

General Mills



Forecasting Tool Solution Case Study

Customer Profile

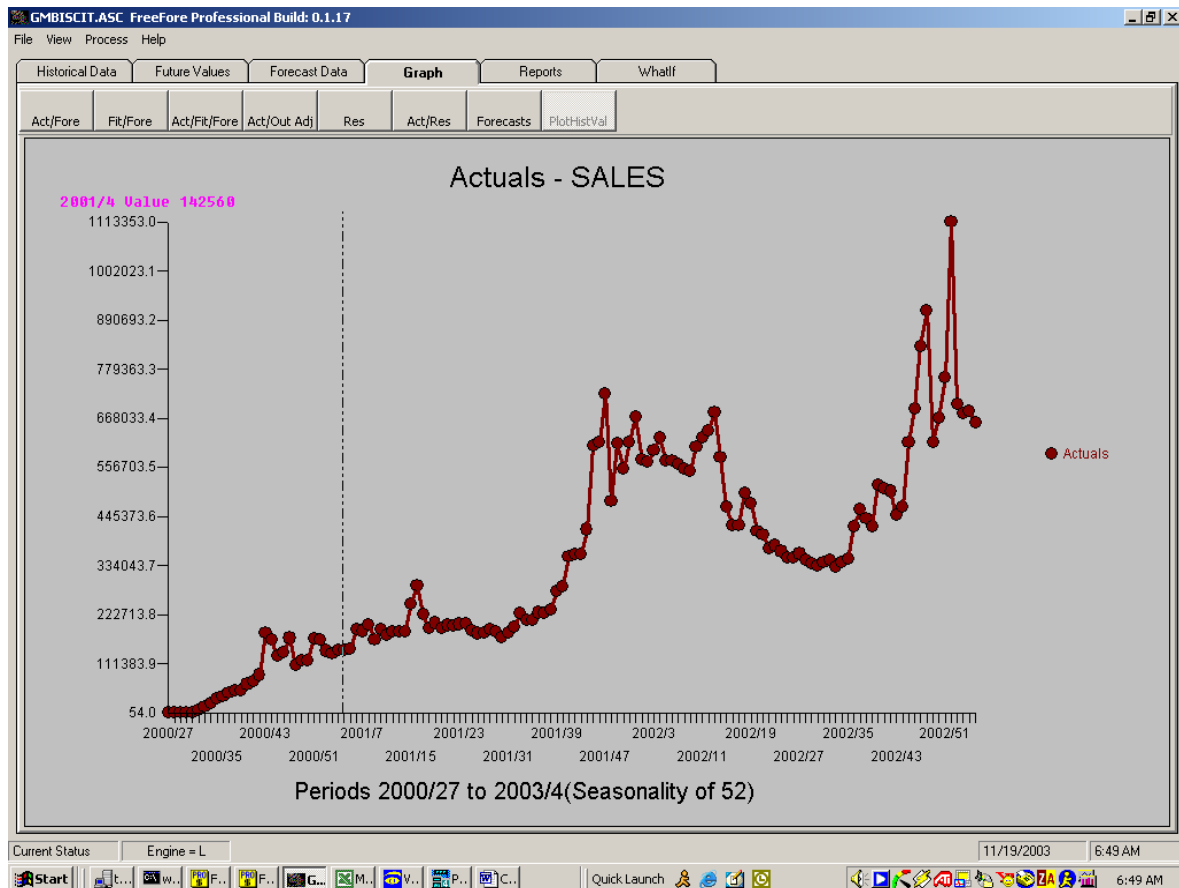
General Mills is a leading supplier of processed food in the United States. One of their high profile products is their Frozen Biscuit product.

Business Problems: Develop accurate forecasts and incorporate significant marketing variables (price, TV ads etc.) into a working model that would allow marketing and logistics to more effectively allocate resources.

Additionally, it was desired to detect “Peculiar data”. Data is peculiar if it represents a peculiar case described by a relatively small number of objects and is very different from other objects in the data set.

By identifying the “Peculiar Data” one can then research and discover the source of the peculiarity. Step 1 is the identification of these data points.

We begin by examining the 134 week sales history from week 27 in 2002.



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Actual data was available for 10 series. This is a snapshot of the first 23 weeks.

1	AUP	FSI	EASTER	TKSGVN	CHRISTM/QM	TD	TPR	TV	SALES
2									
3									
4	2.69	0	0	0	0	0	0	0	54
5	2.69	0	0	0	0	0	1	0	355
6	2.69	0	0	0	0	0	1	0	493
7	2.69	0	0	0	0	0	1	0	500
8	2.77	0	0	0	0	1	2	0	1367
9	2.66	0	0	0	0	0	7	0	5922
10	2.85	0	0	0	0	0	12	0	13012
11	2.87	0	0	0	0	0	17	0	21360
12	2.88	0	0	0	0	0	22	1	30937
13	2.9	0	0	0	0	2	28	0	36928
14	2.91	0	0	0	0	2	33	1	45993
15	2.93	0	0	0	0	3	36	0	49806
16	3.01	0	0	0	0	2	41	1	49476
17	2.97	0	0	0	0	2	44	1	65058
18	2.93	0	0	0	0	1	47	2	70749
19	2.87	0	0	0	0	2	50	3	85602
20	2.78	0	0	0	0	5	54	4	181787
21	2.74	0	0	0	0	7	56	3	165470
22	2.81	0	0	0	0	4	57	5	128660
23	2.89	0	0	0	0	3	61	4	135896
24	2.87	0	0	1	0	4	63	4	169571
25	2.9	0	0	0	0	3	60	3	107621
26	2.92	0	0	0	0	3	62	4	118029

General Mills marketers drive sales through their retail outlets by aggressive pricing and through a number of marketing initiatives including TV campaigns and other sales motivational programs. Sales of this product are quite seasonal and are impacted by a number of causal variables. General Mills desired to measure the historical impact on sales as a result of these variables and to develop a “what if?” functionality in order to more accurately forecast and control future sales.

There were three Holiday Variables under investigation, Price (AUP), # of Outlets (TD) and four other marketing type variables namely FSI,QM,TPR and TV.

The Final Model developed using AUTOBOX was

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$$\begin{aligned}
 Y(T) = & .92863E+06 \\
 & +[X1(T)] [(- .16483E+06)] \\
 & +[X2(T)] [(+ 1.0459)] \\
 & +[X3(T)] [(+ 35358.)] \\
 & +[X4(T)] [(+ 5482.5)] \\
 & +[X5(T)] [(+ 3019.9)] \\
 & +[X6(T)] [(+ 4107.7)] \\
 & +[X7(T)] [(+ .31251E+06)] \\
 & +[X8(T)] [(+ .10303E+06)] \\
 & +[X9(T)] [(+ .26597E+06)] \\
 & +[X10(T)] [(- .14536E+06)] \\
 & +[X11(T)] [(- 55156.)] \\
 & +[X12(T)] [(+ 43341.)] \\
 & +[X13(T)] [(+ 92289.)] \\
 & +[X14(T)] [(- 52403.)] \\
 & + [(1- .981B** 1)]**-1 [A(T)]
 \end{aligned}$$

Analysis for Variable

Y = SALES
 X1 = AUP
 X2 = FSI
 X3 = MOVE_XMAS
 X4 = QM
 X5 = TPR
 X6 = TV

: NEWLY IDENTIFIED VARIABLE	X7 = I~P00130	PULSE
: NEWLY IDENTIFIED VARIABLE	X8 = I~P00078	PULSE
: NEWLY IDENTIFIED VARIABLE	X9 = I~P00126	PULSE
: NEWLY IDENTIFIED VARIABLE	10 = I~P00074	PULSE
: NEWLY IDENTIFIED VARIABLE	11 = I~P00090	PULSE
: NEWLY IDENTIFIED VARIABLE	12 = I~P00041	PULSE
: NEWLY IDENTIFIED VARIABLE	13 = I~P00125	PULSE
: NEWLY IDENTIFIED VARIABLE	14 = I~P00117	PULSE

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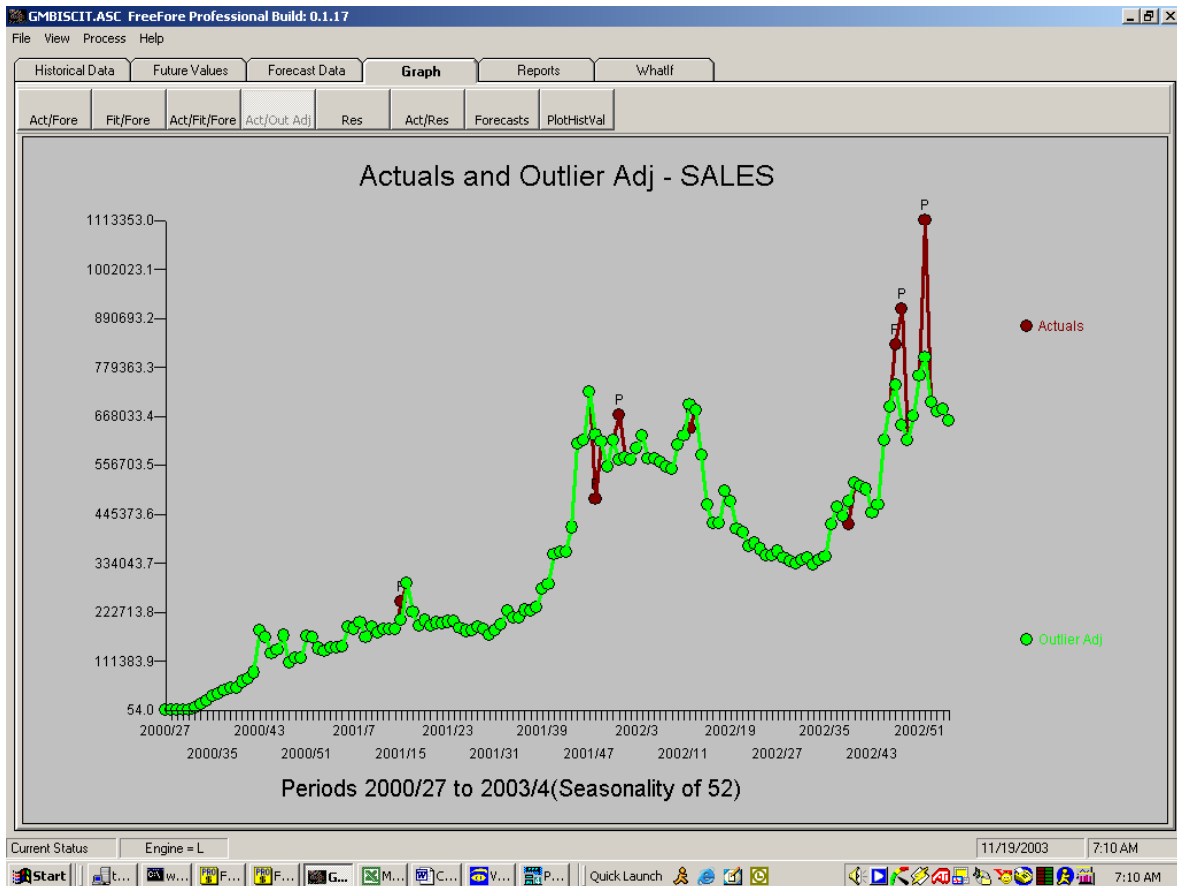
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 & +[X14(T)] [(- 52403. \quad)] \\
 & + [(1- .981B** 1) ** -1 [A(T)]
 \end{aligned}$$

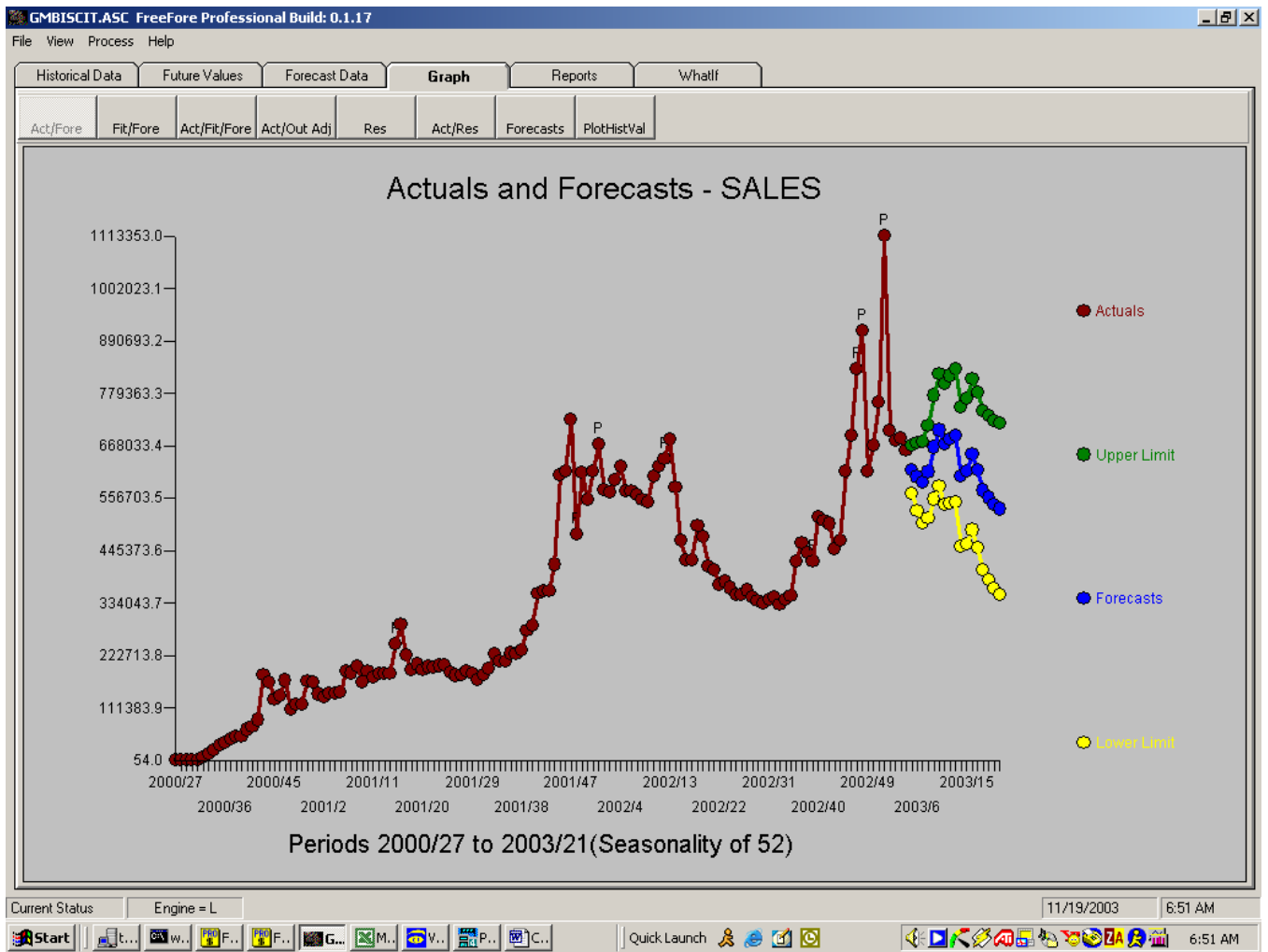
where eight “Peculiar Data Points” were identified as “Newly Identified Variables” and two holidays and one of the marketing variables were deleted as not being statistically significant. If you don’t account for outliers then your model will not be robust for forecasting anything!

A peek at the Peculiar Data Points (in red) ...



This Model was then used to make a projection for the next 17 weeks.

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Of course forecasts require the user to specify the future values of the significant cause variables including Price.

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File View Process Help

Historical Data **Future Values** Forecast Data Graph Reports W/half

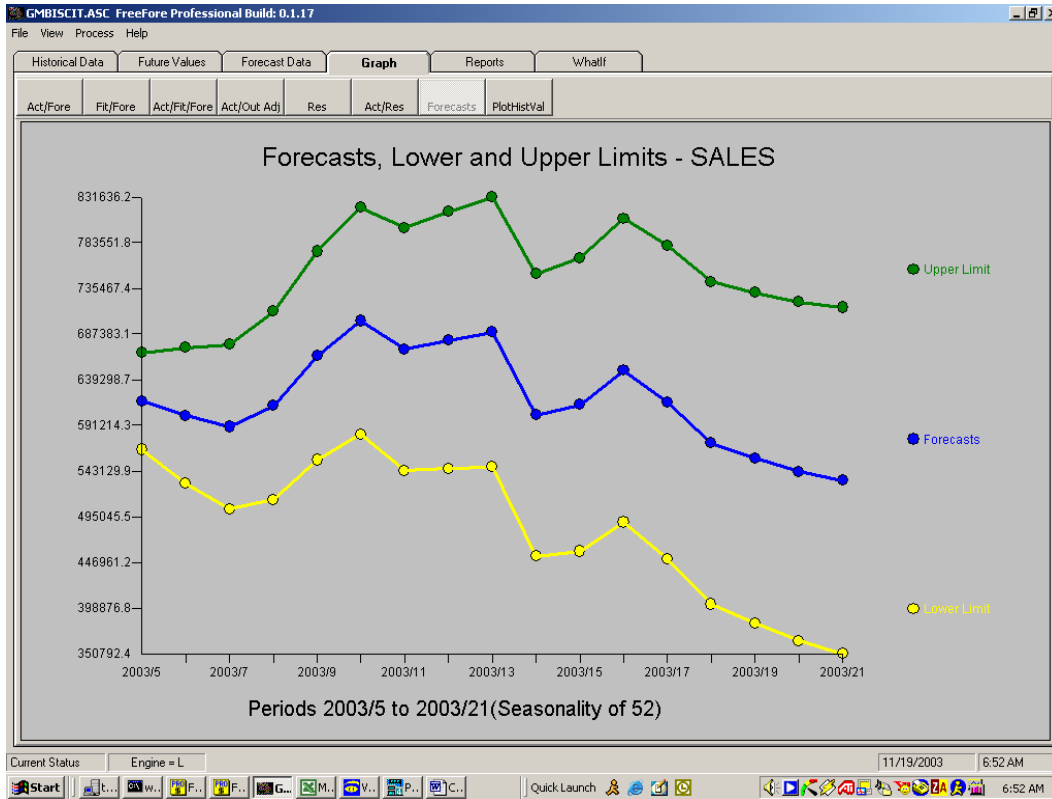
	AUP	FSI	MOVE EAS	MOVE TKS	MOVE XMAS	QM	TD	TPR	TV
2003/5	2.840	12193.000	0.000	0.000	0.000	6.000	290.000	12.000	11.000
2003/6	2.840	6097.000	0.000	0.000	0.000	6.000	290.000	12.000	9.000
2003/7	2.840	3048.000	0.000	0.000	0.000	6.000	290.000	12.000	7.000
2003/8	2.840	1524.000	0.000	0.000	0.000	6.000	290.000	12.000	13.000
2003/9	2.860	762.000	0.000	0.000	0.000	11.000	288.000	15.000	18.000
2003/10	2.860	24381.000	0.000	0.000	0.000	11.000	288.000	15.000	21.000
2003/11	2.860	12191.000	0.000	0.000	0.000	11.000	288.000	15.000	17.000
2003/12	2.860	6095.000	0.000	0.000	0.000	11.000	288.000	15.000	21.000
2003/13	2.860	3048.000	0.000	0.000	0.000	11.000	288.000	15.000	24.000
2003/14	2.930	1524.000	0.000	0.000	0.000	4.000	285.000	10.000	19.000
2003/15	2.930	762.000	0.000	0.000	0.000	4.000	285.000	10.000	22.000
2003/16	2.930	23881.000	1.000	0.000	0.000	4.000	285.000	10.000	25.000
2003/17	2.930	11940.000	0.000	0.000	0.000	4.000	285.000	10.000	20.000
2003/18	2.940	5970.000	0.000	0.000	0.000	4.000	283.000	4.000	16.000
2003/19	2.940	2985.000	0.000	0.000	0.000	4.000	283.000	4.000	13.000
2003/20	2.940	1493.000	0.000	0.000	0.000	4.000	283.000	4.000	10.000
2003/21	2.940	746.000	0.000	0.000	0.000	4.000	283.000	4.000	8.000

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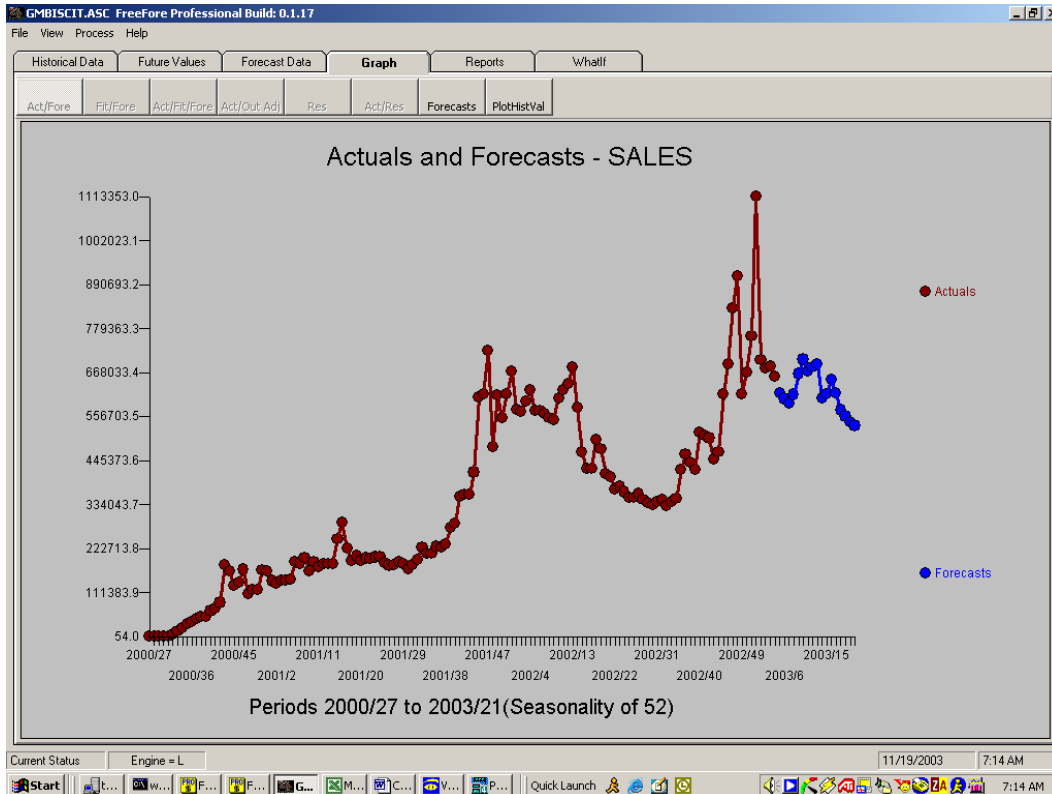
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	SALES
2003/5	616525.668
2003/6	601391.581
2003/7	589454.579
2003/8	611984.068
2003/9	664388.082
2003/10	700911.405
2003/11	671237.156
2003/12	680807.461
2003/13	689468.166
2003/14	601854.074
2003/15	612922.361
2003/16	648976.757
2003/17	615508.275
2003/18	572632.991
2003/19	556763.481
2003/20	542463.482
2003/21	533058.185

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and graphically again.



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In order to demonstrate the “what if ?” capability, we elect to evaluate the impact of Price (AUP) on our forecasts. Using the pop-up menu we simply change our price points.

The price points used in the preceeding analysis for the next 17 weeks were

2.84 week 1-4 ; 2.86 week 5-9 ; 2.93 week 10-13 and 2.94 week 14-17

	AUP
2003/5	2.840
2003/6	2.840
2003/7	2.840
2003/8	2.840
2003/9	2.860
2003/10	2.860
2003/11	2.860
2003/12	2.860
2003/13	2.860
2003/14	2.930
2003/15	2.930
2003/16	2.930
2003/17	2.930
2003/18	2.940
2003/19	2.940
2003/20	2.940
2003/21	2.940

Now consider a different set of price points including an aggressive price cut for weeks 9-11 to 2.6 in order to ramp up sales. We leave all other variables the same in order to illustrate the functionality.

	AUP
2003/5	2.900
2003/6	2.900
2003/7	2.900
2003/8	2.900
2003/9	2.900
2003/10	2.900
2003/11	2.900
2003/12	2.900
2003/13	2.600
2003/14	2.600
2003/15	2.600
2003/16	2.800
2003/17	2.800
2003/18	2.800
2003/19	2.800
2003/20	2.800
2003/21	2.800

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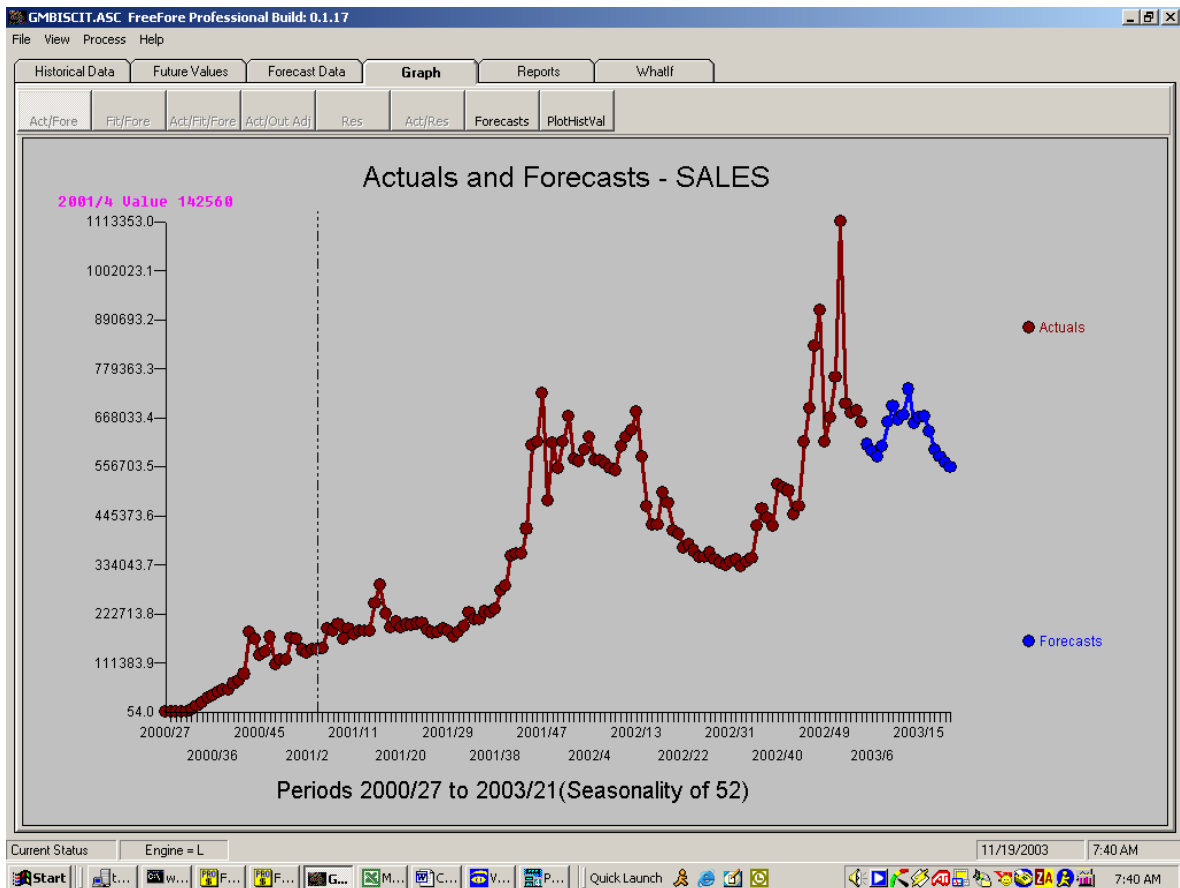
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Historic: Run RunWhatIf Values Forecast Data Graph Reports WhatIf

	AOP	FSI	QM	TPR	TV
2003/5	2.900	12193.000	6.000	12.000	11.000
2003/6	2.900	6097.000	6.000	12.000	9.000
2003/7	2.900	3048.000	6.000	12.000	7.000
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2003/12	2.900	6095.000	11.000	15.000	21.000
2003/13	2.600	3048.000	11.000	15.000	24.000
2003/14	2.600	1524.000	4.000	10.000	19.000
2003/15	2.600	762.000	4.000	10.000	22.000
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2003/17	2.900	11940.000	4.000	10.000	20.000
2003/18	2.900	5970.000	4.000	4.000	16.000
2003/19	2.900	2985.000	4.000	4.000	13.000
2003/20	2.900	1493.000	4.000	4.000	10.000
2003/21	2.900	746.000	4.000	4.000	8.000

	SALES
2004/25	606635.692
2004/26	591501.604
2004/27	579564.603
2004/28	602094.092
2004/29	657794.765
2004/30	694318.087
2004/31	664643.839
2004/32	674214.144
2004/33	732324.730
2004/34	656248.943
2004/35	667317.230
2004/36	670405.039
2004/37	636936.557
2004/38	595709.603
2004/39	579840.093
2004/40	565540.094
2004/41	556134.797

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Solution

The modeling and forecasting solution used was **Autobox**.

Autobox was chosen because it customizes the forecasting equation to the data exploiting profiles and models dependent on a number of variables. Furthermore it captures the lead, contemporaneous and lag structures for events and holiday variables while incorporating level shifts, local time trends and eliminating spurious impacts assignable to outliers/inliers. Additionally it pinpoints the "Peculiar Data" thus drawing attention to omitted variables just waiting to be discovered so that future forecasts will be even more accurate exploiting this acquired knowledge. To learn more about these models and how to build them please see the AFS tutorial on comparing Regression and Box-Jenkins.

Expected Benefits of solution implemented

- Increase revenue by identifying the important driving variables.
- Better planning due to knowledge acquired as to how and when to price the product which is a key goal of General Mills
- Expanded awareness of Outliers and Inliers. The problem is that you can't catch an outlier without a model (at least a mild one) for your data. Else how would you know that a point violated that model? In fact, the process of growing understanding and finding and examining outliers must be iterative. This isn't a new thought. Bacon, writing in *Novum Organum* about 400 years ago said: "Errors of Nature, Sports and Monsters correct the understanding in regard to ordinary things, and reveal general forms. For whoever knows the ways of Nature will more easily notice her deviations; and, on the other hand, whoever knows her deviations will more accurately describe her ways."

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