

Weighted nonlinear fit

Created using Maple 14.01

Jake Bobowski

```
> restart;
with(StringTools) :
with(Statistics) :
with(plots) :
```

```
FormatTime("%m-%d-%Y, %H:%M");
"03-25-2015, 16:17"
```

(1)

In this example, V_r/V_o data from an LRC series circuit will be plotted as a function of angular frequency ω .

This Maple input enters a list of the calculated ratio of V_r/V_o from measurements made in the lab. Also enter the uncertainty in the voltage ratio. Both V_r and V_o have independent uncertainties. Have to use propagation of errors to find $\Delta Vratio$.

```
> Vratio := [.0198, .067, .117, .185, .331, .450, .573, .689, .718, .714, .704, .670, .631, .549, .412,
.318, .249, .186, .138];
σVratio := [.001, .002, .003, .003, .005, .006, .007, .008, .008, .008, .008, .008, .008, .007,
.006, .004, .005, .003, .003];
```

```
Vratio := [0.0198, 0.067, 0.117, 0.185, 0.331, 0.450, 0.573, 0.689, 0.718, 0.714, 0.704, 0.670,
0.631, 0.549, 0.412, 0.318, 0.249, 0.186, 0.138]
```

```
σVratio := [0.001, 0.002, 0.003, 0.003, 0.005, 0.006, 0.007, 0.008, 0.008, 0.008, 0.008, 0.008, 0.008,
0.008, 0.007, 0.006, 0.004, 0.005, 0.003, 0.003]
```

(2)

Calculate the weights for the fit $[(1/\Delta Vratio)^2]$.

```
> Yweights := [seq(1/σVratio[i]^2, i = 1 .. nops(σVratio))];
```

```
Yweights := [1. 106, 2.500000000 105, 1.111111111 105, 1.111111111 105, 40000.00000,
27777.77778, 20408.16327, 15625.00000, 15625.00000, 15625.00000, 15625.00000,
15625.00000, 15625.00000, 20408.16327, 27777.77778, 62500.00000, 40000.00000,
1.111111111 105, 1.111111111 105]
```

(3)

Enter the frequency of the generator in Hz. I'm assuming that the fractional error in the frequency is much less than that of the voltage ratio. Calculate the angular frequency ω .

```
> f := [3000, 10000, 15000, 20000, 25000, 28000, 30000, 32000, 33000, 34000, 35000, 36000,
37000, 39000, 43000, 47000, 52000, 60000, 70000];
```

```
ωdata := evalf(2·Pi·f);
```

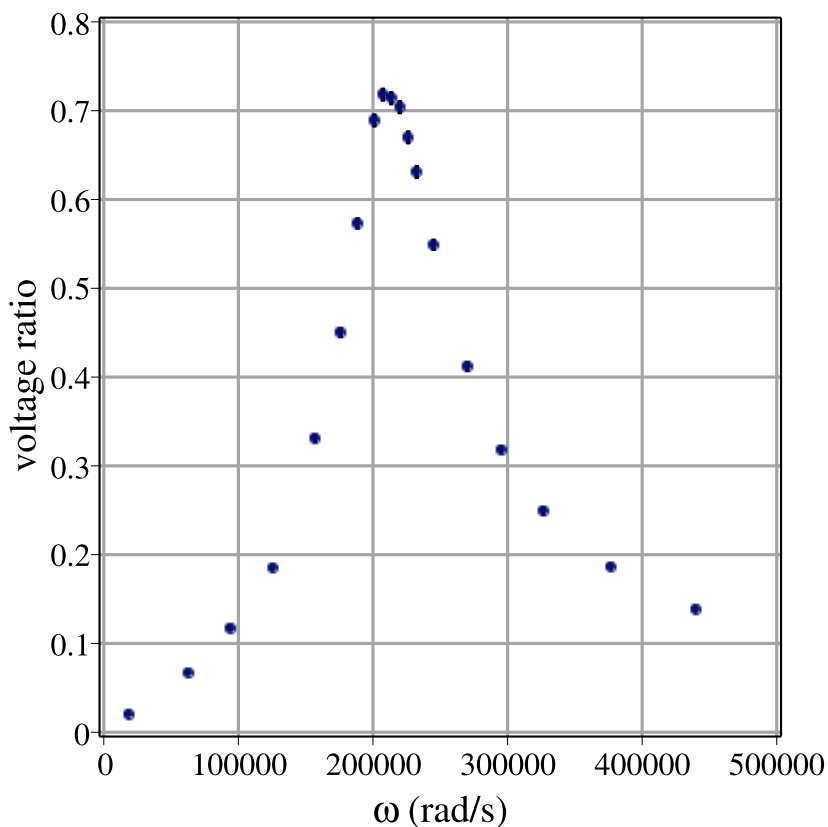
```
f := [3000, 10000, 15000, 20000, 25000, 28000, 30000, 32000, 33000, 34000, 35000, 36000,
37000, 39000, 43000, 47000, 52000, 60000, 70000]
```

(4)

ω data := [18849.55592, 62831.85308, 94247.77962, 1.256637062 10⁵, 1.570796327 10⁵,
 1.759291886 10⁵, 1.884955592 10⁵, 2.010619298 10⁵, 2.073451152 10⁵, 2.136283004 10⁵,
 2.199114858 10⁵, 2.261946710 10⁵, 2.324778564 10⁵, 2.450442270 10⁵, 2.701769682 10⁵,
 2.953097094 10⁵, 3.267256360 10⁵, 3.769911184 10⁵, 4.398229716 10⁵] (4)

Now plot V_{ratio} vs ω .

```
> DataPlot := ScatterPlot( $\omega$ data, Vratio, yerrors =  $\sigma$ Vratio, axes = boxed, view = [0 .. 5e5, 0
  .. 0.8], labels = [typeset(" $\omega$  (rad/s)"), typeset("voltage ratio")], labeldirections
  = ["horizontal", "vertical"], tickmarks = [7, 8], axesfont = [Times, 12], labelfont = [Times,
  14], axis = [gridlines = [thickness = 1]], symbolsize = 10, symbol = solidcircle, thickness = 2)
  :
  display(DataPlot);
```



Now, fit the data to a nonlinear function. We will use the Maple function *NonlinearFit*.

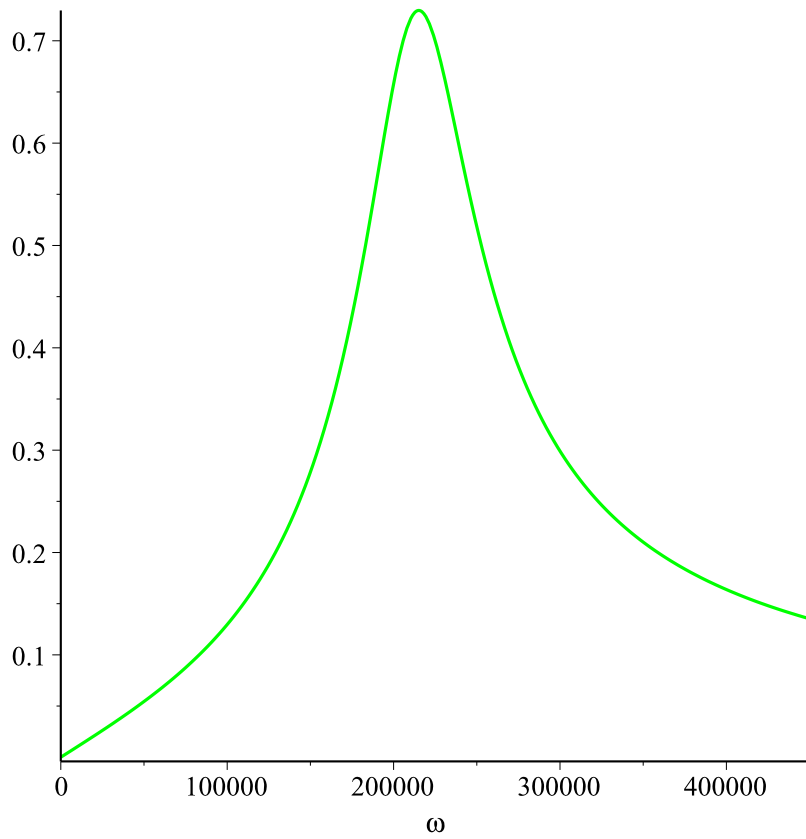
The format of the command below is *LinearFit*(fcn, x data, y data, variable, acceptable ranges of parameters, weights, output options). With the options selected, the output gives the fit function and the best fit parameters (A , g , and ω).

> $fcn := \text{NonlinearFit}\left(\frac{A}{\left(1 + \frac{\omega^2}{g^2} \left(1 - \frac{\omega\omega^2}{\omega^2}\right)^2\right)^{\frac{1}{2}}}, \omega\text{data}, V\text{ratio}, \omega, \text{parameterranges} = [A = 0 \dots 2, g = 0 \dots 300000, \omega\omega = 0 \dots 500000], \text{weights} = Y\text{weights}, \text{output} = [\text{leastsquaresfunction}, \text{parametervalue}]\right);$

$$fcn := \left[\frac{0.729649817392542}{\sqrt{1 + 2.33105403776590 \cdot 10^{-10} \omega^2 \left(1 - \frac{4.62834279414143 \cdot 10^{10}}{\omega^2}\right)^2}}, [A = 0 \dots 2, g = 65497.3651414017, \omega\omega = 2.15135836023231 \cdot 10^5] \right] \quad (5)$$

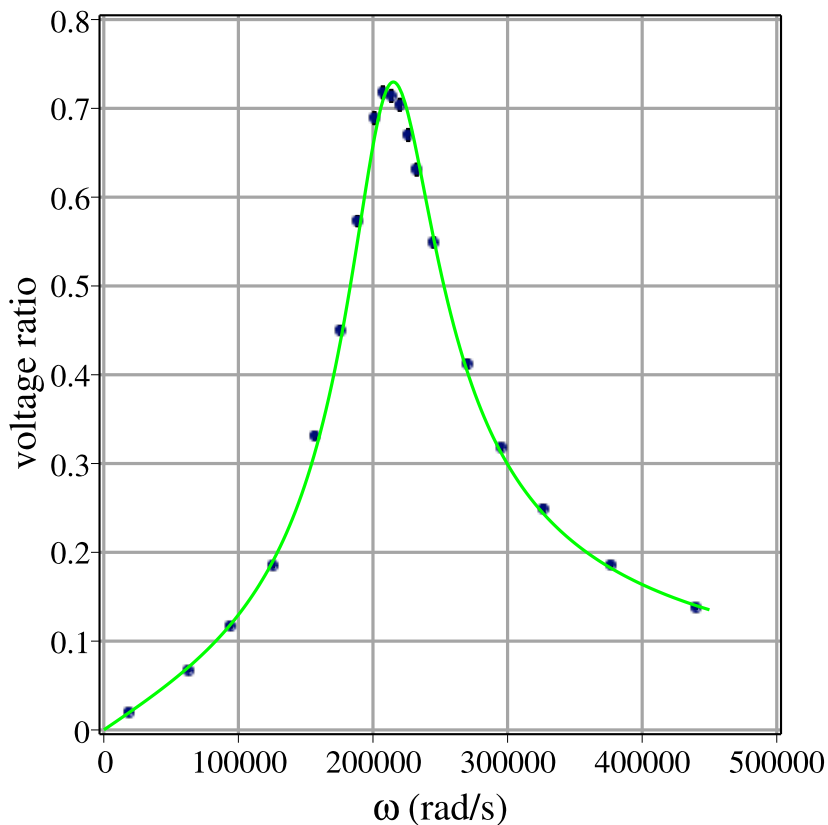
Now plot the fit function defined by fcn over the entire frequency range. Give the plot the name $FitPlot$.

> $FitPlot := \text{plot}(fcn[1], \omega = 0 \dots 450000, \text{colour} = \text{green}) :$
 $\text{display}(FitPlot);$



Use *display* to show both *DataPlot* and *FitPlot*.

```
> display(DataPlot, FitPlot);
```



Note that Maple does not report the uncertainties in the best-fit parameters. We have to do some work to estimate these uncertainties. The first step is to calculate the Chi-Squared value using the best-fit parameters which should correspond to the minimum Chi-Squared value (ChiSqZero). The ' ω ' notation clears any value previously assigned to ω .

```
> ChiSq := 0 :
  for i from 1 to nops(Vratio) do:
    ω := ωdata[i] :
    ChiSq := ChiSq +  $\left( \frac{Vratio[i] - fcn[1]}{\sigma Vratio[i]} \right)^2$  :
  end do:
  ChiSqZero := ChiSq;
  ω := 'ω':
```

$$\text{ChiSqZero} := 73.2231847528438$$

(6)

The next step is to vary one of the parameters away from the value that minimizes ChiSq to see how ChiSq depends on the parameter value. We expect this variation to result in a quadratic dependence. As an example, we'll try finding the uncertainty in the resonance frequency ω . Note, however, the same procedure can be applied to each of the parameters (A , g , ω).

First, load the best-fit parameters determined from the fit into memory.

```
> Astar := rhs(fcn[2, 1]);  
   gstar := rhs(fcn[2, 2]);  
   ωstar := rhs(fcn[2, 3]);  
  
           Astar := 0.729649817392542  
           gstar := 65497.3651414017  
           ωstar := 2.15135836023231 105
```

Next, pick a suitable step size by which to vary ω . This may require some trial and error. Also, define the model function.

```
> ωω := 'ωω';  
   ωωStep := 5e2 :  
  
   y :=  $\frac{Astar}{\left(1 + \frac{\omega^2}{gstar^2} \left(1 - \frac{\omega\omega^2}{\omega^2}\right)^2\right)^{\frac{1}{2}}}$ ;  
  
           y :=  $\frac{0.729649817392542}{\sqrt{1 + 2.33105403776590 \cdot 10^{-10} \omega^2 \left(1 - \frac{\omega\omega^2}{\omega^2}\right)^2}}$ 
```

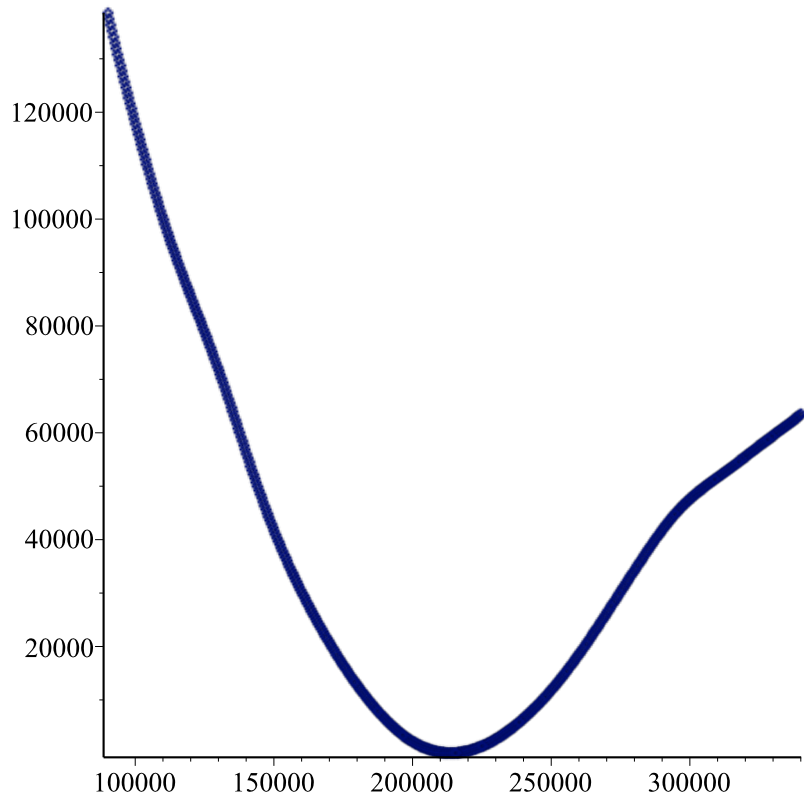
Now use nested loops to recalculate ChiSq at many values of ω that bracket ω star.

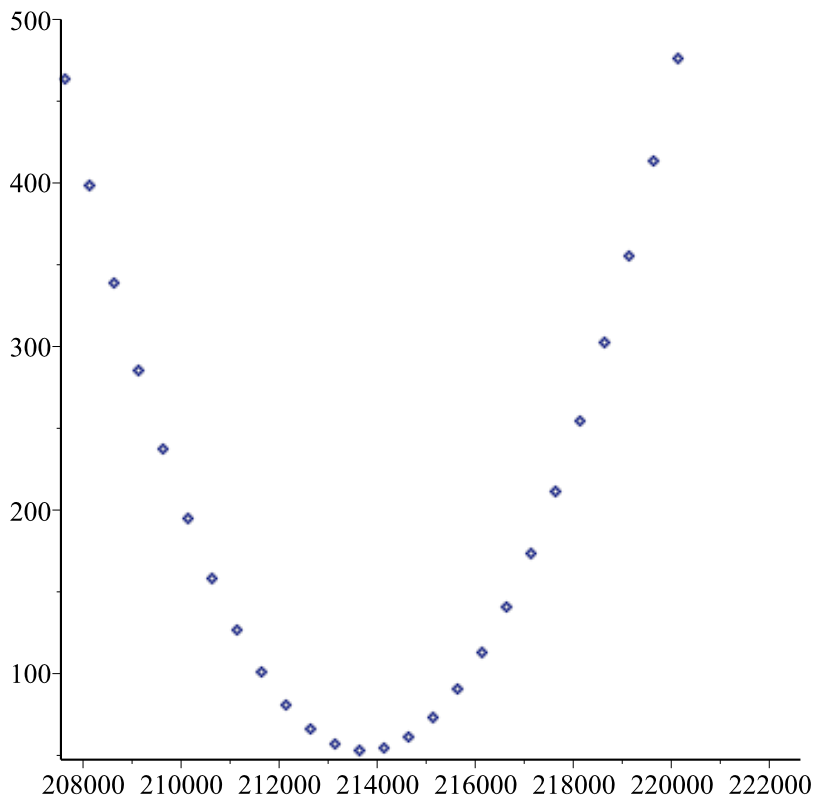
```
> ChiSqList := NULL :  
   ωωList := NULL :  
   for ω from ωstar - 250·ωωStep to ωstar + 250·ωωStep by ωωStep do;  
     ωωList := ωωList, ω;  
  
     ChiSq := 0 :  
     for i from 1 to nops(Vratio) do:  
       ω := ωdata[i] :  
       ChiSq := ChiSq +  $\left(\frac{(Vratio[i] - y)}{\sigma Vratio[i]}\right)^2$  :  
     end do:  
     ChiSqList := ChiSqList, ChiSq;  
     ω := 'ω':  
  
   end do:  
   ωωList := [ωωList] :  
   ChiSqList := [ChiSqList] :
```

Now plot the calculated ChiSq values as a function of the parameter ω . Notice that, over a large range of ω , ChiSq is not strictly quadratic. However, if we zoom in close to the minimum the dependence is very close to quadratic.

```
> ScatterPlot(ωωList, ChiSqList);
```

`ScatterPlot($\omega\omega$ List, ChiSqList, view = [$\omega\omega$ star - 15 · $\omega\omega$ Step .. $\omega\omega$ star + 15 · $\omega\omega$ Step, 50 ..500]);`





Notice that, in this case, we've actually found a set of parameters that gives a *lower* ChiSqZero than Maple found.

The last step is to characterize the shape of the quadratic dependence:

$$\text{ChiSq} = \text{ChiSqZero} + B * (\omega - \omega_{\text{star}})^2$$

There are three unknowns (ChiSqZero, B, and ω_{star}). These could be determined simply by fitting the data above to a quadratic function. Alternatively, if we pick three values of ω near the minimum, we can use the corresponding ChiSq values to determine the unknowns.

```
> ChiSq1 := ChiSqList[244];
   ChiSq2 := ChiSqList[247];
   ChiSq3 := ChiSqList[250];
   Δω := ωList[250] - ωList[247];
           ChiSq1 := 101.128853653468
           ChiSq2 := 56.8734845219439
           ChiSq3 := 61.1699194058887
           Δω := 1500.
```


The value of ω_0 that minimizes ChiSq (ω_0Min) is given below as is the uncertainty in ω_0Min which is determined by how quickly ChiSq increase as we move away from ω_0Min . That is, σ_{ω_0} is determined by the B in the quadratic dependence of ChiSq on ω_0 . The larger the value of B, the lower the σ_{ω_0} .

$$> \omega_0Min := \omega_0List[250] - \Delta\omega_0 \cdot \left(\frac{ChiSq3 - ChiSq2}{ChiSq1 - 2 \cdot ChiSq2 + ChiSq3} + \frac{1}{2} \right);$$

$$\sigma_{\omega_0} := evalf \left(\frac{\text{sqrt}(2) \cdot \Delta\omega_0}{\text{sqrt}(ChiSq1 - 2 \cdot ChiSq2 + ChiSq3)} \right);$$

$$ChiSqZeroFit := ChiSq3 - \frac{1}{2} \cdot (\omega_0List[250] - \omega_0Min)^2;$$

$$\omega_0Min := 2.13753098374103 \cdot 10^5$$

$$\sigma_{\omega_0} := 304.441302317860$$

$$ChiSqZeroFit := 52.7626269021716$$

(10)

Finally, one would report the following for the experimental determination of ω_0 :

$$\omega_0 = (2.138 \pm 0.003) \cdot 10^5 \text{ rad/s}$$

In general, extracting uncertainties in the fit parameters from a nonlinear fit is nontrivial. Above we have given one method for obtaining an **estimate** of the uncertainties in the fit parameters. For more details about uncertainties for nonlinear fits, see **Data Reduction and Error Analysis** by Bevington and Robinson and/or **Numerical Recipes in C** which you can obtain and read for free by visiting <http://www.nrbook.com/a/bookcpdf.php>.