***COURSE: MA 598 – FALL 2013***

PROJECT II: **REGRESSION MODEL – ANALYSIS OF UTILITY CONSUMPTION BASED ON ELECTRIC BILLS**

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***ABSTRACT***

*The dataset contains monthly household electric billing charges for ten years (Jan. 1991 – Dec. 2000), for an-all electric home in the Midwest. Table 1 show us the potential explanatory variables used on this project. The dependent variable for our project is the monthly energy consumption (y).*

*The analysis of the Energy Consumption data vs. the other variables (see Table 1) start to examine it visually and statistically (Graphs).*

*Because of the number of variables, seasonal decomposition, and other factors, it was determined that a multiplicative model is the most appropriate for this time of series. In order to know which models give the best predictions of future observations, we start with the process of building a model. As a result of these calculations we got 6 models. Next, we continue with the analysis to select the best Model by using AIC/BIC/Cp criteria.*

***OBJECTIVES***

*The objective of this work is to select the most efficient variables from the original variables and build an adjusted Regression Model in order to predict future consumption.*

***DESCRIPTION OF THE VARIABLES***

*The explanatory of the variables used on this project are:*

*Table 1*

|  |  |  |  |
| --- | --- | --- | --- |
| **y** | Consumption (Kwh) | **x6** | HDD (Heating Degree Days) |
| **x1** | Num (Observation #) | **x7** | CDD (Cooling Degree Days) |
| **x2** | Year | **x8** | Size (# family members at home) |
| **x3** | Month | **x9** | Meter (yes = 1) |
| **x4** | Bill ($ with taxes) | **x10** | Pump 1 (new = 1) |
| **x5** | Temp (avge T℉) | **x11** | Pump 2 (new = 1) |
|  |  | **x12** | Rider Total (Total charge/Kwh) |

**> data=read.table("C:/Users/Maria/Desktop/COMP STAT/PROJECT 2/projectSTAT.txt",head=T)**

**> data**

**> dim(data)**

[1] 120 13

***GRAPHIC ANALYSIS***

***(1) Boxplot analysis of Consumption***

**> y="consumption"**

**> boxplot(data$y~data$x2,main="Consumption (during 10 years)",xlab="Year",ylab="Kwh",col=7)**

****

***Graph # 1***

*Graphically the mean of the Consumption (Kwh) fluctuate approximately in the range of (1000-5000) from January 1991 through December 2000 during the ten years and the maximum variance happened in 1996 (see graph #1).*

**> ts.plot(data$y,col=3,main="Time Series - Consumption",xlab="Months",ylab="y (Kwh)")**



***Graph # 2***

*It is important to show events over time such as plotting the data as a function of time (for 10 years ≅ 120 months). We can see (graph # 2) that the highest consumption happened between 60th – 65th months, besides of the pronounced seasonality with a downward tendency after 75 months of consumption. Upon inspection of these data in the graph ( y – Months), it seems as if during the interval of 61-64 months (1996) exists unusual high electrical consumption.*

***(2) In order to show events over time, it is helpful to plot the data showing time series.***

**> ts.plot(data$x4,col=4,main="Time Series - Bill",xlab="Months",ylab="$")**

****

***Graph # 3***

*Graph # 3 shows us unusual values (a possible missing value at 37th month and possible outliers at the 104th month and 105th month)*

**>ts.plot(data$x5,col=6,main="Time Series - Temp",xlab="Months",ylab="Temp (F)")**

****

***Graph # 4***

**>ts.plot(data$x6,col=3,main="Time Series - HDD",xlab="Months",ylab="HDD-days")**

****

***Graph # 5***

**> ts.plot(data$x7,col=1,main="Time Series - CDD",xlab="Months",ylab="CDD-days")**

****

***Graph # 6***

*Graphs # 4, 5 and 6 show us similarities in some way. But we cannot confirm yet what direct relationships connect each other.*

**> ts.plot(data$x8,col=2,main="Time Series - Size",xlab="Months",ylab="# Family Members")**

****

***Graph # 7***

**> ts.plot(data$x9,col=10,main="Time Series - New Meter",xlab="Months",ylab="Yes-New Meter")**

****

***Graph # 8***

**> ts.plot(data$x10,col=7,main="Time Series - New Heat Pump 1",xlab="Months",ylab="# New Heat Pump 1")**

****

***Graph # 9***

**> ts.plot(data$x11,col=8,main="Time Series - New Heat Pump 2",xlab="Months",ylab="# New Heat Pump 2")**

****

***Graph # 10***

*According to these graphics, we saw some of them were similar and some of them were not. We can’t assume that the similar might have some relationship. However, it is necessary to continue working on these variables.*

**(3) *Linear Correlation: variables xi vs. y (Consumption)***

**> plot(data$x4,data$y,col=4,main="Correlation Consumption- Bill",xlab="$",ylab="Kwh")**

****

***Graph # 11***

**> plot(data$x5,data$y,col=1,main="Correlation Consumption- Temperature",xlab="Temp (F)",ylab="Kwh")**

****

***Graph # 12***

**> plot(data$x6,data$y,col=2,main="Correlation Consumption-HDD",xlab="HDD days",ylab="Kwh")**

****

***Graph # 13***

**> plot(data$x7,data$y,col=1,main="Correlation Consumption-CDD",xlab="CDD days",ylab="Kwh")**

****

***Graph # 14***

**> plot(data$x8,data$y,col=2,main="Correlation Consumption-Size",xlab="# Family Members",ylab="Kwh")**

****

***Graph # 15***

**> plot(data$x9,data$y,col=3,main="Correlation Consumption-New Meter",xlab="Yes-New Meter",ylab="Kwh")**

****

***Graph # 16***

**> plot(data$x10,data$y,col=4,main="Correlation Consumption-New Heat Pump 1",xlab="# New Heat Pump 1",ylab="Kwh")**

****

***Graph # 17***

**> plot(data$x11,data$y,col=7,main="Correlation Consumption-New Heat Pump 2",xlab="# New Heat Pump 2",ylab="Kwh")**

****

***Graph # 18***

*After examining the relationship between the independent variables and Consumption (y) several hypotheses are likely.*

*Therefore, it is better to work with a multiplicative model.*

***THE PROCESS OF BUILDING THE MODEL***

*In order to know which models give the best predictions of future observations generated from the same process as the original data; we will follow the next steps:*

1. ***First, we have to fit a full model for all variables.***

**> data=read.table("C:/Users/Maria/Desktop/COMP STAT/PROJECT 2/projectSTAT.txt",head=T)**

**> data=na.omit(data)**

**> data** *(see Annex 1)*

**> model=lm(y~x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12,data=data)**

**> model**

Call:

lm(formula = y ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 +

x11 + x12, data = data)

Coefficients:

(Intercept) x2 x3 x4 x5 x6

-3.525e+05 1.749e+02 6.621e+00 4.619e+01 1.365e+01 4.593e-01

x7 x8 x9 x10 x11 x12

8.159e-02 2.841e+02 -1.458e+03 -2.227e+02 4.565e+02 -1.576e+05

*Here, we have to test the condition of autocorrelations between all variables.*

**> library(lmtest)**

**> dwtest(y~x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12,data=data)**

Durbin-Watson test

data: y ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12

DW = 1.4296, p-value = 5.978e-05

alternative hypothesis: true autocorrelation is greater than 0

*Note that the p-value of the DW test is smaller than 0.05 which conclude that errors are positively autocorrelated. Thus, we have to drop some variables which produce the error terms are positively autocorrelated in the following.*

1. ***Perform residual analysis***

**> model=lm(y~x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12,data=data)**

**> par(mfrow=c(2,2))**

**> plot(model)**



***Graph # 19***

*Graphically, we can see some outliers (e.g. x4 in Aug. ’99).*

**> model=lm(y~x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12,data=data)**

**> model**

Call:

lm(formula = y ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 +

x11 + x12, data = data)

Coefficients:

(Intercept) x2 x3 x4 x5 x6 x7

-3.525e+05 1.749e+02 6.621e+00 4.619e+01 1.365e+01 4.593e-01 8.159e-02

x8 x9 x10 x11 x12

2.841e+02 -1.458e+03 -2.227e+02 4.565e+02 -1.576e+05

**> library(car)**

**> outlierTest(model)**

rstudent unadjusted p-value Bonferonni p

105 -5.113232 1.4144e-06 0.00016831

104 4.317726 3.5582e-05 0.00423420

*Thus, we verify that there exists two outliers in the data, they are: x1=104 and x1= 105. Now, the data needs to be transformed to a more steady form in order to decrease the influence of these outliers.*

1. ***Transformation of the original data***

*In order to decrease the influence of outliers, we transform original data to make the model more reliable.*

**> b=boxcox(model)**

****

***Graph # 20***

*Since λ = 1/2, a transformation of the original data is necessary.*

**> model1=lm(y^(1/2)~x2+x3+x4+x5+x6+x7+x8+x9+x10+x11+x12,data=data)**

**> b=boxcox(model1)**

****

***Graph # 21***

*The Graph # 21 shows us that λ is nearly 1. Thus, the model is transformed to:*

**y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 + x12**

1. ***Use Stepwise Regression to choose variables.***

**> library(MASS)**

**> model=stepAIC(model1, direction="both")**

Start: AIC=378.68

y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10 + x11 +

x12

Df Sum of Sq RSS AIC

- x7 1 0.2 2344.3 376.69

- x5 1 4.0 2348.0 376.88

- x9 1 6.4 2350.5 377.01

- x6 1 11.6 2355.7 377.27

- x11 1 11.6 2355.7 377.27

- x10 1 15.2 2359.3 377.45

- x2 1 15.8 2359.9 377.48

<none> 2344.1 378.68

- x3 1 55.0 2399.1 379.44

- x8 1 90.1 2434.2 381.17

- x12 1 590.0 2934.1 403.40

- x4 1 9025.2 11369.2 564.59

Step: AIC=376.69

y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x8 + x9 + x10 + x11 + x12

Df Sum of Sq RSS AIC

- x9 1 6.3 2350.6 375.01

- x11 1 11.5 2355.8 375.28

- x10 1 15.3 2359.6 375.47

- x2 1 16.2 2360.5 375.51

- x5 1 37.2 2381.5 376.57

<none> 2344.3 376.69

- x3 1 55.1 2399.4 377.46

- x6 1 60.2 2404.5 377.71

+ x7 1 0.2 2344.1 378.68

- x8 1 91.8 2436.1 379.27

- x12 1 591.0 2935.3 401.45

- x4 1 9373.7 11718.0 566.18

Step: AIC=375.01

y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x8 + x10 + x11 + x12

Df Sum of Sq RSS AIC

- x11 1 6.5 2357.0 373.34

- x10 1 18.5 2369.1 373.94

- x2 1 21.4 2371.9 374.09

- x5 1 39.5 2390.0 374.99

<none> 2350.6 375.01

- x3 1 48.8 2399.4 375.46

- x6 1 59.9 2410.4 376.00

+ x9 1 6.3 2344.3 376.69

+ x7 1 0.0 2350.5 377.01

- x8 1 86.7 2437.2 377.32

- x12 1 585.1 2935.6 399.46

- x4 1 13071.5 15422.0 596.87

Step: AIC=373.34

y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x8 + x10 + x12

Df Sum of Sq RSS AIC

- x10 1 13.5 2370.5 372.02

- x2 1 15.0 2372.0 372.09

<none> 2357.0 373.34

- x5 1 40.0 2397.0 373.34

- x3 1 52.6 2409.6 373.96

- x6 1 59.6 2416.6 374.31

+ x11 1 6.5 2350.6 375.01

+ x9 1 1.2 2355.8 375.28

+ x7 1 0.0 2357.0 375.34

- x8 1 105.8 2462.9 376.57

- x12 1 742.9 3099.9 403.94

- x4 1 13130.1 15487.1 595.37

Step: AIC=372.02

y^(1/2) ~ x2 + x3 + x4 + x5 + x6 + x8 + x12

Df Sum of Sq RSS AIC

- x2 1 1.7 2372.2 370.10

<none> 2370.5 372.02

- x5 1 45.4 2415.9 372.28

- x3 1 52.1 2422.6 372.60

- x6 1 60.9 2431.4 373.03

+ x10 1 13.5 2357.0 373.34

+ x9 1 4.3 2366.2 373.80

+ x11 1 1.5 2369.1 373.94

+ x7 1 0.1 2370.5 374.01

- x8 1 97.7 2468.2 374.82

- x12 1 3606.1 5976.6 480.06

- x4 1 15120.0 17490.5 607.84

Step: AIC=370.1

y^(1/2) ~ x3 + x4 + x5 + x6 + x8 + x12

Df Sum of Sq RSS AIC

<none> 2372.2 370.10

- x5 1 47.7 2419.9 370.47

- x6 1 63.3 2435.5 371.24

- x3 1 65.8 2438.1 371.36

+ x9 1 5.9 2366.3 371.81

+ x2 1 1.7 2370.5 372.02

+ x11 1 0.2 2372.0 372.09

+ x10 1 0.2 2372.0 372.09

+ x7 1 0.2 2372.1 372.09

- x8 1 147.6 2519.8 375.29

- x12 1 3758.0 6130.2 481.08

- x4 1 16721.5 19093.7 616.28

*Our final model is:* **y^(1/2) ~ x3 + x4 + x5 + x6 + x8 + x12**

*Here, we also have to test the the condition of autocorrelations between all these variables.*

**> library(lmtest)**

**> dwtest(y^(1/2)~x3+x4+x5+x6+x8+x12,data=data)**

Durbin-Watson test

data: y^(1/2) ~ x3 + x4 + x5 + x6 + x8 + x12

DW = 2.0936, p-value = 0.5477

alternative hypothesis: true autocorrelation is greater than 0.

*It is obviously that there is no autocorrelation in this new model. Thus, the variables we choose are:* ***x3, x4, x5, x6, x8,*** *and* ***x12.***

1. ***Select models for further analysis by using regsubsets***

**> library(leaps)**

**> subsets=regsubsets(y^(1/2)~x3+x4+x5+x6+x8+x12,data=data)**

**> summary(subsets)**

Subset selection object

Call: regsubsets.formula(y^(1/2) ~ x3 + x4 + x5 + x6 + x8 + x12, data = data)

6 Variables (and intercept)

Forced in Forced out

x3 FALSE FALSE

x4 FALSE FALSE

x5 FALSE FALSE

x6 FALSE FALSE

x8 FALSE FALSE

x12 FALSE FALSE

1 subsets of each size up to 6

Selection Algorithm: exhaustive

x3 x4 x5 x6 x8 x12

1 ( 1 ) " " "\*" " " " " " " " "

2 ( 1 ) " " "\*" " " " " " " "\*"

3 ( 1 ) " " "\*" " " " " "\*" "\*"

4 ( 1 ) "\*" "\*" " " " " "\*" "\*"

5 ( 1 ) "\*" "\*" " " "\*" "\*" "\*"

6 ( 1 ) "\*" "\*" "\*" "\*" "\*" "\*"

*Analyzing this subset (6 models), we need to choose the elements which can best reflect the relationship between consumption (y) and the other variables (x3 x4 x5 x6 x8 x12).*

1. ***Select the best model by using AIC/BIC/Cp.***

*When using an all-possible-regressions procedure, we are typically given the choice between several numerical criteria on which to rank the models. Next, we analyze the different Models with* ***AIC/BIC/Cp*** *criteria.*

Model1: y^(1/2) ~ x4

Model2: y^(1/2) ~ x4 + x12

Model3: y^(1/2) ~ x4 + x8 + x12

Model4: y^(1/2) ~ x3 + x4 + x8 + x12

Model5: y^(1/2) ~ x3 + x4 + x6 + x8 + x12

Model6: y^(1/2) ~ x3 + x4 + x5 + x6 + x8 + x12

*Comparing models using these criteria: AIC/BIC/Cp.*

> AIC(model1)

[1] 843.8841

> BIC(model1)

[1] 852.2215

*We can get all the AIC and BIC values of all these 6 models.*

*Finally,*

**Table 2**

|  |  |  |
| --- | --- | --- |
| **Model** | **AIC** | **BIC** |
| Model1 | 843.8841 | 852.2215 |
| Model2 | 718.3105 | 729.427 |
| Model3 | 711.7892 | 725.6848 |
| Model4 | 709.7511 | 726.4258 |
| Model5 | 710.1777 | 729.6316 |
| Model6 | 709.8097 | 732.0427 |

*Models 3 and 4 have lower BIC and AIC, in order to decide which one is better we use the Mallows "Cp" criteria :*

**> library(leaps)**

**> subsets=regsubsets(y^(1/2)~x3+x4+x5+x6+x8+x12,data=data)**

**> summary(subsets)$cp**

[1] 260.856741 15.658333 8.767547 6.771605 7.251007 7.000000

*Since our p is 6, then 4th number is most approaching 6. Thus, the model 4 is the best.*

*Next, we can observe that the model 4 has the minimum AIC and the second minimum BIC.*

1. **Make recommendation**

*According to the analysis by using the criteria of AIC, BIC and Cp, the best model we can choose is model 4:*

**y^(1/2)~ x3+x4+x8+x12**

***SUMMARY OF THE OPTIMUM MODEL***

**> model4=lm(y^(1/2)~x3+x4+x8+x12,data=data)**

**> model4**

Call:

lm(formula = y^(1/2) ~ x3 + x4 + x8 + x12, data = data)

Coefficients:

(Intercept) x3 x4 x8 x12

10.9565 -0.2944 0.3243 2.3873 -1445.1728

**> summary(model4)**

Call:

lm(formula = y^(1/2) ~ x3 + x4 + x8 + x12, data = data)

Residuals:

Min 1Q Median 3Q Max

-20.9120 -1.7949 0.4095 1.9525 26.1328

Coefficients:

Estimate Std. Error t value Pr(>|t|)

(Intercept) 1.096e+01 3.770e+00 2.906 0.00440 \*\*

x3 -2.944e-01 1.484e-01 -1.984 0.04970 \*

x4 3.243e-01 9.942e-03 32.623 < 2e-16 \*\*\*

x8 2.387e+00 9.061e-01 2.635 0.00959 \*\*

x12 -1.445e+03 1.083e+02 -13.350 < 2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.638 on 114 degrees of freedom

Multiple R-squared: 0.9504, Adjusted R-squared: 0.9487

F-statistic: 546.6 on 4 and 114 DF, p-value: < 2.2e-16

*The Optimum Model:*

**y = (**-0.2944 **x3 +** 0.3243 **x4 +** 2.387 **x8 +** 1445 **x12)^2**

**Consumption = (**-0.2944 **Month +** 0.3243 **Bill +** 2.387 **Size +** 1445 **Rider Total)^2**

***Recommendations and Conclusions***

* *Missing values and outliers were found in the data (appropriate techniques were used to address them).*
* *We determined that a Multiplicative Model is more appropriate for this time series.*
* *We used DW test to make sure that there is no autocorrelation between every variable after the process of reduction of some variables.*
* *In order to get our best subset for our Multiple Regression Model, it is important to use the function leap.*
* *Comparing models using criteria: AIC/BIC/Cp: Table # 2 compares the values of AIC and BIC taking from models 3 and 4. The AIC penalizes the number of parameters less strongly than does the BIC, therefore we use the value of Cp which is much more approach to p in order to get our best subset.*
* *Up to this point, we can conclude that the Optimal model which will give us the best predictions of future observations is:*

**Consumption = (**-0.2944 **Month +** 0.3243 **Bill +** 2.387 **Size +** 1445 **Rider Total)^2**

**ANNEX**

**1)**

x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 y

1 1 1991 1 162.10 29.1 1229 0 4 0 0 0 -0.0022880 5600

2 2 1991 2 256.90 31.5 999 0 4 0 0 0 -0.0022880 9463

3 3 1991 3 151.15 41.9 734 0 4 0 0 0 -0.0022880 5154

4 4 1991 4 118.76 53.4 373 0 4 0 0 0 -0.0006000 3576

5 5 1991 5 100.71 63.7 162 94 4 0 0 0 -0.0006340 2894

6 6 1991 6 83.97 72.9 4 211 4 0 0 0 -0.0006340 2257

7 7 1991 7 99.40 76.8 0 328 4 0 0 0 -0.0004730 2826

8 8 1991 8 103.64 75.0 0 261 4 0 0 0 -0.0004730 2986

9 9 1991 9 71.59 68.4 52 110 4 0 0 0 -0.0004730 1774

10 10 1991 10 94.92 56.8 326 18 4 0 0 0 -0.0010020 2713

11 11 1991 11 78.83 43.3 644 0 4 0 0 0 -0.0010020 2092

12 12 1991 12 182.85 32.5 1049 0 4 0 0 0 -0.0010020 6109

13 13 1992 1 165.23 29.1 1229 0 4 0 0 0 -0.0008700 5400

14 14 1992 2 197.94 31.5 999 0 4 0 0 0 -0.0008700 6657

15 15 1992 3 146.80 41.9 734 0 4 0 0 0 -0.0008700 4692

16 16 1992 4 127.17 53.4 373 0 4 0 0 0 -0.0026520 4243

17 17 1992 5 112.40 63.7 162 94 4 0 0 0 -0.0026520 3631

18 18 1992 6 70.35 72.9 4 211 4 0 0 0 -0.0026520 1891

19 19 1992 7 72.98 76.8 0 328 4 0 0 0 -0.0015050 1905

20 20 1992 8 82.80 75.0 0 261 4 0 0 0 -0.0015050 2292

21 21 1992 9 70.33 68.4 52 110 4 0 0 0 -0.0015050 1800

22 22 1992 10 76.13 56.8 326 18 4 0 0 0 -0.0019080 2063

23 23 1992 11 75.54 43.3 644 0 4 0 0 0 -0.0019080 2040

24 24 1992 12 130.32 32.5 1049 0 4 0 0 0 -0.0019080 4236

25 25 1993 1 180.08 29.1 1229 0 4 0 0 0 -0.0016430 6163

26 26 1993 2 222.99 31.5 999 0 4 0 0 0 -0.0016430 7864

27 27 1993 3 214.45 41.9 734 0 4 0 0 0 -0.0016430 7526

28 28 1993 4 160.98 53.4 373 0 4 0 0 0 0.0001610 5028

29 29 1993 5 99.34 63.7 162 94 4 0 0 0 0.0001610 2754

30 30 1993 6 75.31 72.9 4 211 4 0 0 0 0.0001610 1868

31 31 1993 7 134.99 76.8 0 328 4 0 0 0 -0.0011900 4294

32 32 1993 8 100.22 75.0 0 261 4 0 0 0 -0.0011900 2940

33 33 1993 9 90.79 68.4 52 110 4 0 0 0 -0.0011900 2573

34 34 1993 10 64.62 56.8 326 18 4 0 0 0 -0.0018690 1599

35 35 1993 11 72.79 43.3 644 0 4 0 0 0 -0.0018690 1926

36 36 1993 12 135.56 32.5 1049 0 4 0 0 0 -0.0018690 4439

38 38 1994 2 158.59 31.5 999 0 4 0 0 0 -0.0031410 5664

39 39 1994 3 183.06 41.9 734 0 4 0 0 0 -0.0031410 6699

40 40 1994 4 115.95 53.4 373 0 4 0 0 0 -0.0039390 4002

41 41 1994 5 82.27 63.7 162 94 4 0 0 0 -0.0039390 2525

42 42 1994 6 69.33 72.9 4 211 4 0 0 0 -0.0039390 1958

43 43 1994 7 91.38 76.8 0 328 4 0 0 0 -0.0015480 2635

44 44 1994 8 80.28 75.0 0 261 4 0 0 0 -0.0014390 2187

45 45 1994 9 70.00 68.4 52 110 4 0 0 0 -0.0014390 1782

46 46 1994 10 56.47 56.8 326 18 4 0 0 0 -0.0116139 2156

47 47 1994 11 56.47 43.3 644 0 4 0 0 0 -0.0116139 2156

48 48 1994 12 71.63 32.5 1049 0 4 0 0 0 -0.0116139 3184

49 49 1995 1 129.06 29.1 1229 0 4 0 0 0 -0.0114160 6980

50 50 1995 2 154.32 31.5 999 0 4 0 0 0 -0.0112570 8573

51 51 1995 3 174.80 41.9 734 0 4 0 0 0 -0.0093220 8751

52 52 1995 4 113.25 53.4 373 0 4 0 0 0 -0.0093220 5163

53 53 1995 5 94.23 63.7 162 94 4 0 0 0 -0.0093220 4055

54 54 1995 6 69.79 72.9 4 211 4 0 0 0 -0.0093220 2630

55 55 1995 7 89.06 76.8 0 328 4 0 0 0 -0.0095160 3798

56 56 1995 8 96.29 75.0 0 261 4 0 0 0 -0.0095160 4225

57 57 1995 9 107.30 68.4 52 110 4 0 0 0 -0.0091060 4754

58 58 1995 10 77.90 56.8 326 18 4 0 0 0 -0.0082480 2911

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65 65 1996 5 107.82 63.7 162 94 4 0 0 0 -0.0106620 5280

66 66 1996 6 77.76 72.9 4 211 4 0 0 0 -0.0106620 3371

67 67 1996 7 70.31 76.8 0 328 4 0 0 0 -0.0106620 2898

68 68 1996 8 80.85 75.0 0 261 4 0 0 0 -0.0106620 3567

69 69 1996 9 56.05 68.4 52 110 4 0 0 0 -0.0106620 1992

70 70 1996 10 49.53 56.8 326 18 4 0 0 0 -0.0123880 1784

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73 73 1997 1 155.99 29.1 1229 0 4 0 1 0 0.0006890 4746

74 74 1997 2 198.82 31.5 999 0 4 0 1 0 0.0006890 6295

75 75 1997 3 106.51 41.9 734 0 4 0 1 0 0.0006150 2966

76 76 1997 4 81.45 53.4 373 0 4 0 1 0 0.0005780 2061

77 77 1997 5 75.95 63.7 162 94 4 0 1 0 0.0005780 1861

78 78 1997 6 60.83 72.9 4 211 4 0 1 0 0.0005780 1312

79 79 1997 7 58.20 76.8 0 328 4 0 1 0 0.0032130 1106

80 80 1997 8 65.61 75.0 0 261 4 0 1 0 0.0032130 1350

81 81 1997 9 57.78 68.4 52 110 3 0 1 0 0.0013920 1166

82 82 1997 10 49.40 56.8 326 18 3 0 1 0 0.0006200 920

83 83 1997 11 52.86 43.3 644 0 3 0 1 0 0.0006200 1021

84 84 1997 12 78.13 32.5 1049 0 3 0 1 0 0.0001230 1975

85 85 1998 1 100.43 29.1 1229 0 3 0 1 0 0.0011540 2691

86 86 1998 2 102.64 31.5 999 0 3 0 1 0 0.0011540 2769

87 87 1998 3 66.77 41.9 734 0 3 0 1 0 0.0009950 1504

88 88 1998 4 65.68 53.4 373 0 3 0 1 0 0.0019840 1413

89 89 1998 5 37.03 63.7 162 94 4 0 1 0 0.0019840 562

90 90 1998 6 37.88 72.9 4 211 4 0 1 0 0.0019840 581

91 91 1998 7 42.44 76.8 0 328 4 0 1 0 0.0019840 698

92 92 1998 8 46.18 75.0 0 261 4 0 1 0 0.0019840 798

93 93 1998 9 42.87 68.4 52 110 3 0 1 0 0.0019840 710

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120 120 2000 12 89.49 32.5 1049 0 2 1 1 1 0.0000210 1462