnt	3.2	1.9	3.4
	186.6	124.1	132.0

- indicates no change from prod. data only predictions

* 371 and 771 NDA & MC were combined in the hourly data

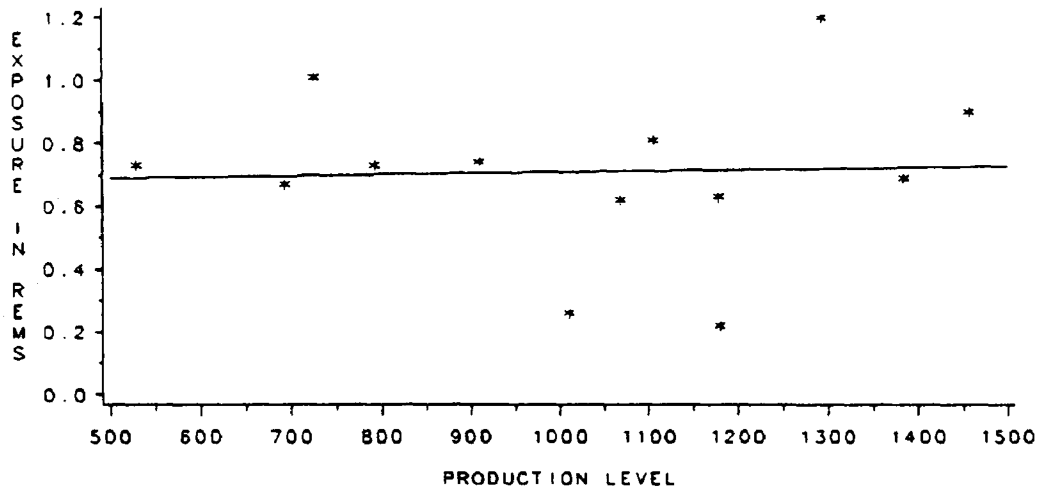
Analysis of the 559 Labs

In Chapter 1, it was shown that many of the regression models for the 19 trend groups were quite poor. Six of these groups had such poor relations between their production index and their exposure total, that a flat regression line was used to model the groups production level. These six trend groups are:

559 Mass Spec
559 Pu Chemistry
559 Pu Spec
707 Quality Acceptance
707 NDT
707 Product Control

A plot of the production induce observations for the trend group, 559 Mass Spec along with the corresponding flat regression line is in Figure 11. A predicted exposure total for this group and any group with a flat regression line, would be the average monthly exposure rate multiplied by six for a given six month period. Moreover, this exposure total will be the same for all six month periods unless a useful production index can be found. Finding a useful production index is proving to be quite difficult for five of the above groups as only the trend group, 707 Product Control, produced a significant regression model when the productive hours data was made available (this was outlined in Chapter 2 of this thesis).

In the attempt to improve the regression models for the three trend groups in the 559 Labs (Mass Spec, Pu Chemistry, and Pu Spec), data concerning the total number of analyses run in all three groups was obtained. Twelve observations were used in this analysis with the total



Month	Year	Index1	Exposure
3	88	1011	0.26000
4	88	1181	0.22000
5	88	1457	0.90000
6	88	1106	0.81000
7	88	1179	0.63000
8	88	1293	1.20000
9	88	1069	0.62000
10	88	725	1.01000
11	88	792	0.73000
12	88	529	0.73000
1	89	1384	0.69000
2	89	910	0.74000
3	89	693	0.67000

Figure 11 Flat Regression Line Example

number of analyses run in the 559 area for each month from April '88 - March '89 being recorded.

After running regression analysis between the attained dose level in each of these three groups and the total number of analyses run, only the group Pu Chemistry produced a significant regression model. As seen by Table 9 (the ANOVA table for Pu Chemistry), the R^2 is equal to 0.4636 and the p-value = 0.0148. While this is not a great regression model when compared to the models of the other 19 trend groups, at least it is a significant model which formulates a starting point.

The two other trend groups in the 559 area, Mass Spec and Pu Spec, produced very weak models with extremely small R^2 values. The ANOVA tables for these two trend groups can be seen in Tables 10 and 11 respectively.

Table 9 ANOVA Table for Pu Chemistry

Analysis of Variance

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	1	0.13191620	0.13191620	8.642	0.0148
Error	10	0.15265046	0.01526505		
Total	11	0.28456667			

R-square : 0.4636 Root MSE : 0.1235518
Adjusted R-square : 0.4099

Parameter Estimates

Variable	df	Parameter Estimate	Standard Error	T for H_0: Parameter=0	Probability of a greater T
Intercept	1	0.34050049	0.12466809	2.731	0.0211
Numanal	1	0.000093486	0.000031802	2.940	0.0148

Table 10 ANOVA Table for Mass Spec

Analysis of Variance

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	1	0.05251674	0.05251674	1.816	0.2075
Error	10	0.28917493	0.02891749		
Total	11	0.34169167			

R-square : 0.1537 Root MSE : 0.1700514
Adjusted R-square : 0.0691

Parameter Estimates

Variable	df	Parameter Estimate	Standard Error	T for H_0: Parameter=0	Probability of a greater T
Intercept	1	0.37926256	0.17158786	2.210	0.0515
Numanal	1	0.000058986	0.000043770	1.348	0.2075

Numanal = total number of analyses run in the 559 Labs

Table 11 ANOVA Table for Pu Spec

Analysis of Variance

Source	df	Sum of Squares	Mean Square	F-value	Probability of a greater F
Model	1	0.000474812	0.000474812	0.008	0.9319
Error	10	0.61861686	0.06186169		
Total	11	0.61909167			

R-square : 0.0008 Root MSE : 0.2487201
Adjusted R-square : -.0992

Parameter Estimates

Variable	df	Parameter Estimate	Standard Error	T for H_o: Parameter=0	Probability of a greater T
Intercept	1	0.72476529	0.25096729	2.888	0.0162
Numanal	1	.00000560867	0.000064019	0.088	0.9319

Numanal = Total number of analyses run in the 559 Labs

Chapter 3

The Macro and Plant Approaches

Chapters 1 and 2 detailed the Micro approach to the Dosimetry Award Program. This chapter will discuss the Macro (building) and Plant levels. In the Macro approach, the 19 trend groups are combined into three large groups. This level differs from that of the micro in that every trend group is not required to submit a production index corresponding to their groups' exposure total for every six month period. The groupings that are found to be the most useful are for buildings 707, 771, and 776. The following table (Table 12), shows the exact combinations.

Table 12

Groupings for the Macro Approach

Name	Trend Groups Included
707 Group	Quality Acceptance NDT Production Control Foundry Assembly Machining Pu Specification Mass Specification Pu Chemistry
771 Group	Maintenance NDA & MC (771 and 371) Plutonium Operations Support Lab Process Operations
776 Group	Hydride Operations Special Assembly Solid Waste Treatment Liquid Waste Operations

The related production indices for the three groups are building 707 Foundry throughput, building 771 throughput, and the molten salt process throughput for building 776. The ANOVA tables for the three groups had to be omitted due to fact that the production indices and regression coefficients of these models are considered to be classified information.

For the plant approach, the production indices for the three macro level buildings are summed and used similarly to predict the total exposure for all employees in the 19 trend groups. Again, the ANOVA table for the plant approach was deleted because it also contains classified information.

The results of the model fitting for the three groups in the macro approach along with the model for the plant approach are on the following table.

Table 13

Macro and Plant Approach
Regression Results

Name	R-square	p-value
707 Group	.53	.0001
771 Group	.21	.0037
776 Group	.17	.0083
Plant	.21	.0034

Table 14 expresses the performances of the regression models from Table 13 on actual exposure data from two of the six month periods.

Because of the weak regression models for the macro and plant approaches, sensitivity toward changing production rates is minimal. For example, the six month period from April '88 to Sept '88 was considered to be a high production period with total of 208.0 rem being recorded. The macro and plant regression models performed adequately with prediction totals of 199.1 rem and 204.8 rem respectively. In the following six month period (Oct '88 to Mar '89), which is considered to be a low production period, only 129.2 rem was recorded. Because the regression models for the macro and plant approaches are weak, predictions from them are not as low as they should be as 180.3 rem and 189.6 rem were predicted for this period.

Table 14

Macro and Plant Predictions
vs. Observed Exposures

	April '88 to Sept '88		Oct '88 to March '89	
Name	Dose	Predicted	Dose	Predicted
707 Group	77.6	79.9	65.1	70.5
771 Group	109.8	97.3	49.1	88.2
776 Group	20.6	21.9	15.0	21.6
Macro Total	208.0	199.1	129.2	180.3
Plant	208.0	204.8	129.2	189.6

Conclusions

One of the goals of this thesis is to determine the best way to model the Dosimetry Award Program at Rocky Flats. Three separate approaches: the micro, the macro, and the plant were studied to determine which one modelled the program the best. Table 15 is a comparison of these three approaches on actual data from two of the six month periods.

Table 15

Comparing the Three Approaches

Approach	April '88 to Sept '88		Oct '88 to March '89	
	Observed	Predicted	Observed	Predicted
Micro	208.0	194.3	129.2	162.8
Macro	208.0	199.1	129.2	180.3
Plant	208.0	204.8	129.2	189.6

As observed by this table, as the methods move from the micro to the plant approach, the regression models are less able to associate the dose levels with the changing production rates. In addition, the one-sigma error estimates for the predictions for each of the three approaches are:

20.6 for the plant

16.9 for the micro

10.2 for the micro

These numbers correspond to the uncertainty associated with each of the three levels. The uncertainty for the plant level was found by squaring the root mean square error associated with this regression model, multiplying by six because the prediction is that for a six-month period, and then taking the square root of this product.

$$RMSE = 8.42$$

$$\sqrt{(8.42)^2 \times 6} = \text{Uncertainty} = 20.6$$

For the macro level:

$$\begin{array}{ccccc} \text{707 group} & & \text{771 group} & & \text{776 group} \\ (RMSE)^2 & + & (RMSE)^2 & + & (RMSE)^2 \end{array}$$

$$\text{Uncertainty} = \sqrt{[(2.63)^2 + (6.33)^2 + (.92)^2] \times 6} = 16.9$$

The uncertainty for the micro level was found in a way similar to that of the macro level with the exception that the RMSE's for all of the 19 trend groups were used.

The smaller the uncertainty associated with an approach, the tighter the prediction bands will be for that approach. Thus, the micro approach will have the tightest prediction band.

Once comparisons between the three approaches to the Dosimetry Award Program were completed, one of the approaches was chosen. Because the micro approach could associate with changing production rates better than the other approaches and because it had a lower uncertainty than the others, it was chosen to be the method of modelling for the Dosimetry Award Program.

Chapter 1 of this thesis detailed how data was obtained for each of the 19 trend groups as is required in the micro approach. Also included in this chapter, the strength of the 19 regression models was determined through the use of ANOVA tables. As is shown by Table 2, the majority of these 19 regression models are quite poor. Fortunately, there are many methods available to this study which greatly improve poor fitting regression models. These methods of improvement are outlined in Chapter 2 of this thesis.

Identifying and deleting outlying observations which were present in the data for many of the 19 trend groups were the first measures taken to improve the regression models. The addition of data concerning productive hours greatly improved 10 of the 19 regression models as was shown in Table 7. When improvements such as these were completed on the 19 regression models, the sensitivity which the micro approach had toward changing production rates increased greatly as seen by Table 8.

At this point, it is necessary to discuss the economic implications of this thesis. The management of Rocky Flats would obviously wish to receive as much money as possible from the Department of Energy for lowering the exposure levels of it's employees. Therefore, it would benefit Rocky Flats management to have regression models that were not sensitive to changing production rates. For example, from Table 8, during the six month period from April '89 to Sept '89, Rocky Flats employees obtained 124.1 rem of exposure to radiation. The regression models which only used the provided production indices predicted a total exposure of 186.6. If this model was used, Rocky Flats would receive payment corresponding to a 62.5 rem reduction. It is, however, the goal of this thesis to obtain regression models which most accurately model exposures at Rocky Flats. Consequently, data concerning productive hours was added to the regression models. Predictions resulting from models containing this productive hours data predicted a total exposure of 132.0 rem for the same above mentioned six-month period. In this case, Rocky Flats would only receive payment for a 7.9 rem reduction.

Recommendations

-- As has been previously mentioned, the micro approach should be the model used for the Dose Reduction Program. Because of this, a great amount of administrative effort is going to be required to obtain production indices for all of the trend groups as is required in the micro approach.

-- Some of the trend groups still do not have significant regression models. Supervisors for these groups as well as the supervisors of those groups with poor fitting regression models, need to analyze their processes further and submit more production indices which correspond to their groups attained dosage.

-- As many production indices as possible should be found for each trend group as this type of information will provide added insights on how particular groups at Rocky Flats come into contact with radiation.

-- A task team should be assembled containing both management and production personnel with the responsibility of overseeing the procurement of new production indices and the associating historical data.

Suggestions For Further Research

It is recommended to anyone seeking further research concerning this topic to remember that most of the group supervisors have little or no previous statistical knowledge. Because of this, the researcher needs to explain him/herself and their purpose in a clear and concise manner as this will greatly improve the working relationships the researcher has with these group supervisors. With these improved relationships, the researcher will find that the supervisors will be more willing to work with them in obtaining production indices concerning their group. As a result, more production indices for each group will be obtained, leading to improved regression models which will be extremely sensitive to changing production rates at Rocky Flats.

Footnotes

1. Munson, L., H., et al., Health Physics Manual of Good Practices for Reducing Radiation Exposures to Levels that are As Low As Reasonably Achievable (ALARA) (Pacific Bell Laboratories Operated for the U.S. Department of Energy by the Batelle Memorial Institute, 1988), 1.2.

2. Munson, L.H. "ALARA", 1.2.

3. Munson, L.H. "ALARA", 1.3.

4. Munson, L.H. "ALARA", iii.

5. Department of Energy, Radiation Protection for Occupational Workers. ([Washington, D.C.]: U.S. Department of Energy Order 5480.11, 1988), 1.

6. Neter, J., W. Wasserman, and M. Kutner. Applied Linear Statistical Models. (Homewood, Illinois: Irwin, 1985), 288.

7. (Neter, Wasserman, and Kutner 1985, 91)

8. (Neter, Wasserman, and Kutner 1985, 407)

9. (Neter, Wasserman, and Kutner 1985, 430)

References

Munson, L.H., "Health Physics Manual of Good Practices for Reducing Radiation Exposure to Levels that are As Low As Reasonably Achievable." Pacific Bell Laboratory, 1988.

Neter, J., Wasserman, W., Kutner, M., Applied Linear Statistical Models. Richard D. Irwin Inc., 1974 and 1985.

U.S. Department of Energy. Order 5480.11. Radiation Protection for Occupational Workers. [Washington D.C.]: U.S. Department of Energy, 1988.

Appendix

Definitions and Terms

p-value: The p-value for a sample outcome is the probability that the sample outcome could have been more extreme than the one observed assuming H_o is true. Large p-values support H_o while small p-values support H_a. A test can be carried out by comparing the p-value with a specified α (alpha) risk. α is the level of significance (ie., the probability of rejecting a true H_o when H_o is assumed to be true). If the p-value equals or is greater than the specified α, H_o is not rejected. If, however, the p-value is less than α, H_a is concluded.

In reference to this study, H_o is the condition in which the slope of the regression line equals 0.00 (ie., there exists no relationship between the attained Radiation exposure and the given production indicator). The risk factor, α, is equal to .05.

Coefficient of Multiple Determination: Denoted by R^2, it is defined as:

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

where:

$SSE = \Sigma e^2_i$ {see Residual for definition of e_i}

SSE stands for the error sum of squares or residual sum of squares. If the SSE = 0, all observations fall on the fitted regression line. The greater the SSE, the greater is the variation of the Y observations around the regression line.

$$SSR = \Sigma(\hat{Y}_i - \bar{Y})^2$$

SSR represents the regression sum of squares. Note that SSR is the sum of squared deviations, the deviations being:

$$\hat{Y}_i - \bar{Y}$$

$\hat{Y}_i$ is the fitted value for the ith observation.

$$SSTO = \Sigma(Y_i - \bar{Y})^2$$

SSTO stands for the total sum of squares. SSTO is the measure of total variation. The greater the SSTO, the greater the variation among the Y observations.

R^2 represents the proportion of the sum of squares of deviations of the y values about their mean that can be attributed to a linear relationship between y and x (or, in the case of this study, the relationship between exposure and the trend group's production indicator).

Note: R^2 is always between 0 and 1, because R is between -1 and +1. Thus, an $R^2 = .60$ means that 60% of the sum of squares of deviations of the y values about their mean is attributable to the linear relationship between y and x.

<u>Coefficient of Correlation</u>: Denoted by R, it is defined as:

$$R = SQRT\ R^2$$

R is a measure of the strength of the linear relationship between two random variables, x and y. A value of R near zero implies that there is little, if any, relationship between the x and y variables. Conversely, an R value near 1 signifies a strong relation between the two random variables. Positive values of R imply that the variables are positively correlated (ie., as x increases, y also increases). Negative R values signify a negative correlation between the two variables (...as x increases, y decreases).

Examples of these are on the following page in Figure 1 on the folowing page.

<u>Adjusted R^2</u>: Denoted by $R^2{}_a$, is a related statistic to R^2 and is defined as:

$$R^2{}_a = \frac{n-1}{n-p}\ \frac{SSE}{SSTO} = \frac{1-MSE}{\frac{SSTO}{n-1}}$$

where n is the total number of observations and p is the number of parameters in the regression equation.

Figure 1

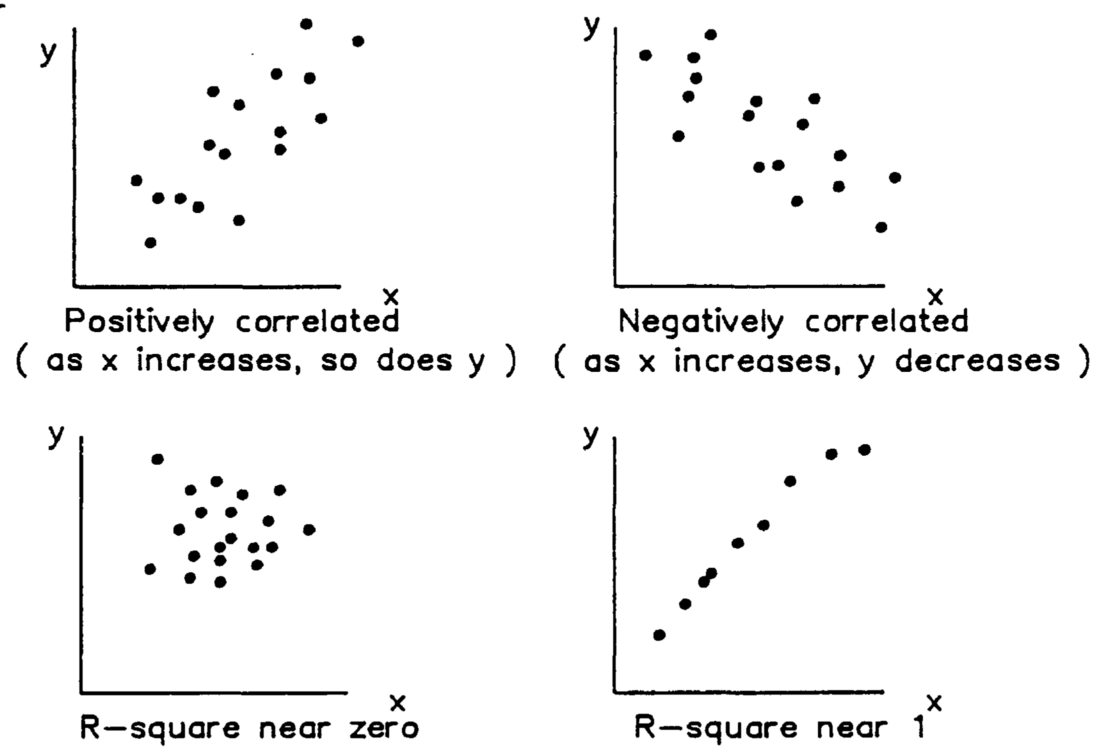
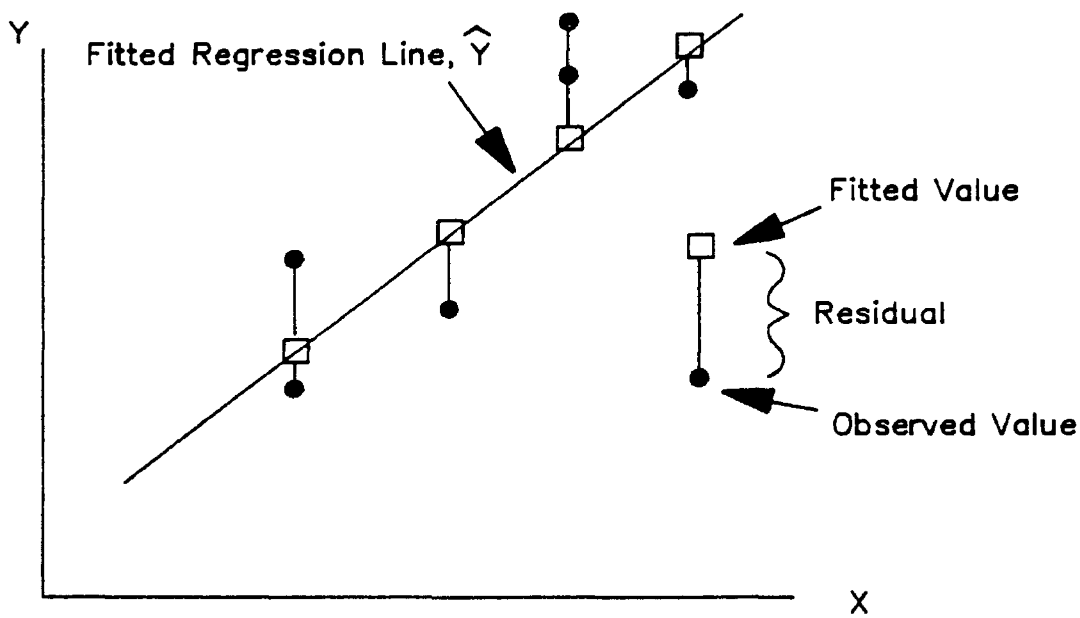


Figure 2



R^2_a takes into account the number of parameters in the model through the degrees of freedom.

Residual: the i^{th} residual is the difference between the observed value Y_i and the corresponding fitted value $\hat{Y}_i$. The ith residual is denoted by e_i and is defined:

$$e_i = Y_i - \hat{Y}_i$$

A residual example is on the previous page in Figure 2.

Studentized Residual: A measure of the ratio of the residuals(e_i) to the unbiased estimator of the standard deviation [$s(e_i)$] and is denoted by e^*_i.

$$e^*_i = \frac{e_i}{s(e_i)}$$

The advantage studentized residuals have over residuals is that studentized residuals have constant variance.

Mean Square Error: Denoted by MSE, is a measure of the variation within samples.

$$MSE = \Sigma \frac{e^2_i}{n-1}$$

where e_i is the i^{th} residual and n is the total number of observations.

Root Mean Square Error (RMSE): The root mean square error is an estimate of the unexplained variability. For a given predicted response, approximately 2/3 of the response values would be expected to fall within one RMSE value in each direction, approximately 95% within two RMSE values, and 99% within three RMSE values. RMSE is defined:

$$RMSE = SQRT(MSE)$$

Cook Distance Measure: D_i, is an overall measure of the impact of the i^{th} observation on the estimated regression coefficients.

$$D_i = \frac{(b - b_{(i)})' X'X (b - b_{(i)})}{p(MSE)}$$

where X is an n x p matrix, b is the usual least squares estimator with all observations included, and $b_{(i)}$ is the least squares estimator after the i^{th} data point has been omitted.

While D_i does not follow the F distribution, it has been found useful to relate the value, D_i, to the corresponding F-distribution and ascertain the percent value. If the percent value is less than 20 percent, the i^{th} observation has little apparent influence on the fitted regression function. If, on the other hand, the percent value is greater than or equal to 50 percent, the i^{th} observation is considered to have substantial influence of the regression function.

<u>Leverage</u>: Denoted by h_{ii}, is another statistic which proves useful in the detection of outliers. The statistic, h_{ii}, is a measure of the distance between the x values for the i^{th} observation and the means of the x values for all n observations. A large leverage indicates that the i^{th} observation is distant from the center of all the x observations.

A leverage value is usually considered to be large if it is more than twice as large as the mean leverage value h, which is:

$$h = \Sigma \frac{h_{ii}}{n} = \frac{p}{n}$$

Hence, leverage values greater than 2p/n are considered by this rule to be outlying observations.

<u>Autocorrelation</u>: In business and economics, many regression applications involve time series data. For such data, the assumption of uncorrelated or independent error terms is often not appropriate;rather, the error terms are frequently correlated positively over time. Error terms that are correlated over time are said to be autocorrelated or serially correlated. A major cause of autocorrelation in business applications, and one that confronted this project at Rocky Flats, is the omission of one or more key variables from the model.
When autocorrelation exists, many problems arise and these are listed below.

1. Regression coefficients will still be unbiased, but will lack the minimum variance property and thus may be quite inefficient.
2. MSE may seriously underestimate the variance of the error terms.
3. The true standard deviation of the estimated regression coefficient

may also be seriously underestimated.

4. Confidence intervals using the t and F distributions will no longer be strictly applicable.

Durbin Watson Test: From above, one can see why it is necessary to test for autocorrelation. The Durbin-Watson is such a test for determining Autocorrelation in error terms. Structurally, this test answers whether or not an autocorrelation parameter, p (rho), is zero. p is a parameter such that $|p| < 1$.

$$H_o : p = 0$$
$$H_a : p > 0$$

The test statistic is obtained by first fitting the ordinary least squares regression function and calculating the residuals, $e_t = Y_t - \hat{Y}_t$. The next step requires calculating the statistic:

$$D = \frac{\Sigma (e_t - e_{t-1})^2}{\Sigma e^2_t}$$

Small values of D lead to the conclusion that $p > 0$ because the adjacent error terms e_t and e_{t-1} tend to be of the same magnitude when they are positively autocorrelated. Hence, the differences in the residuals $e_t - e_{t-1}$, would tend to be small when $p > 0$, leading to a small numerator in D and thus, a small test statistic D.

Stepwise Regression: This is a method of selecting the best set of regressor variables for a regression equation. It precedes by introducing the variables one at a time (stepwise forward) or by beginning with the whole set and rejecting them one at a time (stepwise backwards). The criterion for accepting or deleting a variable usually depends on the extent to which it affects the multiple correlation coefficient, or equivalently, the residual variance.

Radiation Exposure Definitions

Absorbed Dose (D): The energy imparted to matter by ionizing radiation per unit mass of irradiated material at the place of interest in that material. The absorbed dose is expressed in units of rad (or gray) (1 rad = 0.01 gray).

Dose Equivalent (H): The product of absorbed dose (D) in rad (or gray) in tissue, a quality factor (Q), and other modifying factors (N). Dose equivalent (H) is expressed in units of rem (or sievert).

Annual Dose Equivalent: The dose equivalent received in a year. Annual dose equivalent is expressed in unit of rem (or sievert).

Effective Dose Equivalent (H_E): The sum over specified tissues of the products of the dose equivalent in a tissue (H_t) and the weighting factor (W_t) for that tissue, i.e. $H_E = \Sigma W_t H_t$. The effective dose equivalent is expressed in units of rem (or sievert).

Annual Effective Dose Equivalent: The effective dose equivalent received in a year. The annual dose eqiuvalent is expressed in units of rem.

Committed Dose Equivalent: The calculated dose equivalent projected to be received by a tissue or organ over a 50-year period after an intake of radionuclide into the body. It does not include contributions from external dose. Committed dose is expressed in units of rem (or sievert).

Committed Effective Dose Equivalent ($H_{E,50}$): The sum of the committed dose equivalents to various tissues in the body, each multiplied by its weighting factor. It does not include contributions from external dose. Committed effective dose equivalent is expressed in units of rem (or sievert).

Collective Dose Equivalent: The sum of the dose equivalents of all individuals in an exposed population. Collective dose equivalent is expressed in units of person-rem (or person-sievert).

Collective Effective Dose Equivalent: The sum of the effective dose equivalents of all individuals in an exposed population. Collective dose equivalent is expressed in units of person-rem (or person-sievert).

Cumulative Annual Effective Dose Equivalent: The sum of the annual effective dose equivalents recorded for an individual for each year of employment at a DOE or DOE contractor facility.

Extremity: Extremity includes hands and arms below the elbow or feet and legs below the knee.

Non-Stochastic Effects: Effects such as the opacity of the lens of the eye for which the severity of the effect varies with the dose, and for which a threshold may exist.

Stochastic Effects: Malignant and hereditary disease for which the probability of an effect rather than its severity, is regarded as a function of dose without a threshold for radiation protection purposes.