

## A PREVIEW OF OUR FORECASTING SEMINAR

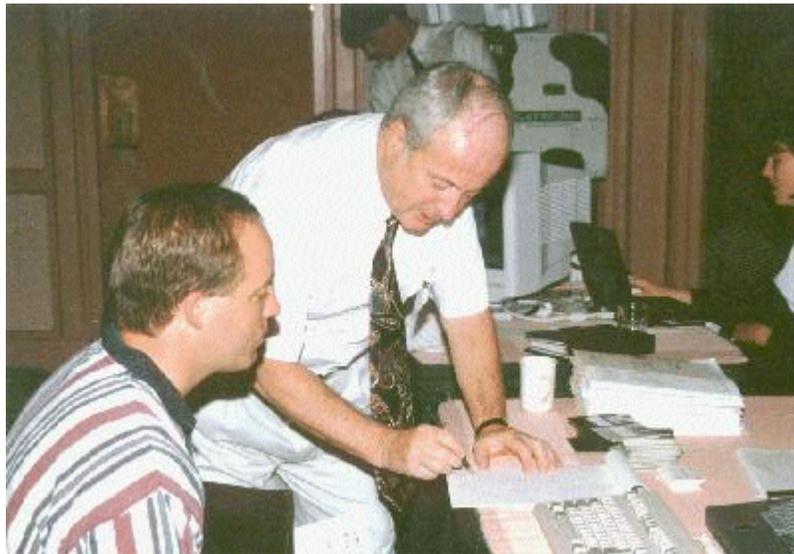
This seminar explains in simple terms some of the why's and the wherefore's of time series analysis.

Consider a case where we only have 4 readings with each one taken an hour apart. By using data at each minute we are able to increase our sample size to 240. We are not increasing the number of samples, but the statistical calculation is done as if we have, and so the number of degrees of freedom for the significance test is incorrectly increased and a spurious conclusion is reached. This is one of primary causes of "spurious correlation". By taking observations at closer intervals we create series with higher and higher autocorrelation. Our job is to somehow adjust for the intra-relationship and its effects on test statistics.

Simple correlation coefficient testing requires that both variables (X and Y) be bivariate normal. If X is the counting numbers (1,2,3,,,T) then it is clear that one of the assumptions is violated (X is Non-Normal) and simple testing of the correlation coefficient is suspect and should be avoided.

[Understanding](#)

This next discussion is a critique of standard techniques for forecasting and some suggestions. Presented by David P. Reilly, Senior Vice-President of Automatic Forecasting Systems.



We study history in order to assess relationships between economic variables. Care has to be taken regarding the assumptions underlying the model. If the statistical assumptions can not be validated then problems might arise.

## Decision Support using Quantitative Methods :

### Forecasting, Correlation and Linear Regression

Early training in statistics emphasized the analysis of cross-sectional data , i.e. non time-series data. If one is analyzing chronological data, using an inappropriate method can become a liability in model formulation.



Regression .... Opportunities and Pitfalls



Detecting and Accounting for Variance Changes via Generalized Least Squares. AUTOBOX has built-in options to detect and to incorporate significant variance changes into the model. This leads to improved estimation of model coefficients and resultant identification of model form.



A side bar on "data cleansing" .

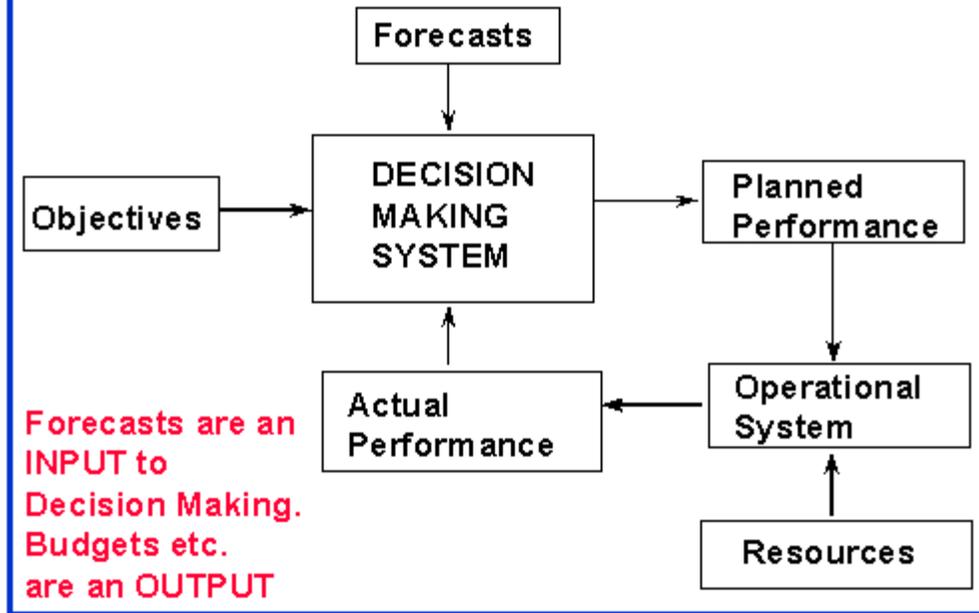


A side bar on "What to look for in a Forecasting Package"



First some words and images on the role of forecasting in the decision process.

### Where should Forecasts fit in?



A side bar on "the role of forecasting in inventory control" .



**Planning ,  
Forecasting  
and Reality**

## **Forecasting and Experience**

- ◆ **Planning for the future implies forecasting**
- ◆ **Estimating the future must be based upon experience**
  - ◆ Experience may be individual and qualitative
  - ◆ Experience may be quantitative
  - ◆ Experience may be applied directly or by analogy
- ◆ **Good Forecasts are unbiased; they are not wish lists**
- ◆ **Forecasting methods and kinds of experience are complementary. Multiple approaches provide mutual support.**

**Typical and broadly incorrect or misleading  
representation of the "FAMILY TREE" .**

This is a typical way of representing the  
different kinds of forecasting methods

- Qualitative
  - Judgemental
  - Analogical
- Quantitative : Time Series Analysis
  - Smoothing
  - Trend Decomposition
  - Decomposition (e.g. Seasonal)
  - Box-Jenkins & Autoregressive Models
- Quantitative : Causal Modelling
  - Linear Regression
  - Multiple Regression
  - Econometric Modelling

**A better representation of the "FAMILY TREE"**

This is a more precise view of the hierarchial structure

- Qualitative
  - Judgemental
  - Analogical
- Quantitative: Time Series Analysis
  - Smoothing
  - Trend Projection
  - Causal Modelling

### **Forecasting Family Tree**

#### Traditional View

- Qualitative
  - Judgemental
  - Analogical
- Quantitative: Time Series Analysis
  - Smoothing
  - Trend Projection
  - Decomposition (e.g. Seasonal)
  - Box-Jenkins & Autoregressive Models
- Quantitative: Causal Modeling
  - Linear Regression
  - Multiple Regression
  - Econometric Modelling

#### Sharpened View

- Qualitative
  - Judgemental
  - Analogical
- Quantitative: Time Series Analysis
  - Smoothing
  - Trend Projection
  - Causal Modelling

**It is important to compare these two approaches as it summarizes the goals and various objectives.**

<b>Forecasting Family Tree</b>		
	Traditional View	Sharpened View
<b>Sharpening the focus.</b>	<ul style="list-style-type: none"> <li>▪ Qualitative               <ul style="list-style-type: none"> <li>Judgemental</li> <li>Analogical</li> </ul> </li> <li>▪ Quantitative: Time Series Analysis               <ul style="list-style-type: none"> <li>Smoothing</li> <li>Trend Projection</li> <li>Decomposition (e.g. Seasonal)</li> <li>Box-Jenkins &amp; Autoregressive Models</li> </ul> </li> <li>▪ Quantitative: Causal Modeling               <ul style="list-style-type: none"> <li>Linear Regression</li> <li>Multiple Regression</li> <li>Econometric Modelling</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>▪ Quantitative: Time Series Analysis               <ul style="list-style-type: none"> <li>History (Weighted Averages)</li> <li>Dummy (Trend, Level Shift, Pulses)</li> <li>Causal (Contemporaneous, lead and lags)</li> </ul> </li> </ul>

<p><b>A structural approach to the "FAMILY TREE". The role of the three (3) kinds of model components.</b></p> <p><b>1 SMOOTHING ( MEMORY )</b></p> <p><b>2 TREND PROJECTION ( DUMMY )</b></p> <p><b>3 CAUSAL</b></p>	
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<p><b>A structural approach to the "FAMILY TREE" with examples.</b></p>	<p style="text-align: center;"> <a href="#"><u>TRADITIONAL MENU SELECTION</u></a>  <a href="#"><u>ADVANCED MENU SELECTION</u></a>  <a href="#"><u>CONFUSING FORECASTING MENU OPTION (NOT OURS)</u></a> </p>
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<p><b>Incorporating the effects of omitted and/or unknown variables into the model.</b></p>	
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<p><b>A side bar on "Lies , Damn Lies &amp; Statistics" . In 1933 M.S. Bartlett wrote a paper in the JRSS entitled "Why do we sometimes get nonsense correlations with time series"</b></p>	
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<p><b>A side bar on "Hypothesis Generation".</b></p>	
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This data will be used to illustrate how forecasting with Linear Regression works. It shows how gas demand levels (target or DEPENDENT variable) varied with the price of the gas (INDEPENDENT variable) for a series of gas utilities in a large country. The data relates to what an economist would call the Price/Demand relationship. We will approach the problem using simple tools and then use more comprehensive techniques to ensure that the statistical assumptions are met.

### Historic Data : Price and Demand for Gas

Demand	Price
134	30
112	31
136	37
109	42
105	43
87	45
56	50
43	54
77	54
35	57
65	58
56	58
58	60
55	73
49	88
39	89
36	92
46	97
40	100
42	102

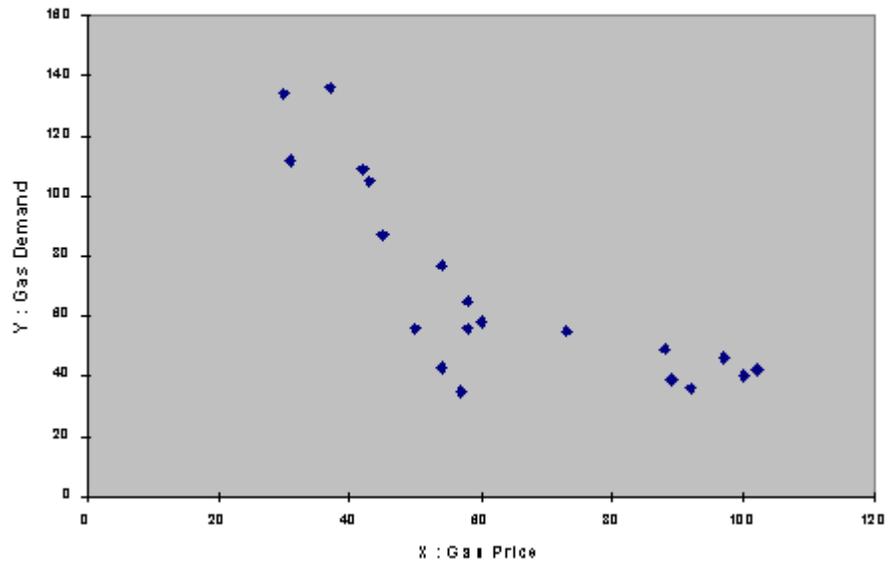
Variable to be Predicted (y)

Predictor Variable (x)

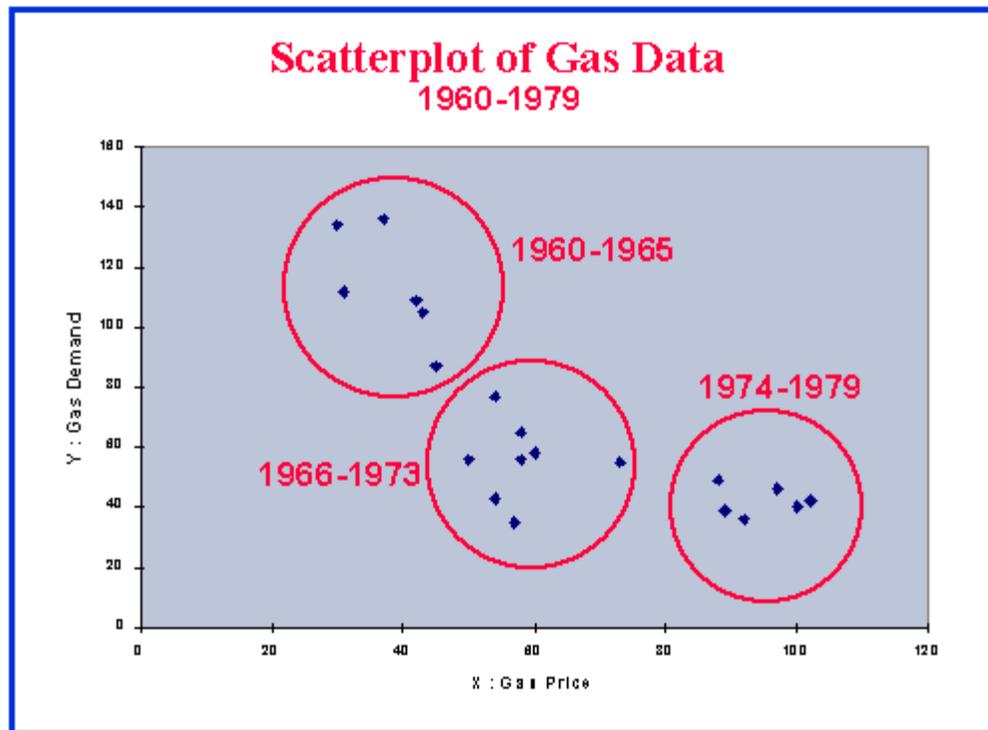
Sample Size (n) = 20

The first step is to plot the Independent (also called Predictor) variable as x (horizontal axis) against the Dependent (also called Predicted) variable as y (vertical axis). Always use this convention. Examination of the SCATTERPLOT suggests a curved relationship. So, a straight line may be too simple a model to extract all the relationship information in the data. Nevertheless, it is useful to see how well a straight line as a model of the Price Demand relationship would work in this case, and how evaluation of the model can bring out the difficulties.

## Scatterplot of Gas Data

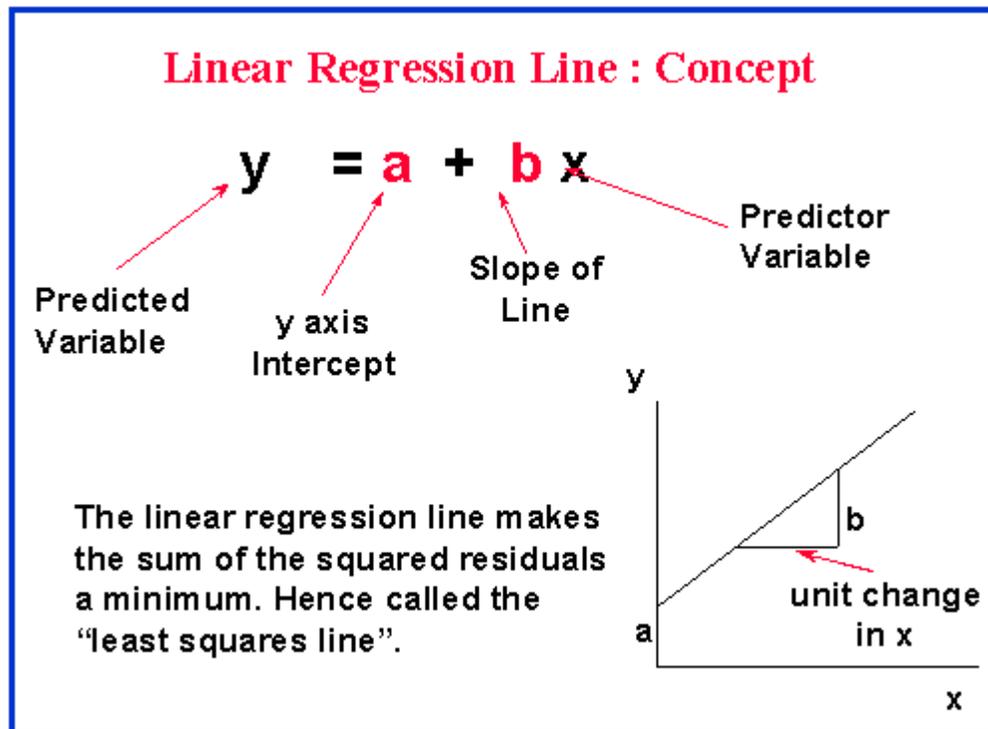


If you control for time a totally different message is perceived. There is no relationship what so ever between these two variables.



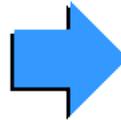
Before we get too ahead of ourselves let us pursue the simple and simply incorrect approach that leads to flawed conclusions. We go down this path to illustrate what is normally done and why it is often inappropriate.

This briefing indicates the interpretation of the different elements of the Linear Regression line. In a slightly different form



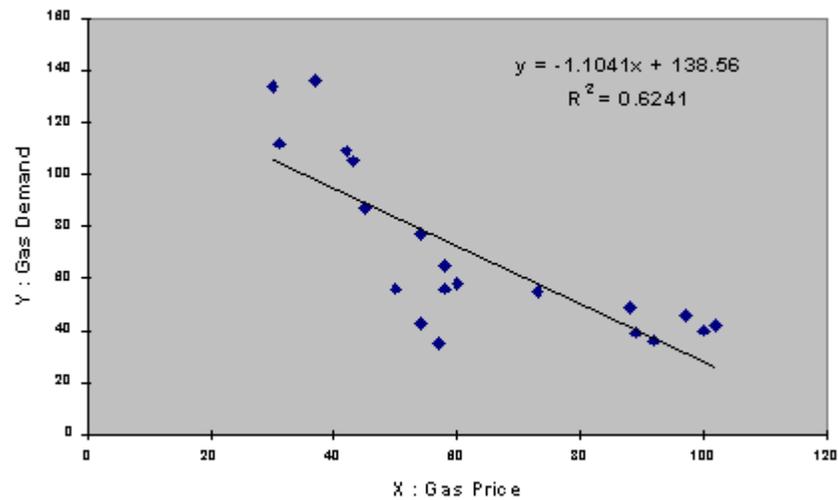
this information was used in the previous unit of work when fitting a straight line.

A side bar on exactly what the assumptions are of a regression model.



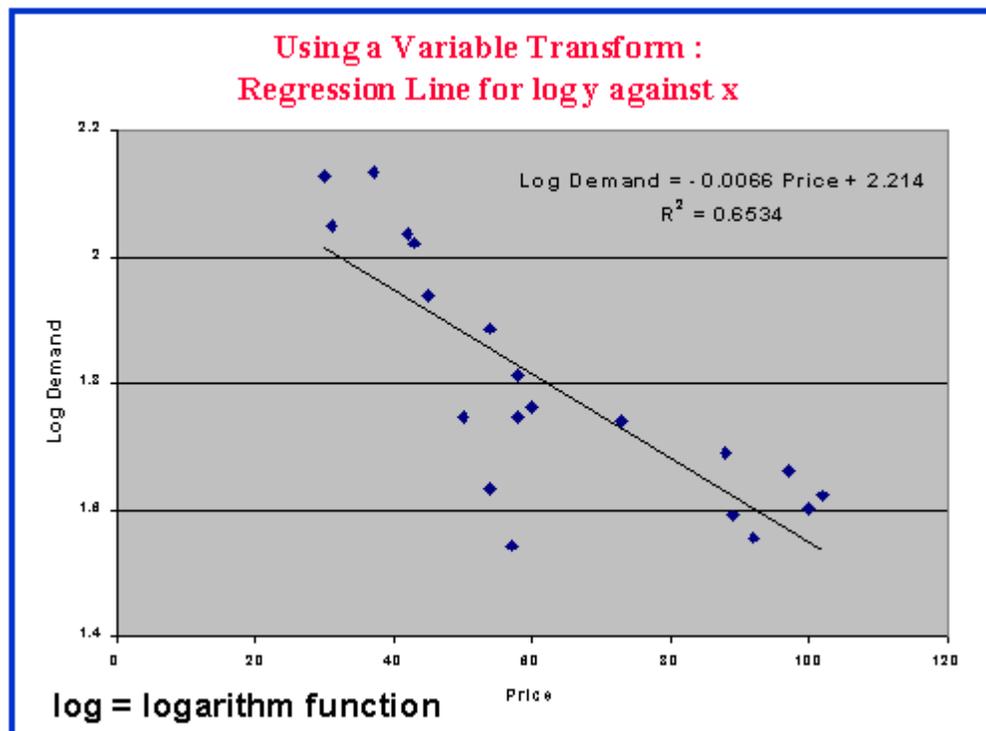
So, we fit a straight line to the data shown in the scatterplot. You could use a ruler, but this doesn't identify the "best fit" line. The simplest statistical way is to use line fitting or regression features in your spreadsheet, statistical or graphics package. Many of these provide a way of finding the line and the line equation, together with R squared (the Coefficient of Determination). These are shown.

### Fitted Straight Line with Gas Data



Excel 5+ "Trendline" facility used [with Equation and  $R^2$ ]

Logs don't help ( in this case ). A logarithmic transformation is sometimes necessary to make the variance of the errors homogenous or constant. If the original data exhibits a correlation between the level of the series and the standard deviation then one should "uncouple" this relationship by taking logs. Similarly if the level and the variance is correlated then a square root transformation might be in order. There can also be cases where the variance changes at specific points in time totally independent of the level of the series. This is referred to as "regime changes".



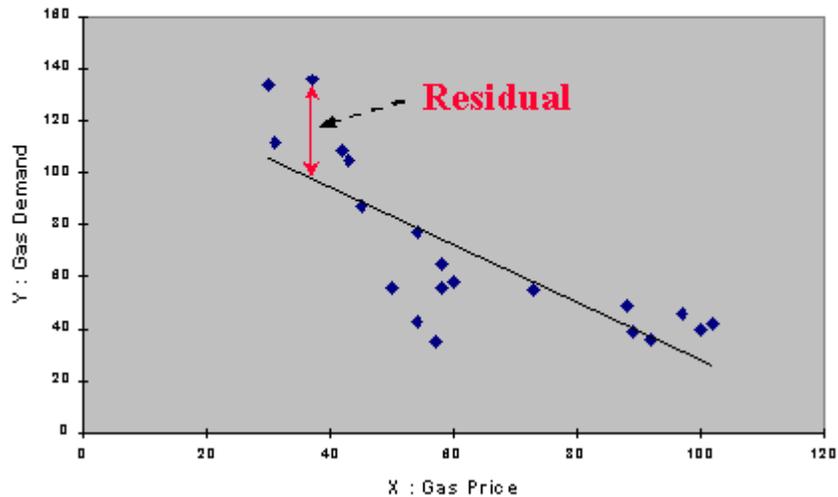
The scatterplot (also called scattergram) suggested earlier that the relationship isn't linear (a straight line), but curves somewhat. We have embarked on using a straight line as a "first try" model! But other steps are useful to check linearity since much of the statistical validity of forecasting will rest on this assumption of linearity. The main technique to use is Residual Analysis. A simple form of this is to chart Residuals against the Predicted values of the Dependent variable (y). Software normally (optionally) generates this (or the data to plot it).

## Is the relationship LINEAR?

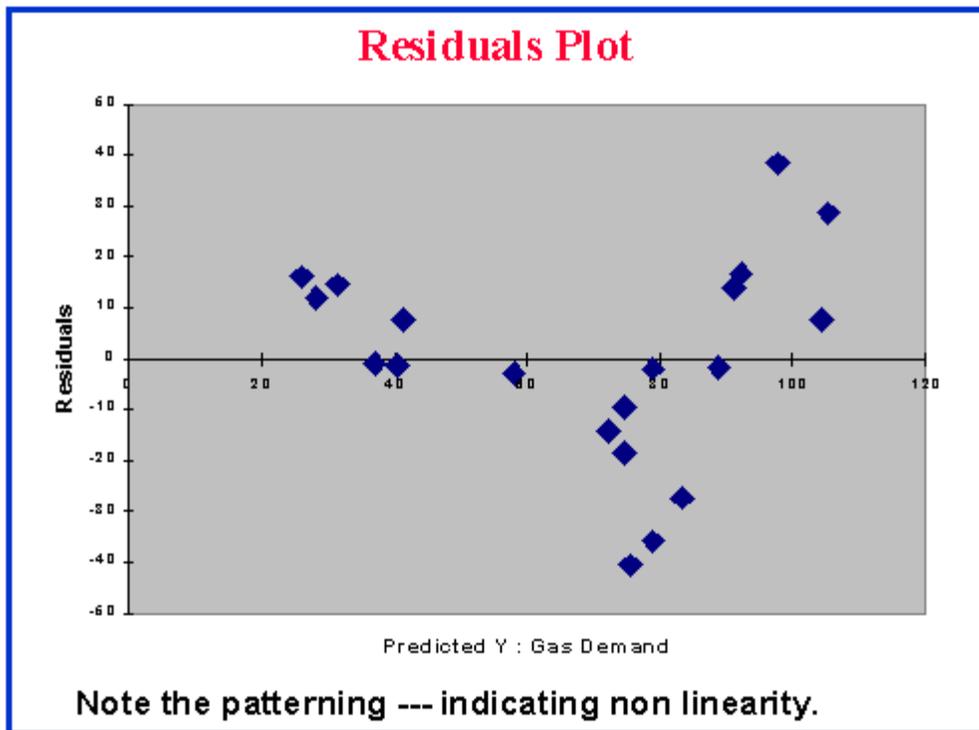
- ◆ Check **Residuals** for absence of pattern when plotted against Y
- ◆ A Residual is the difference between a y data value and the value produced by the line equation for the corresponding x value.
- ◆ Satisfactory regression model explains all x y pattern and leaves only randomly varying residuals. Non linearity is not explained.
- ◆ Use a residuals chart from software

Residuals from a model can reflect omitted structure. The purpose of residual diagnostic checking is to identify the nature and the form of model augmentation suggested by these residuals. Model augmentation can include ARIMA or memory components, additional lags for an input series or the incorporation of dummy (0/1) variables to reflect pulses, seasonal pulses, level shifts or local time trends.

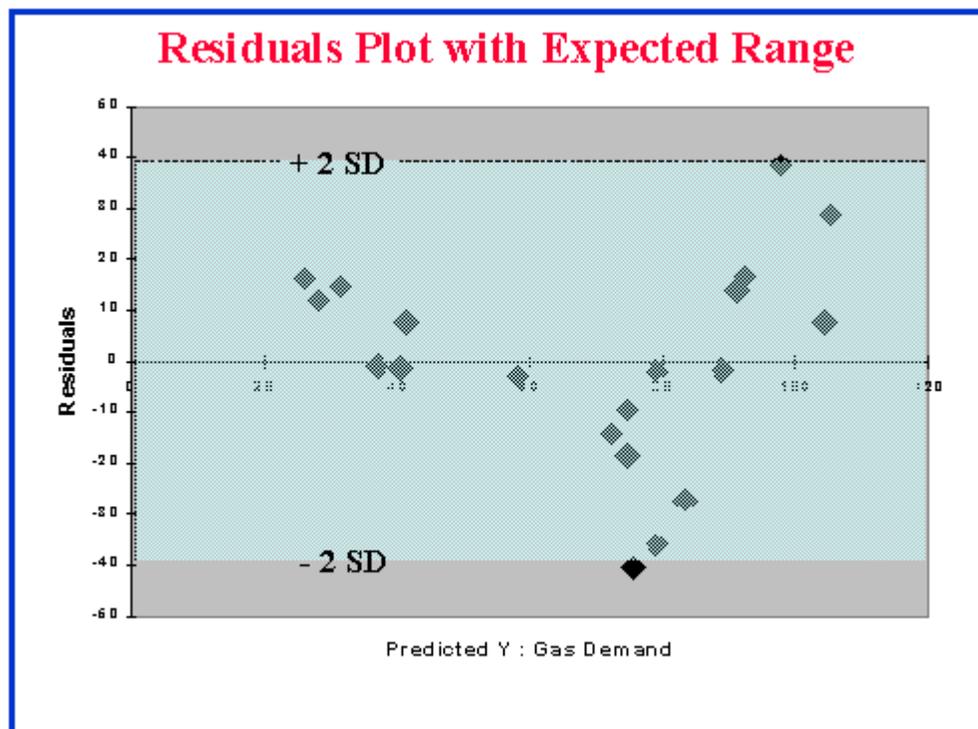
## Residuals : The Unexplained Part of Data



Another view.



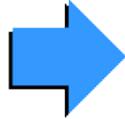
The idea that the expected range for these residuals can be computed using the "standard deviation" requires the strong assumption of independence in the error term. For example if the residuals appeared as 1,-1,1,-1,...1,-1 the standard deviation would be overstated. The range is equal to 6 times the standard deviation when the process is



**N.I.I.D. i.e  
NORMAL.**

**Sometimes things that you get for nothing have a cost. Free forecasting or modelling tools in the spreadsheets are extremely dangerous and should be used with caution.**

**Diagnostic and Remedial Tools (THEORY)**



**Diagnostic and Remedial Tools (PRACTICE)**



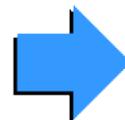
**An intro to ARIMA model identification.**



**Forecasting Weekly Beer Sales**



**A side bar on a modest problem ... from Her Majesties Government**



**More on the modest problem.**

