RESULTS AND CONCLUSIONS
5.1 Results

In this thesis a model has been built to estimate the blood glucose in human body non-invasively by using NIR radiations. The suggested model incorporates the signal obtained from power meter from the system design as proposed in fig. 3.1 & 3.2. This signal is conditioned by PLS regression technique using ‘MATLAB’ tools. For this ‘MATLAB 7.0’ Version with toolboxes namely ‘SIMULINK’ with ‘DSP Generator’ from ALTERA Inc. The model was tested for seven body variants and two physical parameters like temperature and skin complexion. The results obtained from the above model for actual glucose concentration of 95 was close to 97.5, thus an error observed was within the ±2.6 %. Normally as per YSI standard for an instrument to be viable in market the correlation value should be above 90% i.e. 10 % error is admissible for non-critical applications. Our model generates error much less then a stated error and hence has a potential to be integrated into a portable device for medical applications.

We have suggested in chapter 4 an embedded solution to miniaturize an entire signal processing system in a FPGA Cyclone II from ALTERA. The said design has been tested for text based approached for matrix manipulations, which forms bases for multivariate analysis. Here, we have assumed that the expected signal from the proposed design is of similar nature to that of audio signal with base band of 20 KHz. Of course, the actual signal from the power meter will have different set of peaks as compared to audio signal. As long as the system has requisite bandwidth required for processing power meter signal, the testing will not have any discrepancy when used for proposed model.
5.2 Discussions

The problem is multidisciplinary in nature in the domains of Chemistry, Physics, Statistics and Engineering. Most of the models of non-invasive glucose instrumentation have difficulty in satisfying the Clarke Error Grid calibration. This could be due to poor multivariate model. The fine tuning of the same multivariate model is required by incorporating the parameters influencing glucose. With proper understanding of the dynamics of the physiology of the human body and the catabolic processes triggering by signal for the alternative path depending on the situation therein the cell, a closer estimate of glucose is possible as described below.

I. In general, there are three basic types of absorption processes: 1) electronic, 2) vibrational, and 3) rotational. Electronic transition occurs in both atoms and molecules, whereas vibrational and rotational transitions occur only in molecules. The probability of transition between different states or energy levels is governed by complex quantum mechanical rules that depend on the chemical structures, size and symmetry of the molecule. Some transitions are “allowed” and some are “forbidden”. Also its known fact that cell changes its catabolic pathways depends on the constituents present or physiology at that instance and various signal generated by the body. Hence it is possible that constituents change their concentrations giving scope for variation in probability of transition states as mentioned above over a time. These inter transition probability variations makes it very difficult to quantify the transition states thus complicating the modeling of whole blood tissue matrix.

II. For quantification of glucose concentration for diagnosis and control of human diseases, wide range of parameters, like glucose concentration range available across. The glucose concentration for an in-situ cell culture system is in milligrams per deciliter range. The optical path lengths for in vivo control are typically millimeter to centimeters. Also the
environmental challenges associated with in-vivo monitoring make quantifying problem more difficult because of a range of potential confounders that cannot be controlled like temperature and pH variation, confounding chemical species, hydration, blood flow, light scattering (optical pathlengths), overlapping absorption of non-glucose metabolites, ethnic and racial blood, pressure changes and correlated physiological changes. It may be noted that even a slight change in temperature, the absorption of the background water spectrum will shift, severely impacting measurement of the glucose signal.

III The physiological ranges of glucose values seen in the normal human body range is from 80 to 120 mg/dl and should ideally remain around 100 mg/dl (5.5mM). Required accuracy of a useful glucometer is 10mg/dl (0.55mM). For the most identifiable NIR glucose peak at approximately 2.27μm, molar absorptivity is roughly 0.25 M⁻¹ cm⁻¹. The molar absorptivity of water is 0.41 M⁻¹ cm⁻¹ and the concentration of the water in typical body tissue is approximately 39M. Considering transmission measurement made through 1mm of body tissue. The background absorption due to water will be about 1.6 and that due to glucose will be about 1.26 x 10⁻⁴. Further for the accuracy requirement, we must be able to discern an absorption change of about 1.26 x 10⁻⁴ on a background of 1.6 and it is evident that even a change in tissue hydration of 1/1000 of a percent would result in a larger signal change than would a 10mg/dl change in glucose concentration. For this reason, high-order multivariate models that incorporate analysis must use entire spectra to extract NIR glucose information.¹³⁷,¹³⁸

IV. Calibration of the model and validation of the result by incorporating the samples obtained from different patients population, i.e. different ages, sex type, ethnic and racial
origins, blood group, cultural variation, daily diet habits, skin complexion corrections etc. The model then should be calibrated to individual user.

The nine variable simulated systems as describe in thesis can be extended for more parameters, the same system can be properly modeled with the proper confidence interval of the variable associated to generate the required Clerk Error Grid. Once the system is modeled to the satisfaction the same can be extended over the Global population to accommodate the variations as described.

5.3 Scope For Future Work

The table 3.1 described the characteristics of various light sources used in spectroscopy technique. It may be noted that out of the four spectrums seen therein the Tungsten Halogen power source is having the continuous homogenous spectrums compared to Xeon, Globar and Deuterium. As discussed earlier in section 2.5.1, the tissue under investigation has a window in the NIR region of 2000-2500nm and signature of glucose are available upto 2400 nm. Tungsten-Halogen lamp spectra gives a stable, continuous and output with high intensity irradiance in this region, it is proposed to use the lamp with operating power 250 Watts and above for the instrumentation design. With these requirements in mind Tungsten-Halogen lamp is a good option for invasive glucometer system with design flexibility for the up-gradation of power. Here few modules designs will be discussed towards the proposed design of NI glucometer as given in Fig. 3.2.

5.3.1 Proposed Hardware Model

The radiation used in NIR Spectroscopy is safe as long as the intensity employed is below the tissue damage value due to thermal heating. The average optical power reported in these early clinical measurements was of the order of 10 mW at the skin surface at an
irradiance of approximately 50 mWcm$^{-2}$. This is below the safety levels set by the British Standards Institute for skin exposure to laser radiation, and are similar to the intensity of the sun on a sunny day.

Also instruments manufactured for use in a patient environment (defined as being within 2.5 m of a patient) must comply with a number of British (BS5724) and International safety standards (IEC 601-1) on electrical and mechanical safety. A medical instrument must not pose a danger to the patient or operator either from an electrical or mechanical viewpoint.

### 5.3.1.1 Quartz Tungsten Halogen Source Module

Air cooled QTH source designed can be established keeping in mind the available design of the 1,000 watts Oriel Quartz Tungsten Halogen Research Source. The provision for the 250, 600 Watts and 1000 Watts Lamps may be kept in the housing assembly. As seen from the table 2.5, it may be noted that the filaments of the 600 watts and 1000 watts (250 and 600 Watts lamp has same dimension) has two different dimensions and voltage rating, hence to accommodate these filaments in the housing, the provision for the filaments couplers assembly can be taken into consideration for the housing assembly.

Graph indicates at Fig. 5.1 & 5.2 indicates that the spectral irradiance of the 1000 Watts at the 0.5 meter over 250 nm to 2400 nm spectral range and comparison of 600 Watts and 1000Watts respectively. It may be noted that the differences in the spectral irradiance of the 600 & 1000 Watts lamps were found to be in the range of 50 average magnitudes which is a substantial value for the experimentation in the spectral range of 1,000- 2,500 nm, if input power is required to be enhanced.
Fig. 5.1: Spectral irradiance at 0.5 m from the NEWPORT 6315 1000W QTH Lamp.

Fig. 5.2: Graph of spectral irradiance of 600 and 1000 watts (Source: Newport).

Fig. 5.1 shows the spectral distribution of the irradiance from the 1000(NEWPORT 6315) Watts Lamp at its rated voltage. The location and height of the peak emission depend on the model of lamp and operating conditions. The filament temperature, emissivity and transmission of the envelope determine the radiated energy and its spectral distribution.
The luminous output can be measured (measured using different physical quantities as mentioned in table 2.5(b)), is particularly sensitive to the filament temperature, and the shape of the filament is important in the directional distribution of the radiation. It may be noted that the total irradiance at 50 cm, from the 1000 Watts 6315 Lamp, is proportionately much less than ten times that of the 6333 100 W lamp. This is because of differences in filament temperature and shape.

5.3.1.2 Power Supply Module

Spectral irradiance as shown in the Fig. 5.3 from 250 to 500 nm for the 100 W lamp (NETPORT 6333) at different voltages (the filament plane is kept parallel to the slit of the radiometer for maximum irradiance) indicate that as voltage is reduced, total output is reduced and the peak wavelength shifts only slightly towards the red. Also the output is quite stable over the wavelength as shown in Fig. 5.1. The output at blue wavelength can change significantly with a slight change in voltage. Also the graph (Fig. 5.4) indicates that the variation in the rated voltage of the lamp decreases the life span. Newport also guarantees the output power of the calibrated lamps highly stable as compared to the incandescence lamps as shown in Fig 5.5.
Fig. 5.3: Spectral irradiance at 0.5 m from the 6333 100 W QTH Lamp at different voltages.

The lamp is rated for 100 W at 12 V (Newport).

Fig. 5.4: Average life of lamps and variation in operating voltage (Newport).

Fig. 5.5: Running time and the luminous output as compared to conventional lamps (Source: Newport).

To minimize the shift of the wavelength, the supply voltage should be highly regulated and thus the high performance line regulated constant voltage power supply is needed to avoid the wavelength shift and keep constant spectral irradiance (The minor deviation in the voltage is taken care by selecting the dual channel power meter). Also the input power proposed in experimentation is from 250 – 1,000 watts at difference voltages as desired by lamp to get the variable spectral irradiance in the range of 75 – 200 magnitude. Stabilizing the power supply at such high wattages is in itself a great challenge. To keep the
noise level low, it is suggested to use Linear Power Supply (LPS) over Switch Mode Power Supply (SMPS).

The LPS circuit design as shown in the Fig. 5.6 is a simple, based on 7812 series regulator. The bank of transistors with the proper sink for the current amplification required to be connected in parallel for the required load currents. The heavy capacitors must be used with value in the range of 30,000- 40,000 μF for the storage and the high surge current requirements.

![Linear power supply circuit for 600 Watts @ 12 Volts with reconfigurable winding.](image)

**Fig. 5.6:** Linear power supply circuit for 600 Watts @ 12 Volts with reconfigurable winding.

### 5.2.1.3 Suggested monochromator design

![Diagram of a monochromator with entrance slit, collimating mirror, grating, focusing mirror, and exit slit.](image)
The following specifications of the monochromator are optimum keeping in mind the requirement of covering from Near IR to MIR region for proposed experimentation. The spectral range required is from 1,000-2,500nm for the monochromator design. This can be attained by the choice of the grating could be (50mm x 50mm (or 64mm x 64mm, clear aperture) ruled grating, 300 l/mm, blazed @2000nm, maximum efficiency 75% in the region 1333nm – 3000nm. Resolution of around 10nm is enough for the multivariate analysis keeping in mind, the line width of the oscillator of the spectrum of the variants of the human whole blood. The configuration of Czerny-Turner (Fig. 5.7) is will give the required specification. The control is single level as described in section 3.2.

5.4 Conclusions

The Proteomics is an emerging science involving the identification of proteins in the body and the determination of their role in physiological and pathophysiological functions. Whole numbers of proteins generated during the catabolic pathways are complex in nature and yet to be explored by researcher community. This proteomics research will able to answer the question expressed by the multivariate modeling to decide the influencing variants involved in stabilizing the ensemble in mind. Though the glucometer matrix model has less then ±5 % error, this error can be minimized if the pathways are well defined for the catabolism of glucose.

The multivariate analysis has good number of application in smart sensors designs. The industry is interested in the chemical sensors for on-line chemical control of batch and continuous reactors. There are innumerable applications of sensors for biomedical
monitoring of individuals health. Environmental scientists are developing sensors to monitor the fate and distribution of benign and malign chemicals in ecosystems. These diverse applications have following things in common like Sensors should function in multivariate environment, Sensor required being reliable and able to correct for change in operating conditions, Sensor should be autonomous for decision making capability and low power consumption. Novel instrumentations utilizing multivariate analysis to name few are Optical computation, Agricultural Science for mapping soil, Hyperspectral imaging, Surface plasmon resonance analysis etc.

We feel that the research work has good potential and has opened the door for exploring research in the areas of smart sensor designs exploiting the capabilities of programmable microelectronics devices.
Annexure I: Eight Oscillator system MATLAB code.

```matlab
clear
fre=[100; 450; 1200; 1400; 1900; 2500; 3900; 4500; 4900; 5800];
line=[80.1; 150.8; 180.3; 280.5; 350.3; 500.8; 500.0; 300.0; 3900; 350.3; 5.517; 4500; 650.8; 5.517; 4900; 5800; 500.0; 300.0; 5.955; 5.955; 8.590; 8.590; 7.159; 7.159; 15.500; 15.500; 12.300; 12.300; 15.0; 15.0];
Epsilon=1;
k=1;
fre_line=0;
n=0;
for i=1:1:1
    for j=1:1:10
        sum=0;
        for i=1:1:10
            sum=sum + ((o_str(41)*fre(41)^2)/((fre(41)^2)-(j^2)-(sqrt(-1)*j*line(41))));
        end
        sum=sqrt(Epsilon + sum);
        fre_line(k,1)=j;
        n(k,1)=sum/15;
        k=k+1;
    end
end
n
fre_line
plot(fre_line,n);
```

Annexure II: Linear strectas generation using eq. 3.1 approach (Only windowing code is shown).

```matlab
if a<2.05
    z1=a*((0.009*c1+0.0067*c1^2)+(0.003*c2+0.006*c2^2+0.004*c2^3)+(5.004*c3+0.0055*c3^2)+(0.004*c4+0.0055*c4^2)+(0.004*c5+0.0055*c5^2)+(0.004*c6+0.0055*c6^2)+(0.004*c7+0.0055*c7^2));
elseif ((a>=2.05)&&(a<2.115))
    z1=a*((0.09*c1+0.067*c1^2)+(0.03*c2+1.06*c2^2+0.04*c2^3)+(5.04*c3+0.055*c3^2)+(0.04*c4+0.055*c4^2)+(0.04*c5+0.055*c5^2)+(0.04*c6+0.055*c6^2)+(0.04*c7+0.055*c7^2));
elseif ((a>=2.115)&&(a<2.125))
    z1=a*((100.09*c1+10.067*c1^2)+(10.03*c2+10.067*c2^2+0.04*c2^3)+(5.04*c3+0.055*c3^2)+(0.04*c4+0.055*c4^2)+(0.04*c5+0.055*c5^2)+(0.04*c6+0.055*c6^2)+(0.04*c7+0.055*c7^2));
elseif ((a>=2.125)&&(a<2.25))
    z1=a*((0.09*c1+0.067*c1^2)+(0.03*c2+1.06*c2^2+0.04*c2^3)+(5.04*c3+0.055*c3^2)+(0.04*c4+0.055*c4^2)+(0.04*c5+0.055*c5^2)+(0.04*c6+0.055*c6^2)+(0.04*c7+0.055*c7^2));
elseif ((a>=2.25)&&(a<2.26))
    z1=a*((0.09*c1+0.067*c1^2)+(0.03*c2+1.06*c2^2+0.04*c2^3)+(5.04*c3+0.055*c3^2)+(0.04*c4+0.055*c4^2)+(0.04*c5+0.055*c5^2)+(0.04*c6+0.055*c6^2)+(0.04*c7+0.055*c7^2));
elseif ((a>=2.26)&&(a<2.27))
    z1=a*((10.09*c1+10.067*c1^2)+(10.09*c2+10.067*c2^2)+(15.09*c3+10.067*c3^2)+(10.09*c4+0.067*c4^2)+(0.09*c5+0.067*c5^2)+(0.09*c6+0.067*c6^2)+(0.09*c7+0.067*c7^2));
elseif ((a>=2.27)&&(a<2.295))
    z1=a*(110.09*c1+110.067*c1^2)+(110.09*c2+110.067*c2^2)+(110.09*c3+110.067*c3^2)+(110.09*c4+0.067*c4^2)+(0.09*c5+0.067*c5^2)+(0.09*c6+0.067*c6^2)+(0.09*c7+0.067*c7^2));
else
    z1=a*(110.09*c1+110.067*c1^2)+(110.09*c2+110.067*c2^2)+(110.09*c3+110.067*c3^2)+(110.09*c4+0.067*c4^2)+(0.09*c5+0.067*c5^2)+(0.09*c6+0.067*c6^2)+(0.09*c7+0.067*c7^2));
end
```
\[ z_1 = a \left( (5.99c_1 + 2.96c_1^2) + (4.9c_2 + 5.967c_2^2) + (5.9c_3 + 0.67c_3^2) + (0.09c_4 + 0.067c_4^2) + (0.09c_5 + 0.067c_5^2) + (0.09c_6 + 0.067c_6^2) + (0.09c_7 + 0.067c_7^2) \right) \]

\[ \text{elseif } (a \geq 2.295 \text{ and } a < 2.32) \]
\[ z_1 = a \left( (10.09c_1 + 10.067c_1^2) + (10.09c_2 + 10.067c_2^2) + (6.09c_3 + 0.067c_3^2) + (0.09c_4 + 0.067c_4^2) + (0.09c_5 + 0.067c_5^2) + (0.09c_6 + 0.067c_6^2) + (0.09c_7 + 0.067c_7^2) \right) \]

\[ \text{elseif } (a \geq 2.32 \text{ and } a < 2.40) \]
\[ z_1 = a \left( (10.09c_1 + 10.067c_1^2) + (0.09c_2 + 0.067c_2^2) + (5.09c_3 + 0.067c_3^2) + (0.09c_4 + 0.067c_4^2) + (0.09c_5 + 0.067c_5^2) + (0.09c_6 + 0.067c_6^2) + (0.09c_7 + 0.067c_7^2) \right) \]

\[ \text{else } (a \geq 2.40 \text{ and } a < 2.50) \]
\[ z_1 = a \left( (0.09c_1 + 0.067c_1^2) + (0.09c_2 + 0.067c_2^2) + (5.09c_3 + 0.067c_3^2) + (0.09c_4 + 0.067c_4^2) + (0.09c_5 + 0.067c_5^2) + (0.09c_6 + 0.067c_6^2) + (0.09c_7 + 0.067c_7^2) \right) \]

end

Annexure III: Lorentz oscillator modeling for eight oscillators for spectra’s for samples.

\[ \text{fre} = [2000; 2050; 2150; 2200; 2280; 2300; 2320; 2400; 2430; 2500]; \]
\[ \text{line} = [20.1; 10.8; 30.3; 20.5; 50.3; 10.8; 30.3; 15.8; 15.0; 30.0]; \]
\[ \text{fid} = \text{fopen('Lortzpls_cal.txt', 'wt');} \]
\[ \text{countl} = \text{fprintf(fid, 'Tem')}; \]
\[ \text{countl} = \text{fprintf(fid, 'SColx')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c1')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c2')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c3')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c4')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c5')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c6')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c7')}; \]
\[ \text{countl} = \text{fprintf(fid, 'c8')}; \]

for \( j = 2000 \text{ to } 2500 \)
\[ \text{fid} = \text{fopen('Lortzpls_cal.txt', 'at');} \]
\[ \text{count} = \text{fprintf(fid, 'd', j)}; \]
\[ \text{count3} = \text{fprintf(fid, 'n')}; \]
end
\[ \text{count3} = \text{fprintf(fid, 'n')}; \]
\[ \text{initialwave} = 2000; \]
\[ \text{finalwave} = 2500; \]
\[ \text{resolution} = (\text{finalwave} - \text{initialwave}) / 50; \]
\[ \text{%resolution} = 30; \]
\[ \text{o_str1} = o_str2 = o_str3 = o_str4 = o_str5 = o_str6 = 0; \]
\[ a = 10; b = 50; \]
\[ x = a + (b - a) * \text{rand}(5); \]
\[ \%o_str1 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str2 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str3 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str4 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str5 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str6 = a + (b) * \text{rand}(1, \text{resolution}); \]
\[ \%o_str7 = a + (b) * \text{rand}(1, \text{resolution}); \]
o_str1=rand(1,resolution);
o_str2=rand(1,resolution);
o_str3=rand(1,resolution);
o_str4=rand(1,resolution);
o_str5=rand(1,resolution);
o_str6=rand(1,resolution);
o_str7=rand(1,resolution);
fid = fopen('Lortzpls_cali.txt','at');

l=1;
fre_line=0;
n1=0;

c1= Glucose(70-110 mgm/dl); c2= Serum Cholesterol(130-220 mgm/dl);
c3=Serum Triglycerides(65-160 mgm/dl), c4=serum triglycerides(65-160 mgm/dl),
c5=HDL cholesterol(35-60 mgm/dl), c6=LDL cholesterol(130-150),
c7=LDL(130-150mgm/dl) and lambda= 0.4 to 0.7
%Temperature t=25-40 degrees, Skin complexion s = 0.2 - 0.4 .

for t=0.25:0.05:0.25
  for s=0.2:0.1:0.2
    for cl =90:10:100
      for c2 =145:30:180
        for c3 =30:5:40
          for c4 =70:20:100
            for c5 =45:5:50
              for c6 =140:10:150
                for c7 =145:5:150
                  count3 = fprintf(fid,'	%d',t);
p
                  count3 = fprintf(fid,'	%d',c1);
                  count3 = fprintf(fid,'	%d',c2);
                  count3 = fprintf(fid,'	%d',c3);
                  count3 = fprintf(fid,'	%d',c4);
                  count3 = fprintf(fid,'	%d',c5);
                  count3 = fprintf(fid,'	%d',c6);
                  count3 = fprintf(fid,'	%d',c7);

                  o_str1=t*s*cl*o_str1/10;
                  o_str2=t*s*c2*o_str2/10;
                  o_str3=t*s*c3*o_str3/10;
                  o_str4=t*s*c4*o_str4/10;
                  o_str5=t*s*c5*o_str5/10;
                  o_str6=t*s*c6*o_str6/10;
                  o_str7=t*s*c7*o_str7/10;

                  Epsilon=1;
                  k=1;

                  for j=2000:2:2500
                    sum1=0;sum2=0;sum3=0;sum4=0;sum5=0;sum6=0;sum7=0;
                    for i=1:1:10
                      sum1 = sum1 + ((o_str1(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum2 = sum2 + ((o_str2(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum3 = sum3 + ((o_str3(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum4 = sum4 + ((o_str4(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum5 = sum5 + ((o_str5(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum6 = sum6 + ((o_str6(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                      sum7 = sum7 + ((o_str7(i,1)*fre(i,1)^2)/((fre(i,1)^2)-(j^2)-(sqrt(-1)*j*line(i,1))));
                    end

                    sum1 = sqrt(Epsilon + sum1);\%n1(i,k)=sum1/15;
Annexure IV: SIMPLE Algorithm MATLAB code.

Note: (Few data format generated for the wavelengths ‘A’ matrix, Combination of concentrations (Variants) ‘X’, are also given in italic fonts)

```
clear
2022 2024 2026 2028 2030 2032 2034 2036 2038 2040 2042 2044
2046 2048 2050 2052 2054 2056 2058 2060 2062 2064 2066 2068
2070 2072 2074 2076 2078 2080 2082 2084 2086 2088 2090 2092
2094 2096 2098 2100 2102 2104 2106 2108 2110 2112 2114 2116
2118 2120 2122 2124 2126 2128 2130 2132 2134 2136 2138 2140
2142 2144 2146 2148 2150 2152 2154 2156 2158 2160 2162 2164
2166 2168 2170 2172 2174 2176 2178 2180 2182 2184 2186 2188
2190 2192 2194 2196 2198 2200 2202 2204 2206 2208 2210 2212
2214 2216 2218 2220 2222 2224 2226 2228 2230 2232 2234 2236
2238 2240 2242 2244 2246 2248 2250 2252 2254 2256 2258 2260
2262 2264 2266 2268 2270 2272 2274 2276 2278 2280 2282 2284
2286 2288 2290 2292 2294 2296 2298 2300 2302 2304 2306 2308]
```

(Note: Single Spectra can be generated just by customizing the concentration control structure.)
<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>90 145 30 70 45 140 145</td>
<td>2.500000e-001 2.000000e-001 90 145 30 70 45 140 145;</td>
</tr>
<tr>
<td>90 150</td>
<td>2.500000e-001 2.000000e-001 90 145 30 70 45 150 145;</td>
</tr>
<tr>
<td>100 175 40 90 50 140 150</td>
<td>2.500000e-001 2.000000e-001 100 175 40 90 50 150 150;</td>
</tr>
</tbody>
</table>

% Few sample are given above to indicate the format of data!
% Only one spectra is given to indicate the format of data!

\[\text{I:}\]

Corresponding data sets from the spectra generated i.e spectra (As the data sets is large is not included)

\[\text{I:}\]

\[
\text{\%For each } h=1, \ldots, c, \text{ where } A_0=X'Y, M_0=X'X, C_0=I, \text{ and } c \text{ given, } \\
m=9; \% \text{ number of Variable} \\
n=251; \% \text{ Number of Lambdas} \\
W=0; \\
P=0; \\
Q=0; \\
C_0=0; \\
A_0=0; \\
M_0=0; \\
A_0=X'*Y; \%4X7(\text{number of variant X Number of lambda}) \\
M_0=X'*X; \%4X4 (\text{Number of variants X Number of Variants}) \\
C_0=\text{eye}(m) \\
\]

\[
\text{for } i=1:1:1 \\
\% \text{ Computing} \\
\text{value}=i \\
g=A_0'*A_0; \\
[V,qh]=\text{eig}(g); \\
V; \\
qh; \\
wh=A_0*qh \\
wh_{\text{mat}}=[wh(1,n); \; \; wh(2,n); \; \; wh(3,n); \; \; wh(4,n);wh(5,n); \; \; wh(6,n); \; \; wh(7,n);wh(8,n); \; \; wh(9,n);] \\
wh=wh_{\text{mat}} \\
ch=wh*M_0*wh \\
ch_{\text{sq}}=\sqrt{ch} \\
wh=wh/ch_{\text{sq}} \\
\]

\[
\text{for } k=1:1:m \\
W(k,i)=wh(k,1); \\
\text{end} \\
\% \text{ Computing } W \\
W \\
\% \text{ Computing P} \\
wh=[W(1,i); \; \; W(2,i); \; \; W(3,i); \; \; W(4,i);W(5,i); \; \; W(6,i); \; \; W(7,i);W(8,i); \; \; W(9,i);]; \\
ph=M_0*wh; \\
\text{for } k=1:1:m \\
P(k,i)=ph(k,1); \\
\text{end} \\
\% \text{ Computing P} \\
P \\
\% \text{ Computing Q} \\
wh=[W(1,i); \; \; W(2,i);W(3,i);W(4,i);]; \\
qh=A_0'*wh; \\
\text{for } p=1:1:n \\
Q(p,i)=qh(p,1); \\
\text{end} \\
Q \]
\( ph = [P(1,i); P(2,i); P(3,i); P(4,i); P(5,i); P(6,i); P(7,i); P(8,i); P(9,i)]; \)
\( vh = CO \times ph \)
\( av_vh = \frac{vh(1,i) + vh(2,i) + vh(3,i) + vh(4,i) + vh(5,i) + vh(6,i) + vh(7,i) + vh(8,i) + vh(9,i)}{m}; \)
\( vh = \frac{vh}{av_vh}; \)
\( C1 = CO - vh \times vh; \)
\( MI = MO - ph \times ph'; \)
\( A1 = CO \times A0; \)
\( A0 = A1; \)
\( CO = C1; \)
\( end \)

\( \% T = X \times W \)
\( B = W \times Q' \)
\( \% Y = T \times Q' \)
\( \% ph = [P(1,1) P(2,1) P(3,1) P(4,1) P(5,1) P(6,1) P(7,1)]; \)
\( Xun = [2.500000e-001 \ 2.000000e-001 \ 90 \ 145 \ 30 \ 70 \ 45 \ 140 \ 150]; \)
\( Y = B' \times Xun' \)
\( \% \% X = B' \times X = Y \)
\( \% \% X = Y / B \) solves for \( X \) in \( X \times B = Y \)
\( \% Y = X \times B + E, \) where \( B = W \times Q, \)
\( Y = [2.311909e+001 \ 2.171334e+001 \ 2.030843e+001 \ 1.913200e+001 \ 1.829059e+001 \ 1.778674e+001 \ 1.757335e+001 \ 1.759267e+001 \ 1.787670e+001]; \)
\( 8.892988e-000 \ 9.072612e-000 \ 9.303482e-000 \ 9.675287e-000 \ 1.011510e+001 \ 1.064427e+001 \ 1.123592e+001 \ 1.185175e+001 \ 1.245961e+001]; \)
X = Y'B;
X=X*220000
plot(X,'--rs','LineWidth',2,...
    'MarkerEdgeColour','k',...
    'MarkerFaceColour','g',...
    'MarkerSize',10)
xlabel('Variable number');
ylabel('Concentration of glucose in dc-lit');