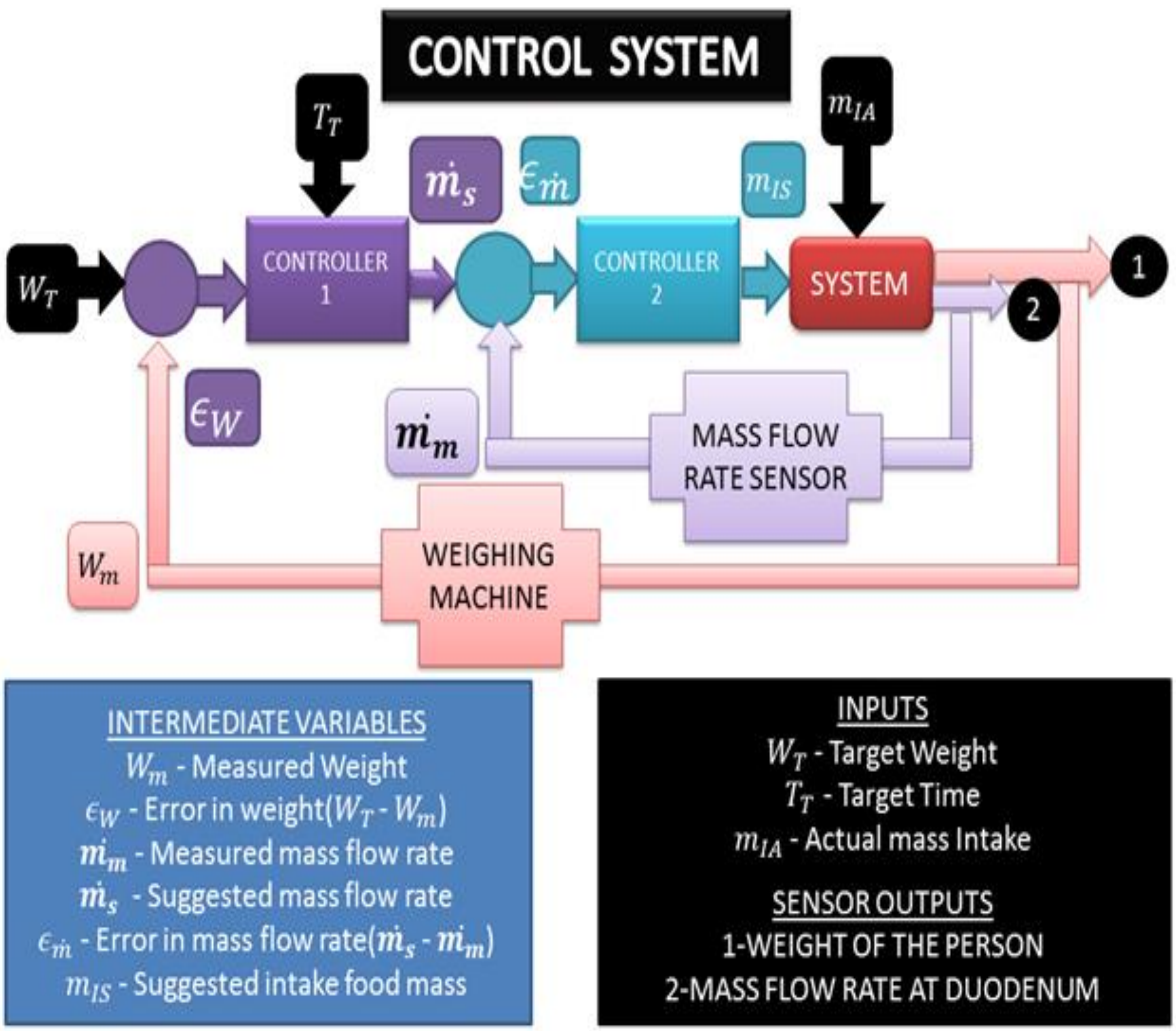
WEIGHT LOSS CONTROL SYSTEM

INTRODUCTION TO THE PROJECT

The aim of the project is to aid in weight loss by monitoring the amount of food intake and suggesting a suitable food intake mass based on various factors like metabolism rate, weight, height, weather, etc. and also taking into account the amount and duration of weight to be lost

CONTROL SYSTEM PROPOSED



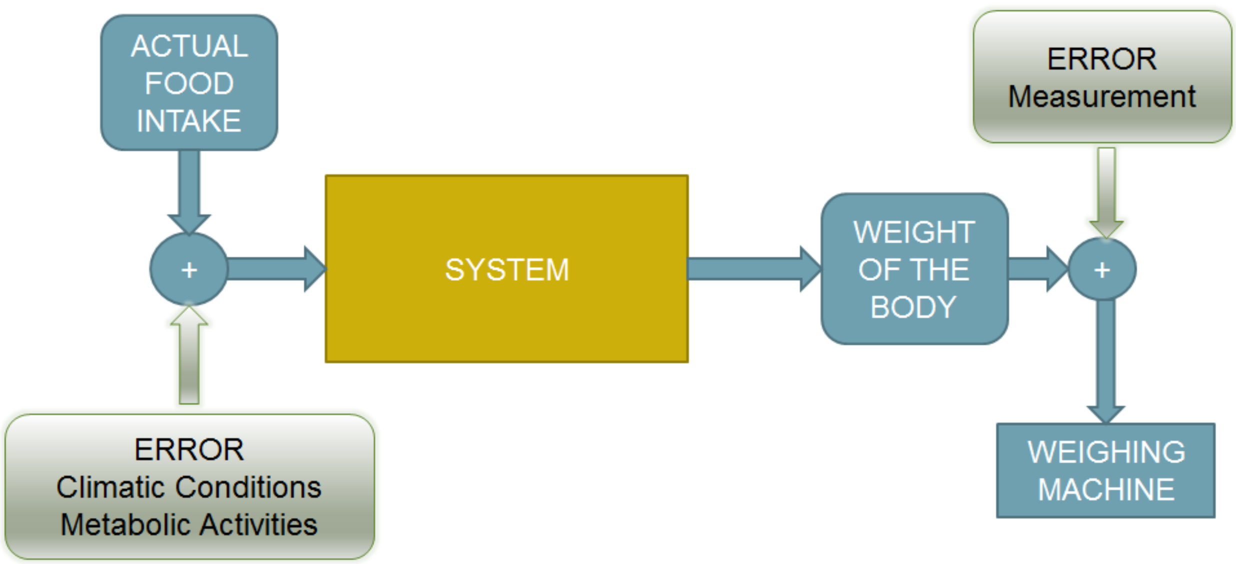
METHODOLOGY OF APPROACH

1. Modeling the system using system identification
    1.1. Develop a model for the food mass intake as input and the weight of the body as output.
    1.2. Develop a model for the food mass intake as input and the mass flow rate as jejunum as output.
2. Design the controller2 and complete the inner control loop
3. Find the suggested mass flow rate for various values of the target weight and target time by iterating the suggested mass flow rate and running the inner control loop and generate data with the target weight and target time as input and the suggested mass flow rate as output.
4. Use system identification to model the first controller
5. Design experiment to get better data and iterate the process till a good model is obtained

NOTE: Controller 2 only suggests a value but it is up to the user to eat what he wants. So the entire control system only suggests suitable values.

PRIMARY OBJECTIVE

To develop a model of the system with the actual food intake as the input and the weight of the body as output.



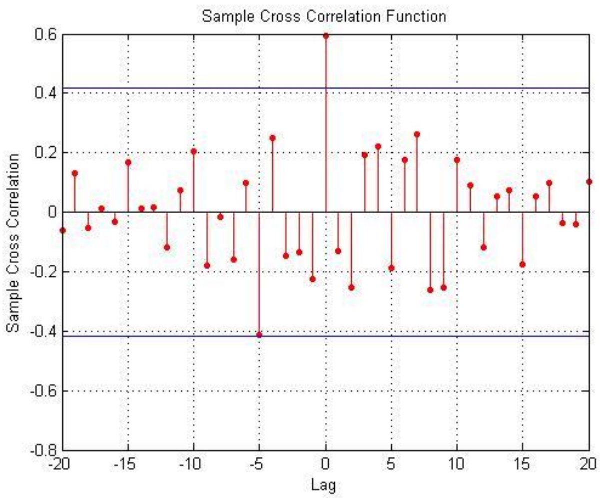
ASSUMPTIONS MADE IN THE MODEL DEVELOPMENT

1. The system is linear time invariant. We start with this and extend it to time varying models.
2. The calorie density (calorie intake per gram of food mass intake) is assumed to be constant.
3. The food intake is averaged over the entire time interval.

VALIDATING THE ASSUMPTION THAT THE CALORIE DENSITY IS CONSTANT

CROSS CORRELATION APPROACH

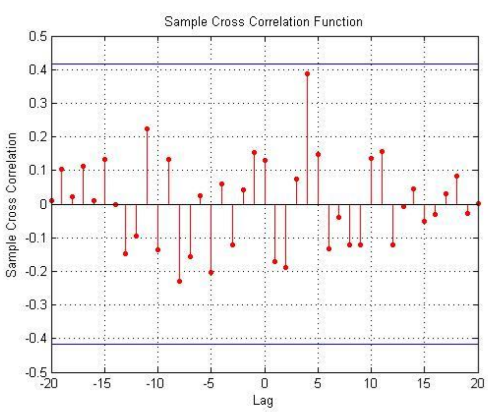
1. **Food mass input without water and food caloric input**



(Blue lines indicate the significance limits)

This strongly suggests that the kth sample of 1st sequence (food mass intake without water) is strongly correlated with only the kth sample of the 2nd sequence (food caloric input) implying linear relation.

2. **Food mass intake with water and food caloric intake**



(Blue lines indicate the significance limits)

This plot tells that no lag is within a significant range. So the two sequences are highly uncorrelated.

From the above, it can be inferred that either the food caloric intake or the food mass intake which excludes water can be taken as input. They are linearly related by a constant factor and that can be found out by method of linear least squares.

LINEAR FIT APPROACH

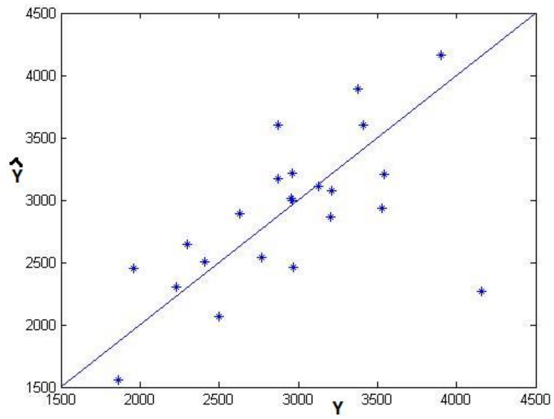
$$Y = XA \implies A_{LS} = (X'X)^{-1}X'Y$$

1. **Food mass input without water and food caloric input**

Taking Y as the food calorie input and X as the food mass input, we arrive at A=1.6212

On the training data it yields a Root Mean Square Error of 522.0693.

The percentage error is $\frac{RMSE}{MEAN} * 100 = 17.73\%$

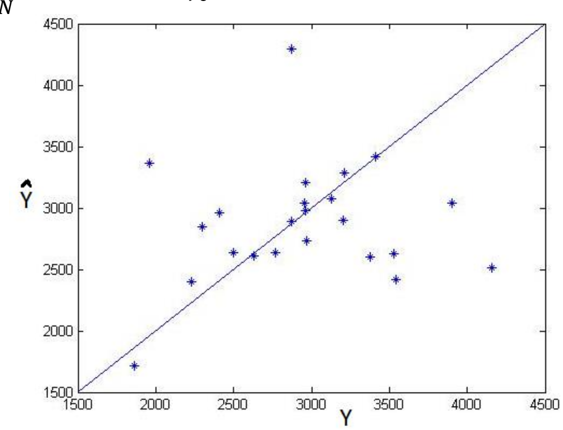


2. **Food mass intake with water and food caloric intake**

Taking Y as the food calorie input and X as the food mass input, we arrive at A=0.6783

On the training data it yields a Root Mean Square Error of 691.9663.

The percentage error is $\frac{RMSE}{MEAN} * 100 = 23.5\%$



Both seem to work significantly well suggesting that further tests are required to find whether the food mass intake with water or without water is linearly related to the caloric intake.

DATASETS USED

Matlab implicitly introduces a Zero Order Hold Delay on the process in addition to the existing process delay. The Zero Order Hold assumes that the input is constant until the next input is given. So we exploit this fact and give the average intake in the sampled time (food intake in sampled time/sampling time). Zero Order Hold is compensated by distributing the input over the whole sampling period. So the process delay can be taken as such and ignore the zero order hold.

DATASET 1 – This dataset contains data obtained by Dr.Ben with 21 data points with a sampling interval of one day. It assumes that the food intake for the whole day is distributed uniformly over the whole day so that the Zero Order Hold is compensated.

DATASET 2 – This dataset contains data obtained by Dr.Ben with 41 points with a sampling interval of 12 hours. It assumes that nothing is consumed for half the day and whatever is consumed over the remaining day is distributed uniformly over the remaining half day so that the Zero Order Hold is compensated.

DATASET 3 – This dataset contains data obtained from internet with 93 data points with sampling interval of one day since weight measurement is available for only one time per day.

COMMON PREPROCESSING OF THE DATA

Remove the mean from the data so as to facilitate a linear model as

$$y = ax + b \qquad \text{(Taken as an example)}$$

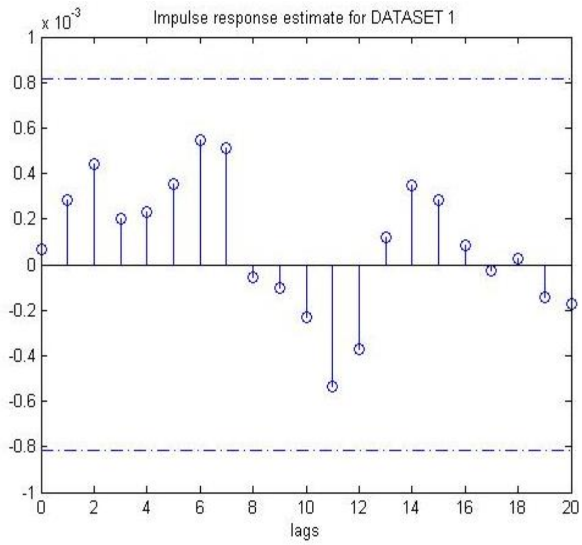
is not exactly linear because of the presence of ‘b’ . So the model is generally taken as

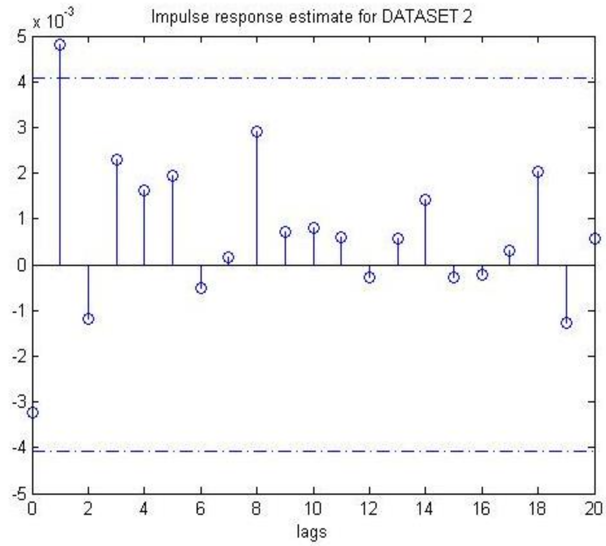
$$y - y_0 = a(x - x_0)$$

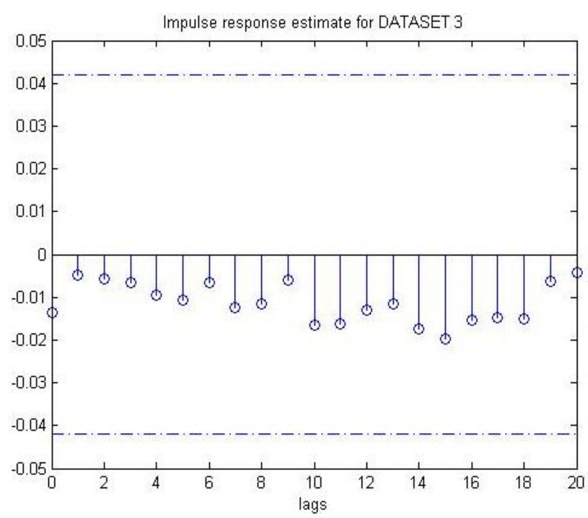
So the mean of x and y is generally subtracted as it is a good estimate of the existing data. By shifting data by their mean we make the model pass through origin and not get an offset term. Note that in the vicinity of approximation of linear time invariant region, it is assumed that mean does not change with time.

NON PARAMETRIC ANALYSIS

THE IMPULSE RESPONSE ESTIMATE







DATASET 1 and DATASET 3 give no estimate of delay. Reason is because of the sampling time. There is a delay visible in the DATASET 2 but there is only one significant impulse response. This suggests that we need a better sampling time. Hence we head towards the step response.

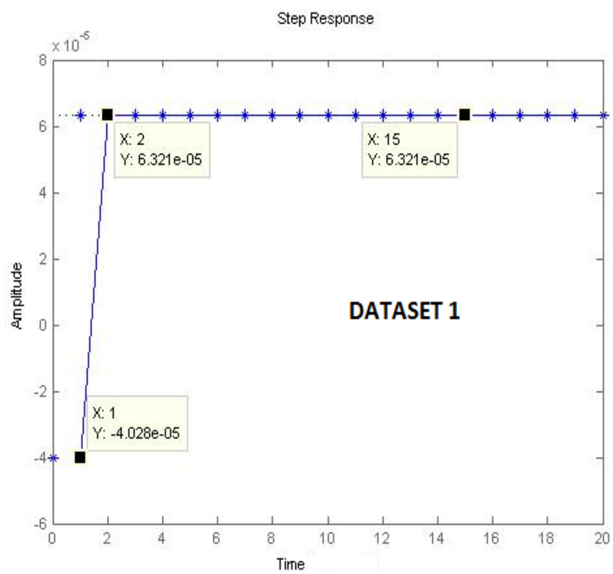
In the DATASET 2, the delay comes out to be one sampling interval which is equal to 12 hours.

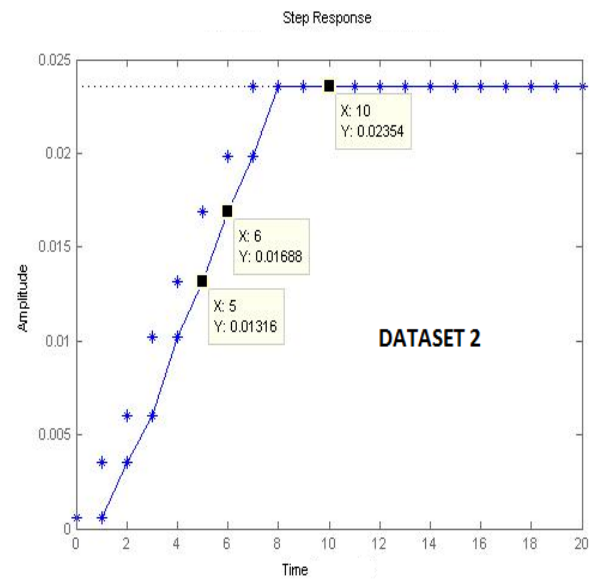
STEP RESPONSE

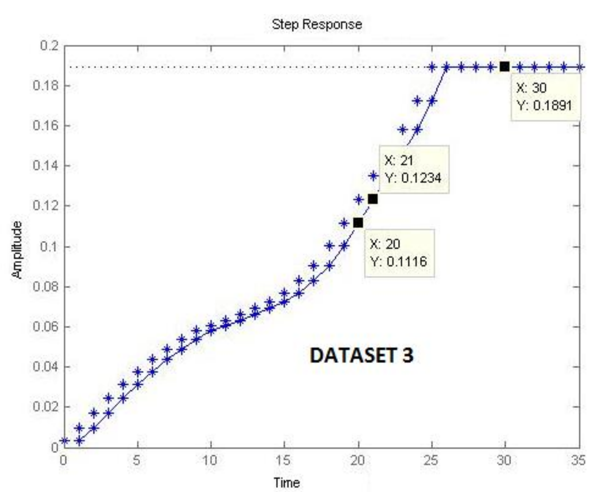
The step responses are obtained using MATLAB and general heuristics are used

- Time Constant = Time taken to reach 63.2% of the total amplitude.
- Corner Frequency = 1/(Time Constant)
- Bandwidth = 3 x Corner Frequency
- 0.1 x Time Constant < Sampling Time < 0.2 x Time Constant
- Sampling Frequency = 2 x π / Sampling Time
- Normalized Bandwidth = (3 x Corner Frequency)/(Sampling Frequency/2)

In the graphs, the x axis scale is 1 unit time corresponds to 1 day.



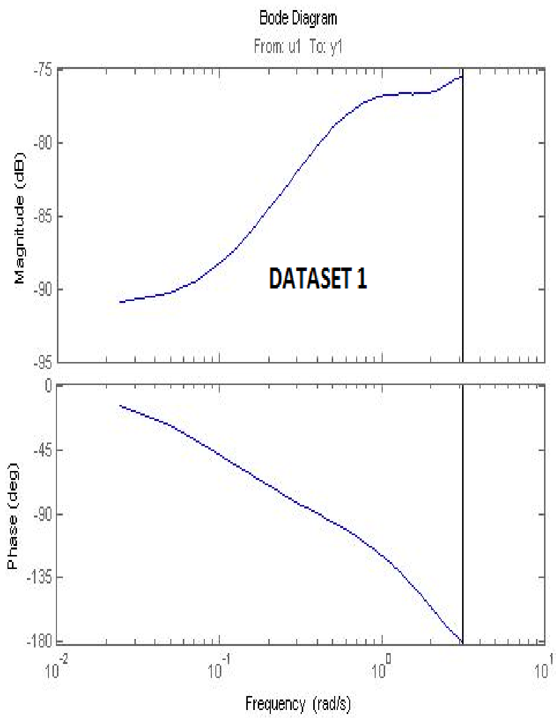


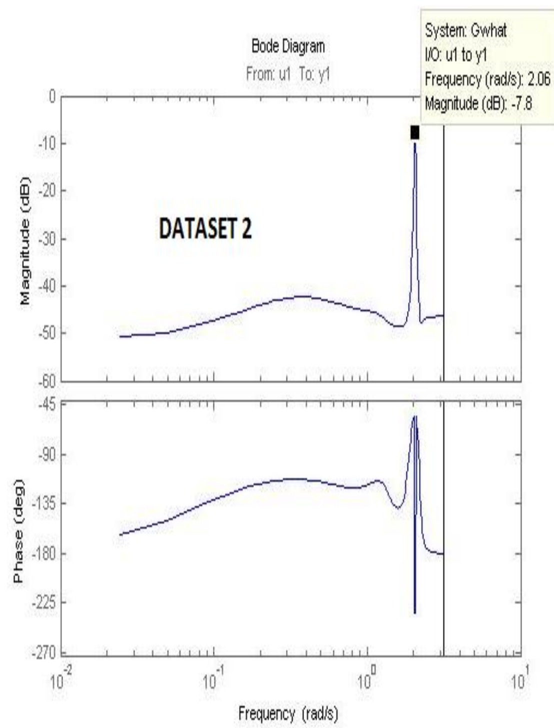


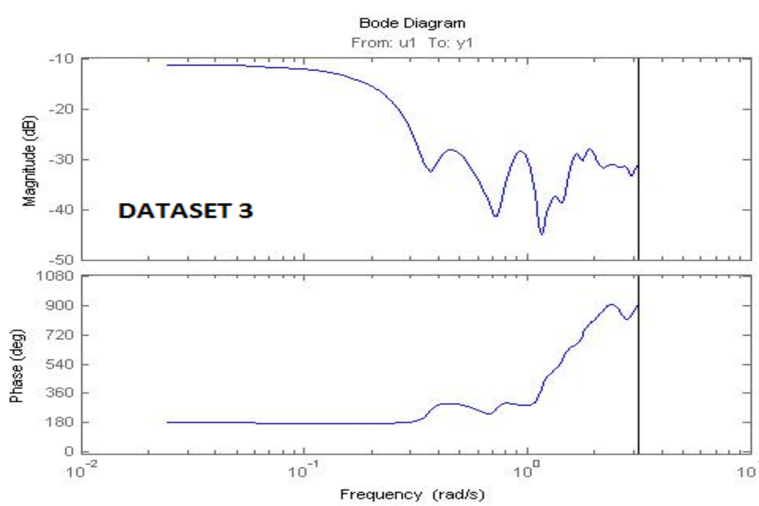
	SAMPLING TIME(IN DAYS)	
	LOWER BOUND	UPPER BOUND
DATASET 1	0.063	0.126
DATASET 2	0.45	0.9
DATASET 3	1.95	3.9

	LEAST VALUE	HIGHEST VALUE	63.2% OF AMPLITUDE	TIME CONSTANT (in days)	TIME CONSTANT (in secs)	CORNER FREQUENCY	BANDWIDTH
DATASET 1	-4.03E-05	6.32E-05	2.51E-05	0.63	54432	1.83715E-05	5.51146E-05
DATASET 2	0	0.02354	1.49E-02	4.5	388800	2.57202E-06	7.71605E-06
DATASET 3	0	0.19	1.20E-01	19.5	1684800	5.93542E-07	1.78063E-06

FREQUENCY RESPONSE



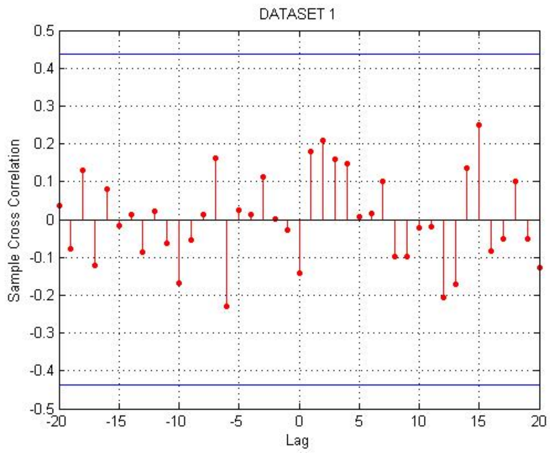


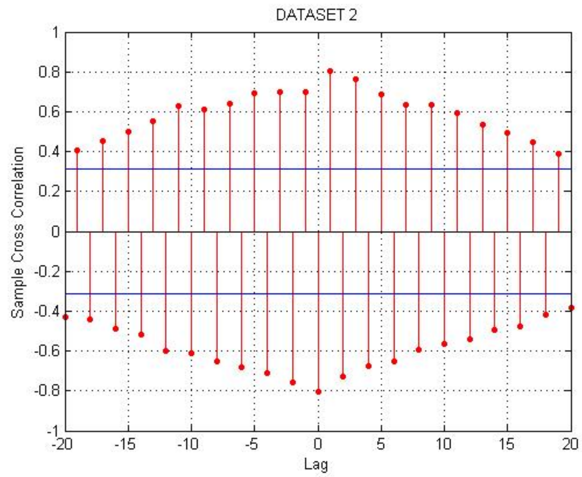


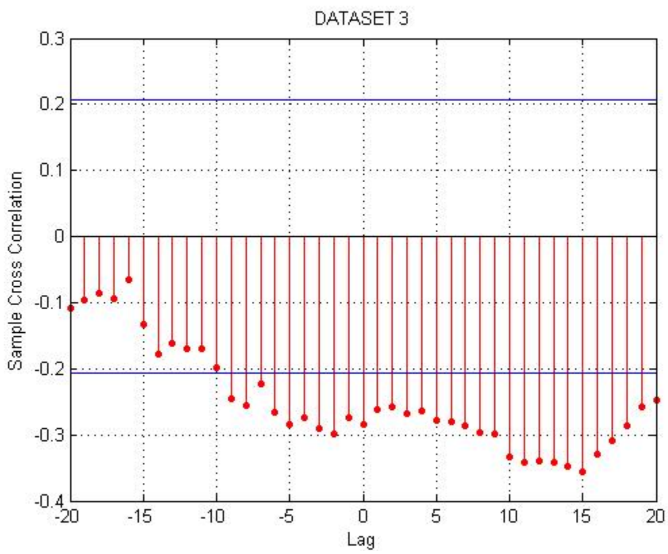
PARAMETRIC ANALYSIS

Now, initially we take y=0. Then the residuals in prediction is same as that of y. So we see if there is any predictability initially between input and output and the following graphs are obtained.

NOTE: The blue lines in the graphs indicate the significance levels







DATASET 1 has no predictability. Hence its sampling time is highly insufficient. Hence that data cannot be used. DATASET 2 and DATASET 3 have some predictability. But DATASET 3 has no significance impulse response. Hence no delay can be estimated from it. Henceforth in further analysis we will drop the DATASET 1 and DATASET 3 and we head towards parametric modeling.

CRITERIA FOR OVER ESTIMATION OF MODEL

In the predicted model, the errors come with an estimate which is the standard deviation (σ) of the estimate. For 95% confidence we generally take$\pm 1.96\sigma \approx \pm 2\sigma$. If this interval contains zero, then we have overestimated the model and this parameter should not be considered at all.

PARAMETRIC MODEL ANALYSIS FOR DATASET 2

EQUATION ERROR MODEL

About the model

This model assumes that the error enters from the input side. So this model assumes that the error and the system have common dynamics. So this equation is of the form

$$y[k] = \frac{B(q^{-1})}{A(q^{-1})}u[k] + \frac{1}{A(q^{-1})}e[k]$$

y--output q--shift operator d-process delay k-time instant e-error

This model is a good place to start as in our process we could tell that errors due to climatic conditions, physical activity of the body, etc. enter through the input (mass intake)

NOTE: Due to limited number of data points, we initially try to get a good model using the whole data as a training set

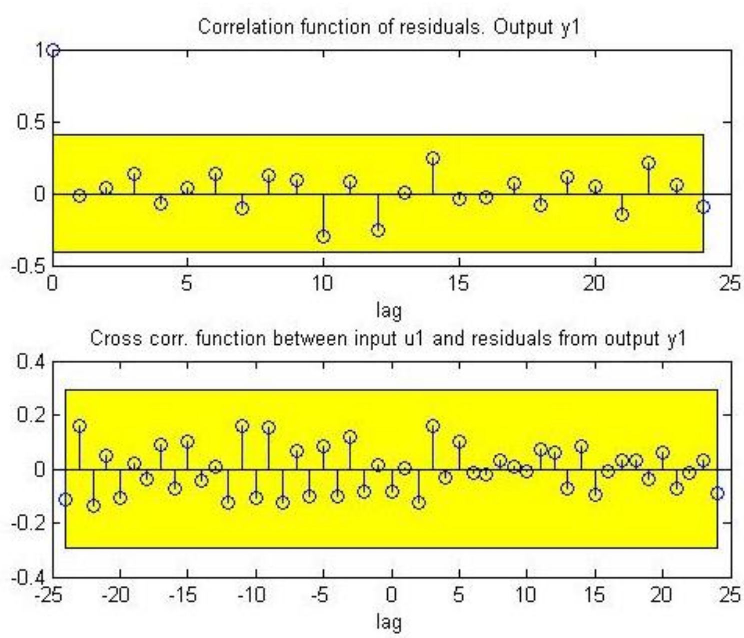
Valid Models Obtained for DATASET 2

A(z) = 1 - 0.5972 (+/- 0.1241) z^-1 B(z) = 0.007418 (+/- 0.0006869) z^-1

Fit to estimation data: 55.69% (prediction focus)

FPE: 0.1088, MSE: 0.1016

The residuals are

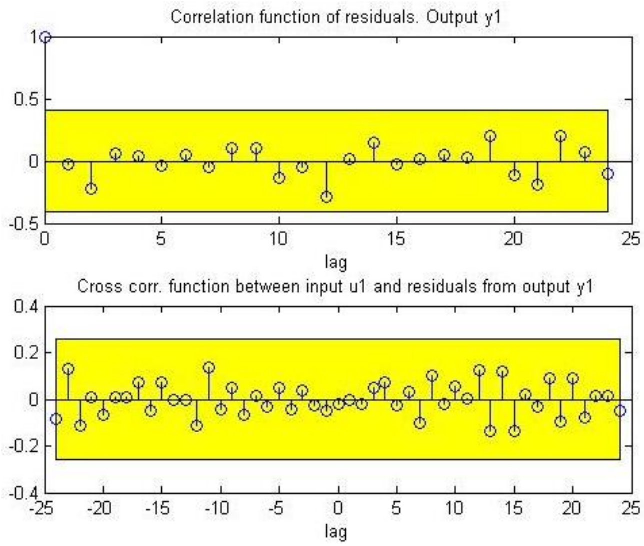


A(z) = 1 - 0.4805 (+/- 0.1224) z^-1 - 0.3761 (+/- 0.1237) z^-2 B(z) = 0.005289 (+/- 0.0009984) z^-1

Fit to estimation data: 61.05% (prediction focus)

FPE: 0.08783, MSE: 0.07853

The residuals are



Hence among the two candidates, the better one is the 2nd one since it has a better fit and lower Mean Square Error.

OUTPUT ERROR MODEL

About the Model

This model assumes that the error is completely due to White Noise. Because of that it gets the best estimate of the deterministic part. It has the structure of

$$y[k] = \frac{B(q^{-1})}{F(q^{-1})} u[k] + e[k]$$

y--output q--shift operator k-time instant e-error

This gives us a good initial guess of the deterministic part for the Box-Jenkins model.

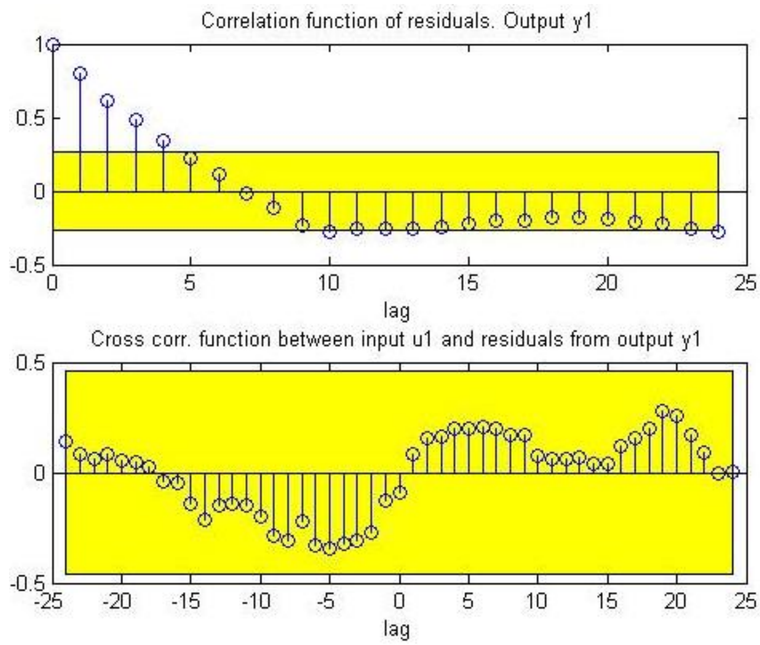
Best Model Obtained

B(z) = -0.001257 (+/- 0.0002555) z^-1   F(z) = 1 - 1.975 (+/- 0.005329) z^-1 + 0.9782 (+/- 0.005176) z^-2

Fit to estimation data: 83.42% (prediction focus)

FPE: 0.4931, MSE: 0.4273

The residuals are



It can be seen that the deterministic portion predicts very well. But it can be seen that there is some stochastic part that is to be modeled. This is therefore taken as an initial guess to the Box-Jenkins approach.

Box-Jenkins Model

This model assumes that the input and error are independently related to the output. It has the structure

$$y[k] = \frac{B(q^{-1})}{F(q^{-1})}u[k] + \frac{C(q^{-1})}{D(q^{-1})}e[k]$$

y--output   q--shift operator   k-time instant   e-error

Valid Models

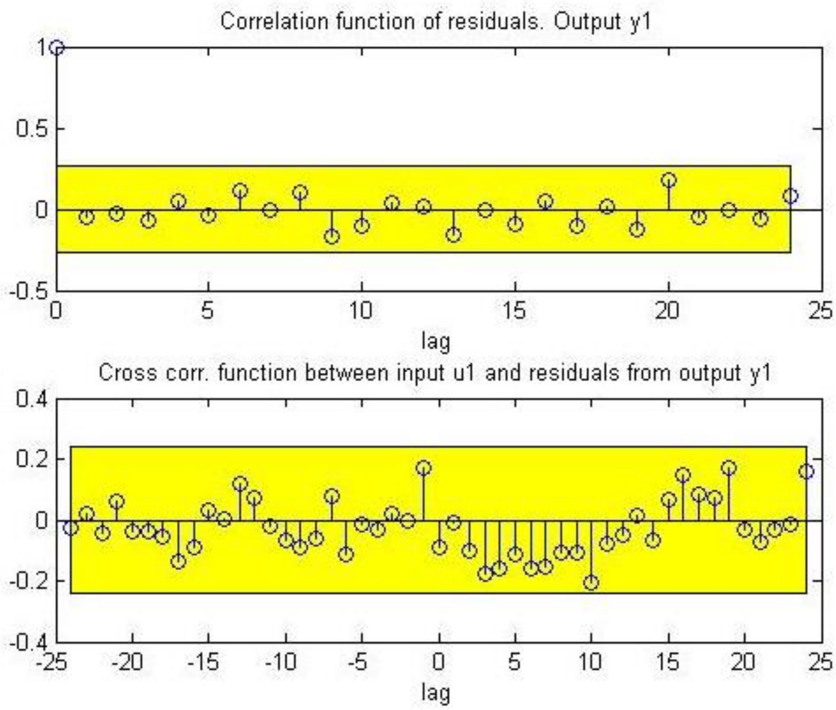
B(z) = 0.006986 (+/- 0.002335) z^-1   C=1   D(z) = 1 - 1.013 (+/- 0.01044) z^-1

F(z) = 1 - 0.9764 (+/- 0.01024) z^-1

Fit to estimation data: 92.71% (prediction focus)

FPE: 0.08578, MSE: 0.08272

The residuals are



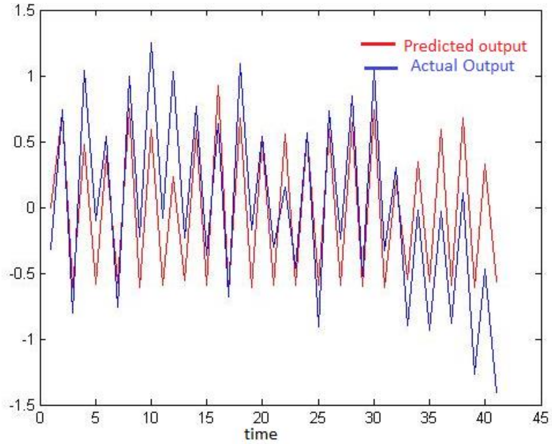
There is nothing else left to predict. Hence it is an optimal model. This is better compared to the model obtained by output error hence it has almost the same MSE and it has a very good fit compared to the equation error model

Hence the model that we obtained with just the training set is

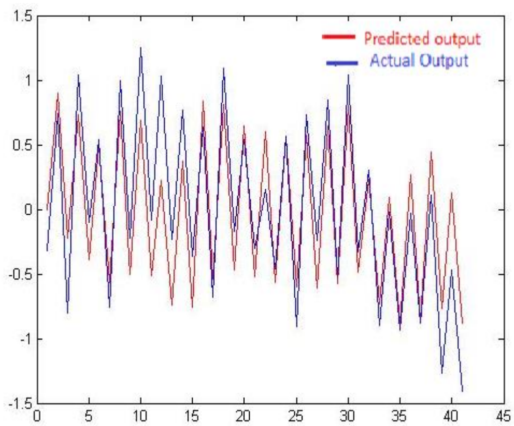
$$y[k] \; = \frac{0.006986 \, q^{-1}}{1 - 0.9764 \, q^{-1}} u[k] \; + \; \frac{1}{1 - 1.013 \, q^{-1}} e[k]$$

$$\begin{aligned} y[k] \; = &\; (1.9894 \, y[k-1] - 0.9891 \, y[k-2]) \; + (0.006986 \, u[k-1] - \; 0.007077 \, u[k-2]) \\ &+ \; (e[k] - \; 0.9764 e[k-1]) \end{aligned}$$

FIT OF THE BOX-JENKINS MODEL TO THE TRAINING DATA



FIT OF THE EQUATION ERROR MODEL TO THE TRAINING DATA



Both the models seem to work well with the training data. Hence the criteria for differentiation of the two models is to have a test data and see how well it predicts on the test data.

Now we resolve the dataset into a training data containing 25 points and test data containing 16 points and we repeat the whole process. In this way, the impulse response estimate itself fails. Hence we cannot proceed further in this direction.

Conclusion

Based on the acquired data, the best linear time invariant models have been identified. But they are highly insufficient to explain the dynamics of the process. The future work involves modeling the system by first principles and identifying the parameters of the model adaptively.