UNIVERSITY OF WESTERN ONTARIO
FACULTY OF ENGINEERING

DEPARTMENT OF ELECTRICAL & COMPUTER EGINEERING

ECE-9407 – Embedded Systems and Wireless Sensor Networks

(Graduate Summer Course, 2016)
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Final Project Report

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Prediction-based Energy saving in wireless sensor networks: Combining Kalman Filter and Grey Model

1. Description:

This project aims to create a device that can measure and predict the surrounding temperature using Kalman Filter and Grey Model. The project is based on the research in [1] and on LAB 3 in the curriculum. The model communication will be done through Bluetooth and the actual temperature will be generated in the C main function as a saw tooth signal. In this project, a prediction–based energy saving solution combining Kalman Filter and Grey Model will be implemented in CYPRESS Bluetooth Low Energy (BLE) platform. The one step predictor of Kalman Filter (KF) algorithm and Ending-point fixed Discrete Grey Model (EDGM) will be combined with weight parameters for measured value prediction. Both algorithms have low computational complexity but high prediction accuracy. Experiment results show that the sensor can reduce almost high time to sending and updating value to receiver. From this scenario, if the clusters or receivers in WSNs run the same algorithms with sensors, they do not need to update value from sensors but use the predicted value from their integrated algorithms. The energy consumption from sensors will be reduced by this prediction approach. The lifetime of WSNs could be prolonged.

2. Equipment& Objectives:

1. Equipment:

Hardware: BLE Pioneer Kit (CY8CKIT-042-BLE)

Software : PSoC Creator 3.3 SP2, CySmart 1.2, and Android App

2. Objectives:

1. Simulate a temperature changed from 10℃ to 40 ℃
2. Implement Kalman Filter one step predictor algorithm
3. Implement EDGM algorithm for one step prediction
4. Combine the predicted value from KF and EDGM as final prediction value
5. Calculate the percentage of energy saving
6. Sending the percentage value Android phone to by Bluetooth protocol by using heart rate profile and app.

3. Preparing and Understanding

This project will be implemented two one-step prediction algorithms named Kalman Filter and EDGM. Every one step prediction will be combine two algorithms with equal weights (0.5 for KF, 0.5 for EDGM). If the error ($e(t+1) = |\hat{y}(t+1) - y(t+1)|$) of next step is less than threshold, this means that the accuracy of predicted value can be accepted. Based on this prediction result and the prediction-based aggregation approach from [1], an prediction-based energy saving solution can be implemented.

The prediction-based energy saving scenario in WSNs will be composed of sensors and clusters or receiver. Taking a peer-to-peer communication for example. The sensor and receiver will be embedded as same prediction algorithms. So if the error ($e(t+1)=|\hat{y}(t+1)-y(t+1)|$) of next step is less than threshold, the sensor will not send the latest value to receiver. The receiver will use this predicted value as t+1 step of value to instead of actual value. On the contrary, if error is greater than the threshold, the latest value will be sent to receiver, the matrix of value will be synchronized. It is stated that the power consumption of transmission is far more than the power consumption of computation[2]. In this scenario, the more accurate value can be predicted, the less data will be transmitted from sensor to receiver, and the less power will be consumed.

Based the above solution and approach, the one prediction algorithms including Kalman Filter and EDGM will be programmed and implemented in Cypress BLE system. If the whole energy saving scenario would be implemented, the same prediction algorithms should be executed both in BLE hardware and receiver (iOS or Android phone App). However, due to the time limitation, there is no time to develop Apps, which runs Kalman Filter and EDGM algorithms. The alternative solution is that we will calculate a percentage value, which is the numbers of saving energy over numbers of temperature value sampling. To show this result significantly, this percentage value will be shown on iOS or Android phone, which is based on the Lab03 heart rate BLE profile. In summary, a percentage value, which means the energy saving, will be shown on Apps of iOS and Android phone based on BLE heart rate App.

4. Block Diagram:

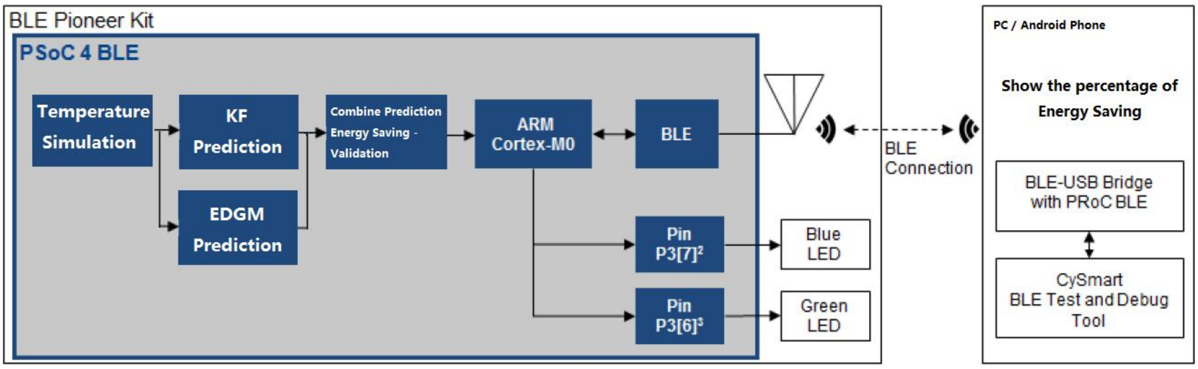


Figure 1: Block Diagram and Overview

5. Theory

Grey Model

The Grey Model is intervenient between the white system and the black system. This theory provides a powerful tool for modeling discrete series with a few data items and forecasting the near future value based on determination of an exponential equations[1]. The GM(1,1) is a basic model constructed on a single sequence in Grey Model theory. It uses only the behavioral sequence (output sequence or background values) of the system without considering any externally acting sequences (or referred to as input sequences, or driving quantities) [3].

The grey action quantity in the GM(1,1) model is a value derived from the background values. It reflects changes contained in the data and its exact intension is grey. This quantity realizes the extension of the relevant intension. To implement GM(1,1) into embedded system for on-line prediction, we need its discrete grey prediction models (DGM) . The details of DGM derivation will be introduced.

Definition 1

The equation

$$x^{(1)}(k+1)=\beta_1 x^{(1)}(k)+\beta_2 \tag{1}$$

is referred to as a discrete grey model (DGM) or a discretization of the GM(1,1)model.

Theorem 2

Let $X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\cdots x^{(0)}(n))$ be a nonnegative sequence and its accumulation generation. $X^{(1)}=(x^{(1)}(1),x^{(1)}(2),\cdots x^{(1)}(n))$, where $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)$, $k=1,2,\cdots,n$. If $\hat{\boldsymbol{\beta}}=(\beta_1,\beta_2)^T$ is the parametric sequence and

$$Y=\begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}, \mathrm{B}=\begin{bmatrix} x^{(1)}(1) & 1 \\ x^{(1)}(2) & 1 \\ \vdots & \vdots \\ x^{(1)}(n-1) & 1 \end{bmatrix} \tag{2}$$

Then the least squares estimates of the parameters of the discrete model $x^{(1)}(k+1)=\beta_1 x^{(1)}(k)+\beta_2$ satisfy $\hat{\boldsymbol{\beta}}=(\beta_1,\beta_2)^T=(B^TB)^{-1}B^TY$, where

$$B^TB=\begin{bmatrix} \sum_{k=1}^{n-1}(x^{(1)}(k))^2 & \sum_{k=1}^{n-1}x^{(1)}(k) \\ \sum_{k=1}^{n-1}x^{(1)}(k) & n-1 \end{bmatrix} \tag{3}$$

$$(B^TB)^{-1}=\frac{1}{(n-1)\sum_{k=1}^{n-1}(x^{(1)}(k))^2-[\sum_{k=1}^{n-1}x^{(1)}(k)]^2}\times\begin{bmatrix} n-1 & -\sum_{k=1}^{n-1}x^{(1)}(k) \\ -\sum_{k=1}^{n-1}x^{(1)}(k) & \sum_{k=1}^{n-1}(x^{(1)}(k))^2 \end{bmatrix} \tag{4}$$

$$B^T Y = \begin{bmatrix} \sum_{k=1}^{n-1} x^{(1)}(k) \cdot x^{(1)}(k+1) \\ \sum_{k=1}^{n-1} x^{(1)}(k+1) \end{bmatrix} \tag{5}$$

$$\hat{\boldsymbol{\beta}} = (B^T B)^{-1} B^T Y = \begin{bmatrix} \dfrac{\sum_{k=1}^{n-1}(x^{(1)}(k+1) \cdot x^{(1)}(k)) - \dfrac{1}{(n-1)}[\sum_{k=1}^{n-1} x^{(1)}(k+1)] \cdot [\sum_{k=1}^{n-1} x^{(1)}(k)]}{\sum_{k=1}^{n-1}(x^{(1)}(k) \cdot x^{(1)}(k)) - \dfrac{1}{(n-1)}[\sum_{k=1}^{n-1} x^{(1)}(k)] \cdot [\sum_{k=1}^{n-1} x^{(1)}(k)]} \\ \dfrac{1}{(n-1)}[\sum_{k=1}^{n-1} x^{(1)}(k+1) - \beta_1 \sum_{k=1}^{n-1} x^{(1)}(k)] \end{bmatrix}$$
$$= (\beta_1, \beta_2)^T \tag{6}$$

Theorem 3

Let $B, Y, \hat{\beta}$ be the same as defined in Theorem 2, and $\hat{\boldsymbol{\beta}} = (B^T B)^{-1} B^T Y = (\beta_1, \beta_2)^T$. Then it can be derived as following:

The iteration equations:

$$\hat{x}^{(1)}(k+1) = \beta_1^k x^{(1)}(1) + \frac{1-\beta_1^k}{1-\beta_1} \bullet \beta_2; or$$
$$\hat{x}^{(1)}(k+1) = \beta_1^k [x^{(1)}(1) - \frac{\beta_2}{1-\beta_1}] + \frac{\beta_2}{1-\beta_1};$$
$$k = 1, 2, \cdots n-1 \tag{7}$$

The restored values are

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (\beta_1 - 1)[x^{(1)}(1) - \frac{\beta_2}{1-\beta_1}] \cdot \beta_1^{k-1} \quad k = 1, 2, \cdots, n-1 \tag{8}$$

where $\hat{x}^{(1)}(1) = x^{(0)}(1)$. This form of the discrete grey model is referred with fixed starting points, so called SDGM.

Theorem 4

Based on the similar derivation, the form of the discrete grey model with fixed end points, so called EDGM. The iteration equations is given by

$$\hat{x}^{(1)}(k) = \beta_1^{(k-n)}[x^{(1)}(n) + \beta_3 - \frac{\beta_2}{1-\beta_1}] + \frac{\beta_2}{1-\beta_1} \tag{9}$$

where $k = 1, 2, \cdots, n-1$, and the restored valued given by

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) = \beta_1^{(k-n)}(1-\beta_1^{-1})[x^{(1)}(n) + \beta_3 - \frac{\beta_2}{1-\beta_1}],\ k = 2, 3, \cdots, n, ... \tag{10}$$

If we need a one-step prediction, so $k = n+1$, the equation (10) will be changed as

$$\hat{x}^{(0)}(n+1) = \hat{x}^{(1)}(n+1) - \hat{x}^{(1)}(n) = \beta_1(1-\beta_1^{-1})[x^{(1)}(n) + \beta_3 - \frac{\beta_2}{1-\beta_1}] \tag{11}$$

This equation will be implement in this project for one-step prediction.

Kalman Filtering Predictor Equations

Form [4] the Kalman Filter Based on one-step prediction is shown as following

State equations:

$$\begin{aligned} x_{k+1} &= A_k x_k + B_k u_k + w_k \\ y_k &= C_K x_k + v_k \end{aligned} \tag{12}$$

Assumptions:

x_0 is gaussian with mean $\overline{x}_0$ and covariance P_0

w_k, v_k are gaussian, zero-mean, white process independent with x_0

Everything is Gaussian- linear operations preserve gaussian properties.

$$E(w_k)=0, E(v_k)=0,$$
$$E\left(\begin{bmatrix} w_k \\ v_k \end{bmatrix}\begin{bmatrix} w_l^T & v_l^T \end{bmatrix}\right)=\begin{bmatrix} Q_k & 0 \\ 0 & R_k \end{bmatrix}\delta_{k,l} \quad , \quad Q_k, R_k \geq 0 \ \forall k \tag{13}$$

Kalman Predictor:

$$M_k = A_k \Sigma_{k|k-1} C_k^T (C_k \Sigma_{k|k-1} C_k^T + R_k)^{-1} \tag{14}$$

$$\hat{x}_{k+1|k} = (A_k - M_k C_k)\hat{x}_{k|k-1} + B_k u_k + M_k y_k \tag{15}$$

$$\Rightarrow \hat{x}_{k+1|k} = A_k \hat{x}_{k|k-1} + B_k u_k + M_k (y_k - C_k \hat{x}_{k|k-1}) \tag{16}$$

$$\Sigma_{k+1|k} = A_k \Sigma_{k|k-1} A_k^T - A_k \Sigma_{k|k-1} C_k^T (C_k \Sigma_{k|k-1} C_k^T + R_k)^{-1} C_k \Sigma_{k|k-1} A_k^T + Q_k \tag{17}$$

$$\Rightarrow \Sigma_{k+1|k} = A_k \Sigma_{k|k-1} A_k^T - M_k C_k \Sigma_{k|k-1} A_k^T + Q_k \tag{18}$$

$\Sigma_{k|k-1}$ satisfies a Riccati Difference Equation (RDE)

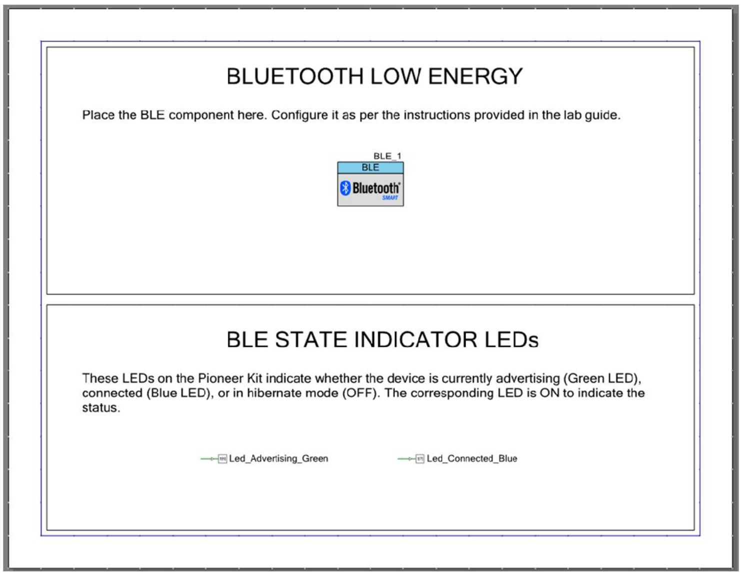
Based on the equation (14)-(18), the one step prediction of Kalman Filter will be implement in this project. The correlation matrix of system noise Q could be set as 0.04, and the correlation matrix of measurement noise R could be set as 0.01. The initial value of covariance $\Sigma_{0|-1}$ is set as 1.

6. Firmware:

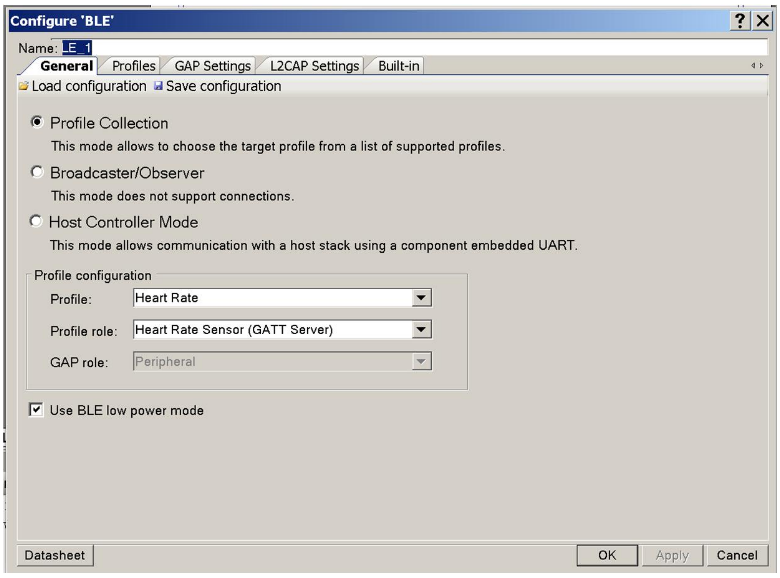
File Name (Sample time=1 sec)	Function Name	Description
FinalProjectProgram	• Simulate Real Temperature • GM1stepprediction • KalmanFilterPredictor1 • EnergySavingValidation	• This is to generate a simulated temperature signal from 10 degrees to 40 degrees every sample time (1 second). It changes by 0.5 degrees every one second. We add a random noise from 0.02 to 0.2 degrees. • This uses the Grey Model prediction to predict one temperature for one step. • This uses the Kalman filter to predict temperature for one step. • This checks the energy saving percentage of the system. The sensor will not need to send an updated temperature as long as the difference between the predicted and the actual temperature is less than error threshold (0.1 degrees)
Heartrateprocessing.c	This file handles the energy saving validation percentage value. It repeats every one second to show the performance of the prediction.	HR_WSNESPercentage= (unit8)(WSNESPercentageLF*100.0); This is the final value for sending

7. Steps:

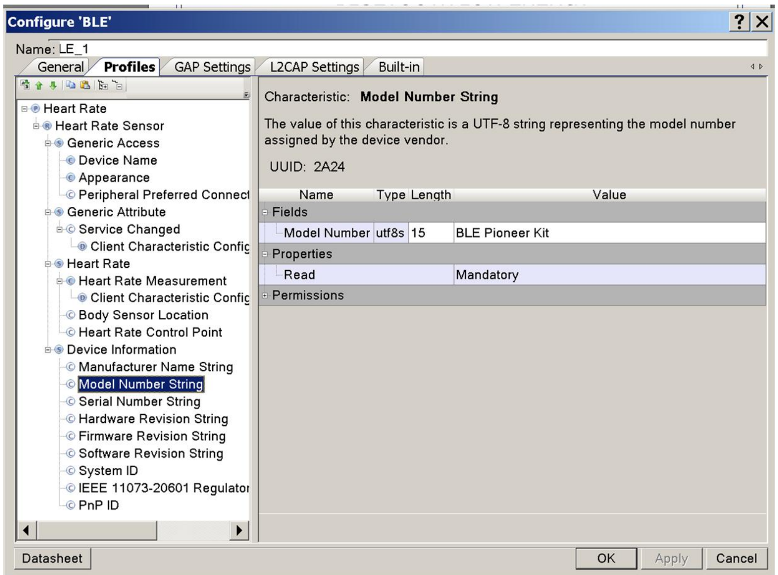
1. In the following, we used LAB 3 procedure and heart rate communication to send the energy saving percentage value. This has been done in addition to modifications in the C code.
2. Create a new project named Final Project:



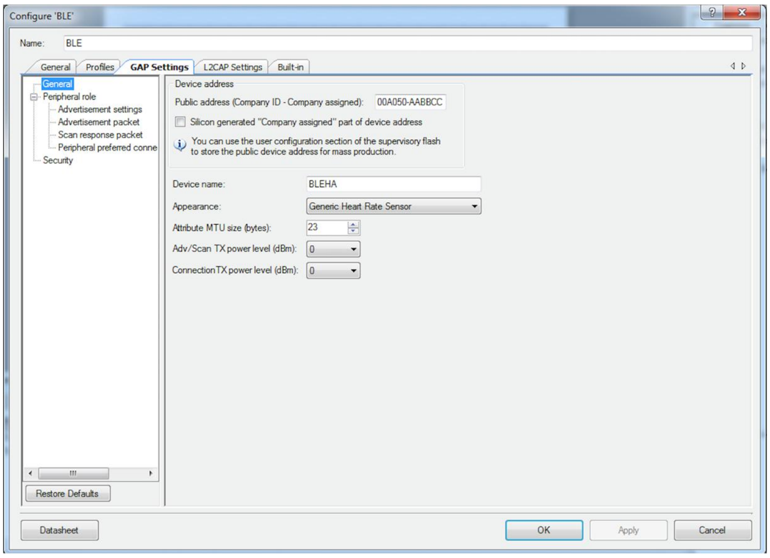
3. Click on the BLE component to open the configuration. Change the profile to Heart Rate, and make the role Heart Rate Sensor. This is shown in the figure below:



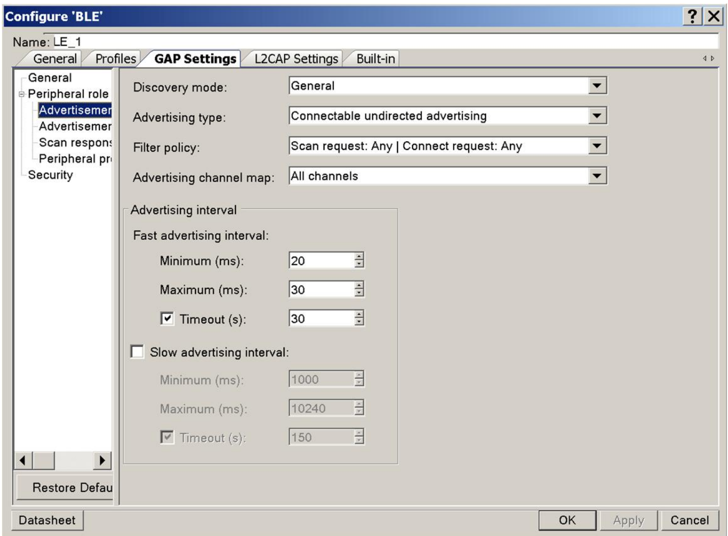
4. No changes are done in the profile tab as below:



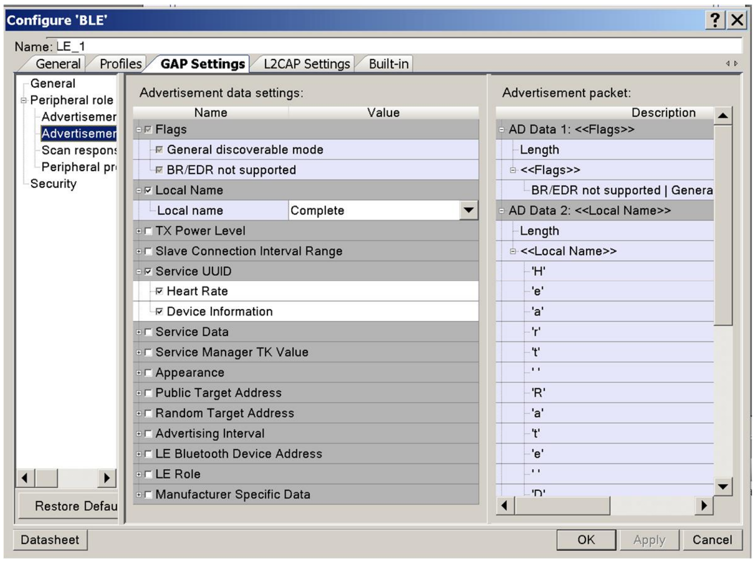
5. Click on the GAP settings, and change the device name and appearance as below:



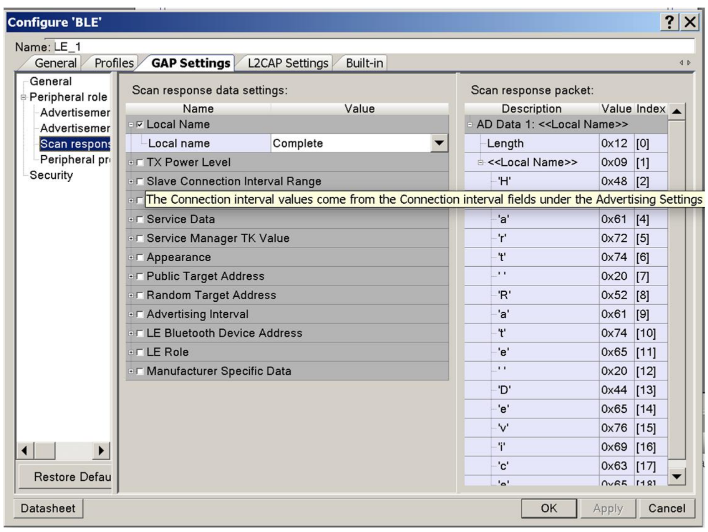
6. From the left click on advertisement settings then change the settings as below:



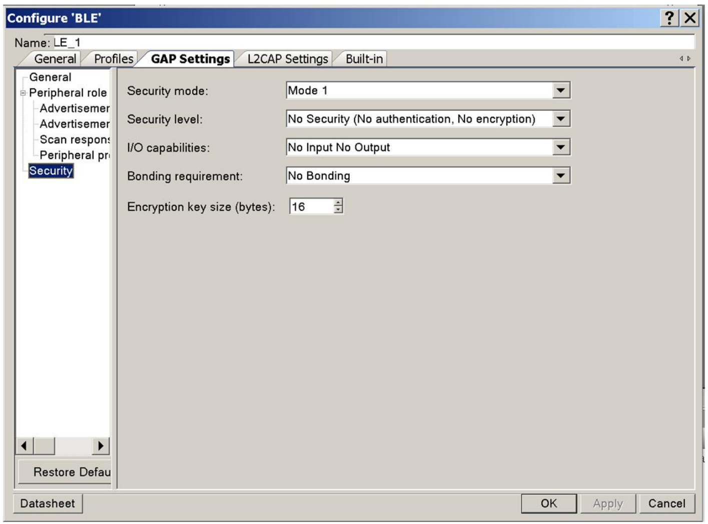
7. Click on Advertisement Packet from the left then apply the changes below:



8. Change the properties of the scan response as below:

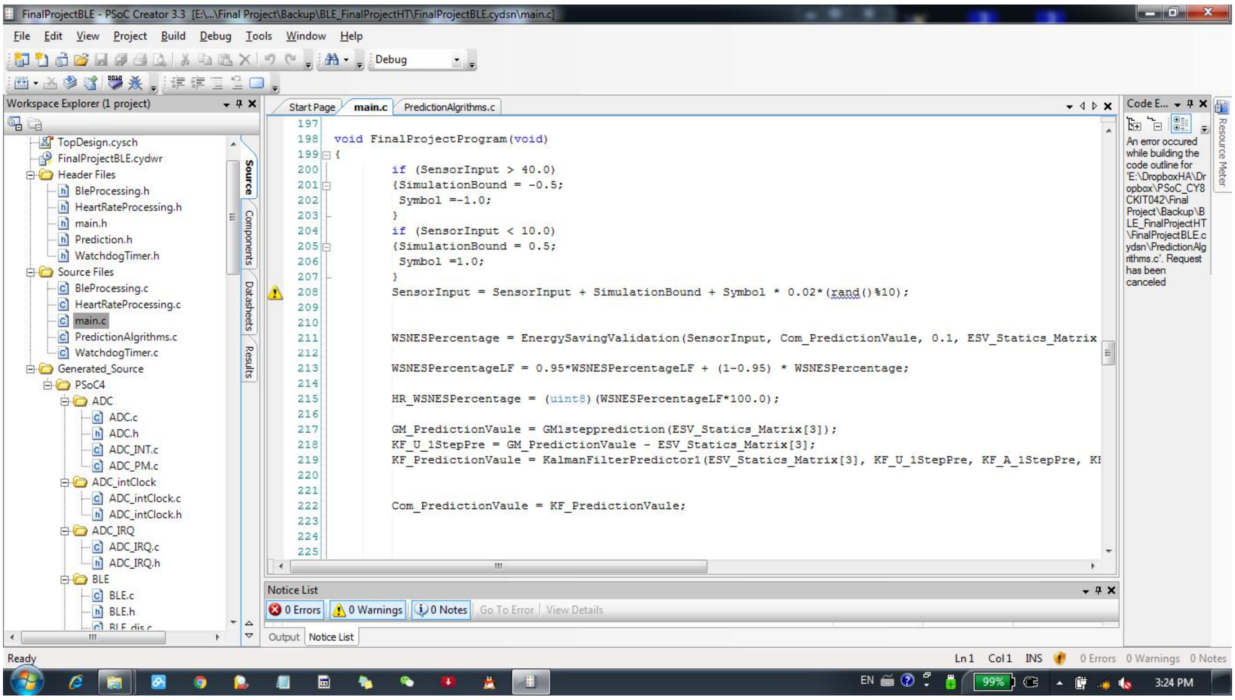


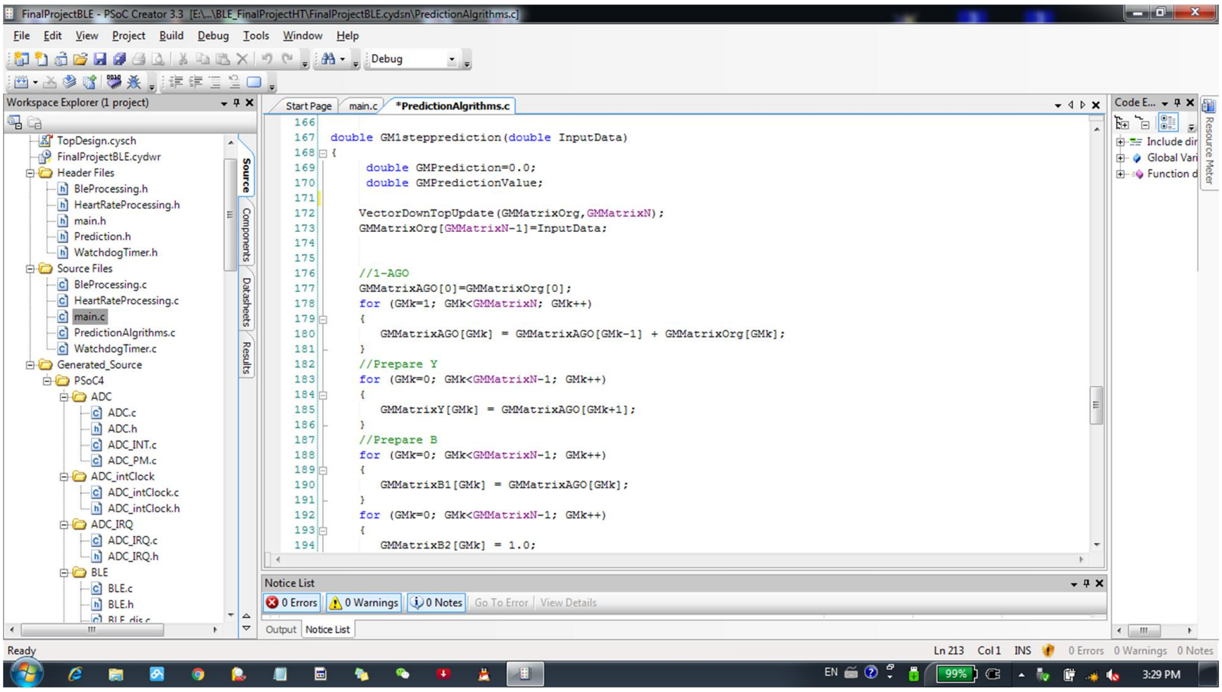
9. Change the security settings as below, then click ok to save and close the configuration settings.

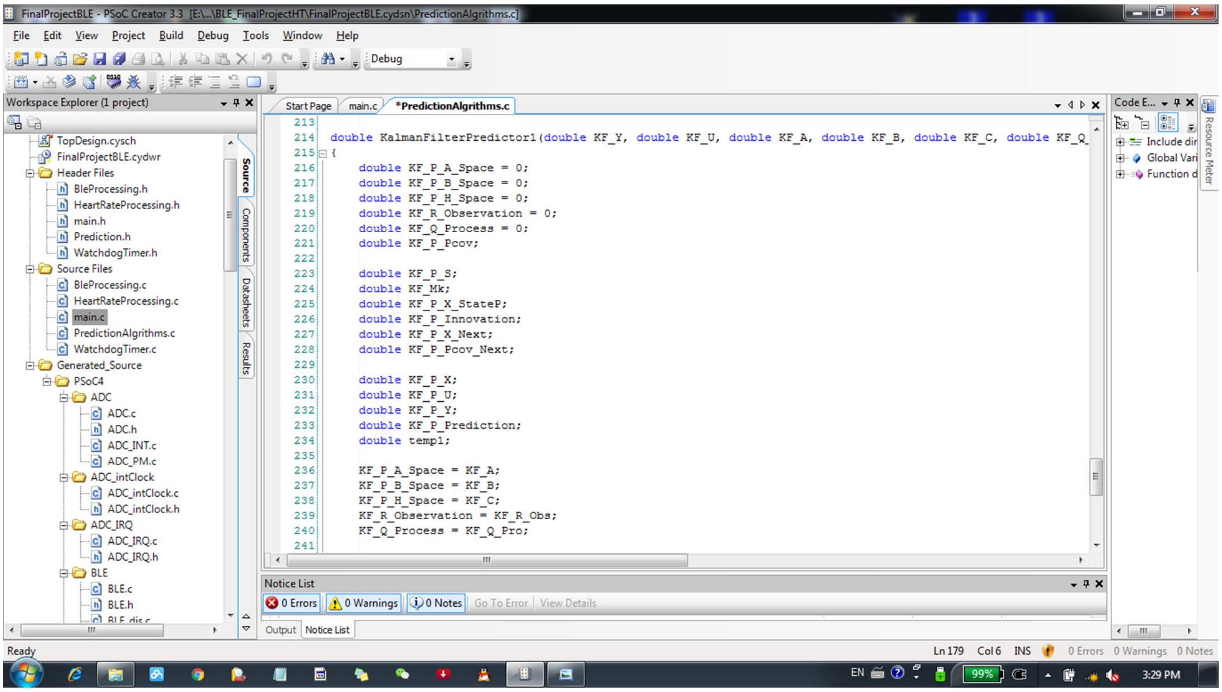


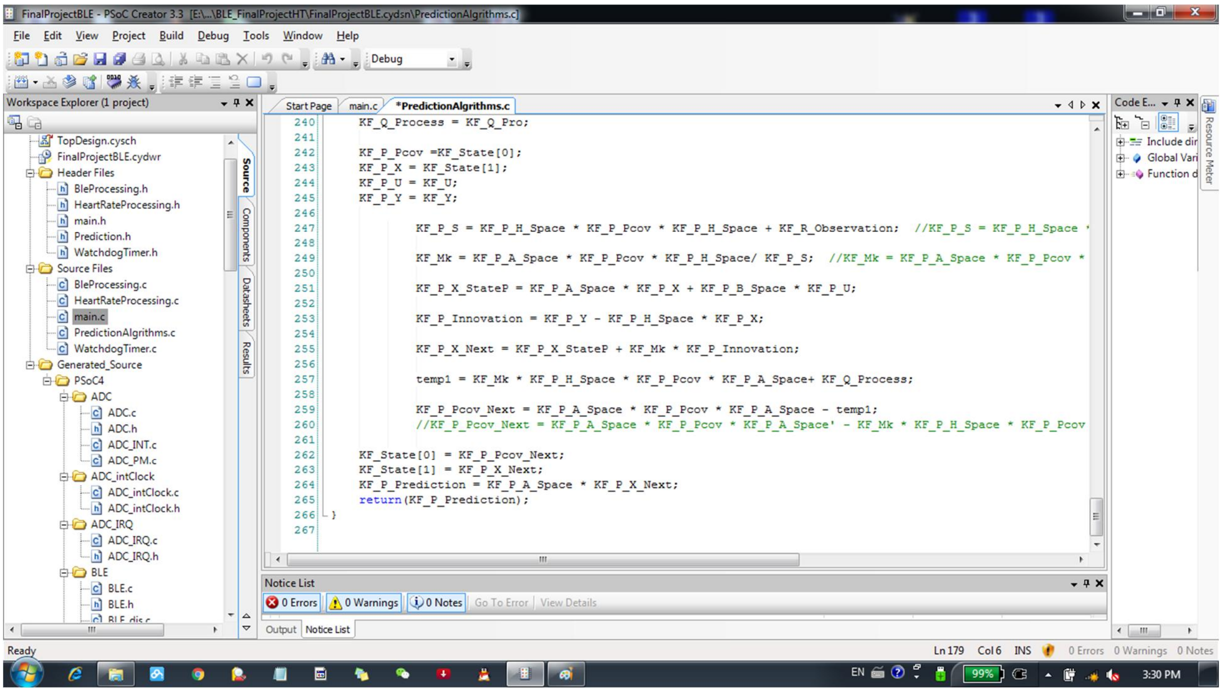
10. Click on Build the select Build BLE Final Project to compile the C code, make sure there are no errors after compiling the code.

    The following screenshots are main code from this project.

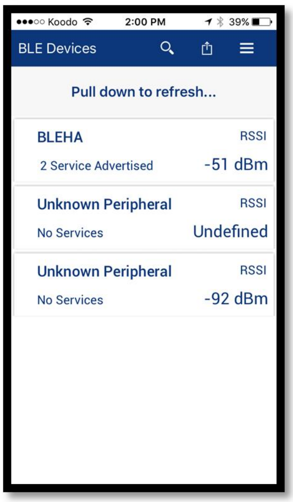



FinalProjectBLE - PSoC Creator 3.3 [E:\...\BLE_FinalProjectHT\FinalProjectBLE.cydsn\PredictionAlgrithms.c]
*PredictionAlgrithms.c
double GM1stepprediction(double InputData)
{
double GMPrediction=0.0;
double GMPredictionValue;
VectorDownTopUpdate(GMMatrixOrg,GMMatrixN);
GMMatrixOrg[GMMatrixN-1]=InputData;
//1-AGO
GMMatrixAGO[0]=GMMatrixOrg[0];
for (GMk=1; GMk<GMMatrixN; GMk++)
{
GMMatrixAGO[GMk] = GMMatrixAGO[GMk-1] + GMMatrixOrg[GMk];
}
//Prepare Y
for (GMk=0; GMk<GMMatrixN-1; GMk++)
{
GMMatrixY[GMk] = GMMatrixAGO[GMk+1];
}
//Prepare B
for (GMk=0; GMk<GMMatrixN-1; GMk++)
{
GMMatrixB1[GMk] = GMMatrixAGO[GMk];
}
for (GMk=0; GMk<GMMatrixN-1; GMk++)
{
GMMatrixB2[GMk] = 1.0;

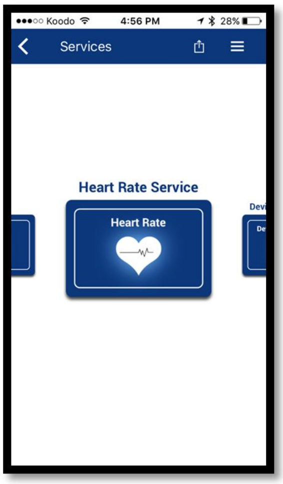

FinalProjectBLE - PSoC Creator 3.3 [E:\...\BLE_FinalProjectHT\FinalProjectBLE.cydsn\PredictionAlgrithms.c]
*PredictionAlgrithms.c
double KalmanFilterPredictor1(double KF_Y, double KF_U, double KF_A, double KF_B, double KF_C, double KF_Q_
{
double KF_P_A_Space = 0;
double KF_P_B_Space = 0;
double KF_P_H_Space = 0;
double KF_R_Observation = 0;
double KF_Q_Process = 0;
double KF_P_Pcov;
double KF_P_S;
double KF_Mk;
double KF_P_X_StateP;
double KF_P_Innovation;
double KF_P_X_Next;
double KF_P_Pcov_Next;
double KF_P_X;
double KF_P_U;
double KF_P_Y;
double KF_P_Prediction;
double temp1;
KF_P_A_Space = KF_A;
KF_P_B_Space = KF_B;
KF_P_H_Space = KF_C;
KF_R_Observation = KF_R_Obs;
KF_Q_Process = KF_Q_Pro;



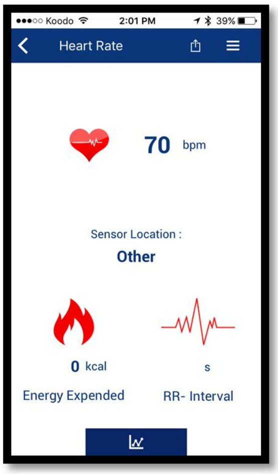
11.To test the configuration on IPhone, install CySmart App on the phone.



12.Choose the heart rate service as follows:



13. Read the value of energy saving:



The values were jumped around 60 to 70. They means the energy will be saving 60-70% in real scenario.

8. Conclusion:

The project aimed to simulate a practical temperature sensor and predictor. This sensor used the Grey Model and the Kalman Filter to predict the temperature. We used the Bluetooth model presented in lab 3 in the curriculum to send the energy saving percentage validation and used the heart rate measure as a tool to present this value. The percentage we got varied from 60 to 70 percent, which means that the sensor doesn't need to send the updated measured temperature information around 70 percent of the time and save energy in the real case if the receiver and the sensor are running the same algorithms. For the future work, we can redesign the mobile application to make it a real temperature sensor and add another device as a receiver (or LCD) to receive the measured temperature. It could be a very good approach to save energy in WSNs.

9. References:

[1] G. Wei, Y. Ling, B. Guo, B. Xiao, and A. V. Vasilakos, "Prediction-based data aggregation in wireless sensor networks: Combining grey model and Kalman Filter," *Comput. Commun.*, vol. 34, no. 6, pp. 793–802, May 2011.

[2] M. Chen and M. L. Fowler, "Data compression trade-offs in sensor networks," 2004, vol. 5561, pp. 96–107.

[3] S. Liu and Y. Lin, *Grey Systems: Theory and Applications*, vol. 68. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011.

[4] S. S. Haykin, *Adaptive filter theory*, 4th ed. Upper Saddle River, N.J: Prentice Hall, 2002.