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COMPARATIVE ANALYSIS OF THE CCCD AND BOX-BEHNKEN DESIGNS FOR A PROLONG WIRELESS SENSOR NETWORK LIFETIME THROUGH AN ADAPTIVE NONPARAMETRIC REGRESSION MODEL

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Abstract*:* In a Wireless Sensor Network (WSN) with multi-response application, Design of Experiment (DOE) techniques plays a vital role in suggesting the most appropriate choice of factors and their respective coded levels that would satisfy the process requirement either for research or industrial applications. Hence, in this work, two DOE techniques namely; the Box-Behnken Design (BBD) with coded design levels, $-1, 0, +1$ and the Circumscribed Central Composite Design (CCCD) with coded design levels, $-\alpha, -1, 0, +1, +\alpha$ were introduced. In the application, the two designs, the BBD and CCCD were subjected to Response Surface Methodology (RSM) data and were analyzed. The result in terms of goodness-of-fit statistics show that the BBD outperformed the CCCD suggesting that the design do not require α (axial points) and as such the BBD is the appropriate DOE technique for the multi-response problem with responses; Delay transmission, Idle power consumption and Transition time.

Keywords: Box-Behnken Design, Circumscribed central composite design, Delay transmission, Idle power consumption, Transition time, Wireless Sensor Network

Introduction*:* RSM is a gathering of mathematical and statistical methods employed by Industrial Statistician and Engineers for observed model building. In the modeling and analysis of data, the response is influenced by one or more factors (Eguasa *et al.*, 2022). There are three main phases in RSM, namely, the Experimental Design Phase, the Modeling Phase, and the Optimization Phase (Castillo, 2007).

In the Modeling phase of RSM, a fundamental assumption is that the relationship between the response variable y and k explanatory variables $x_1, x_2, \dots, x_k$, can be represented as:

$$y_i = f\left(x_{i1,}\ x_{i2}, \dots, x_{ik}\right) + \varepsilon_i, \quad i = 1,2,\dots,n \tag{1}$$

where the mean function f denotes the true but unknown relationship between the response variable and the k explanatory variables, ε_i, $i = 1,2,\dots,n$, are random error terms assumed to have a normal distribution with mean zero and constant variance and n is the sample size (Myers *et al*., 2009; Wan and Birch, 2011).

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Materials and Methods

The knowledge behind the adaptive local linear regression model is because it is flexible and can adjust favourably in solving boundary bias problem and is not limited to user specified form for the data (Eguasa *et al*., 2022; Akhideno and Eguasa 2022).

Locally Adaptive Bandwidths

The bandwidth is the most vital parameter in nonparametric regression estimation because of its smoothing properties (Kohler *et al.*, (2014), Eguasa *et al.*, (2022)).

Eguasa *et al.* (2022) presented data-driven locally adaptive bandwidths:

$$b_{ij} = T_{1j}\left(\frac{1}{2} - \frac{x_{ij}}{T_{2j}}\right)^2, \ i = 1,2, \ \dots, n; j = 1,2,\dots,k \tag{2}$$

where, $0 < b_{ij} \le 1,$, $T_{1j} > 0$, $T_{2j} > 0$.

The $b*_{ij}$ of the locally adaptive optimal bandwidths from (2) is obtained at an optimally selected values of T_{1j}, T_{2j}, (hereafter referred to as T_{1j}^* and T_{2j}^*, respectively), $j = 1,2,\dots,k$, based on the minimization of the $PRESS^{**}$ criterion as given in (Eguasa, 2020).

The Local Linear Regression (LLR)

The LLR model is a nonparametric regression version of the weighted least squares model (Fan and Gijbels, 1995; Hardle *et al*., 2005; Kohler *et al*., 2014).

The LLR estimate, $\hat{y}_i^{(LLR)}$ of y_i, is given as:

$$\hat{y}_i^{(LLR)} = \tilde{\boldsymbol{x}}_i(\tilde{\boldsymbol{X}}^T\boldsymbol{W}_i\tilde{\boldsymbol{X}})^{-1}\tilde{\boldsymbol{X}}^T\boldsymbol{W}_i\boldsymbol{y} = \boldsymbol{h}_i^{(LLR)}\boldsymbol{y}, \tag{3}$$

where $\tilde{\boldsymbol{x}}_i$ is the i^{th} row of the LLR model matrix $\tilde{\boldsymbol{X}}$ given as:

$$\tilde{\boldsymbol{X}} = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}_{n\times(k+1)},$$

where x_{ij}, $i = 1,2,\dots,n$, $j = 1,2,\dots,k$, denotes the value of the j^{th} explanatory variable in the i^{th} data point, $\boldsymbol{W}_i$ is a $n \times n$ diagonal weights matrix given as:

$$\boldsymbol{W}_i = \begin{bmatrix} w_{1i} & 0 & \cdots & 0 \\ 0 & w_{2i} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & w_{ni} \end{bmatrix}_{n\times n} \tag{4}$$

For instance, w_{1i}, $i = 1$, is obtained from the product kernel as:

$$w_{11} = \prod_{j=1}^{k} K\left(\frac{x_{ij}-x_{1j}}{b}\right) \Big/ \sum_{i=1}^{n}\prod_{j=1}^{k} K\left(\frac{x_{ij}-x_{1j}}{b}\right), i = 1,2,\dots,n, j = 1,2,\dots,k, \tag{5}$$

where $K\left(\frac{x_{ij}-x_{1j}}{b}\right) = e^{-\left(\frac{x_{ij}-x_{1j}}{b}\right)^2}$ is the simplified Gaussian kernel function and b_i, $0 < b \le 1$, $i = 1,2,\dots,n$, $j = 1,2,\dots,k$, is the fixed bandwidth (smoothing parameter) (Myers *et al*., 2009; Eguasa, 2020; Akhideno and Eguasa, 2022).

Thus,

For $i = 1$ in equation (5), we have:

$$\boldsymbol{W}_1 = \begin{bmatrix} w_{11} & 0 & \cdots & 0 \\ 0 & w_{12} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{1n} \end{bmatrix}_{(n\times n)} \tag{6}$$

$$w_{11} = \frac{\prod_{j=1}^{k} K\left(\frac{x_{1j}-x_{1j}}{b_{1j}}\right)}{\sum_{p=1}^{n}\prod_{j=1}^{k} K\left(\frac{x_{pj}-x_{1j}}{b_{1j}}\right)},$$

$$p = 1, 2, \dots, n; j = 1, 2, \dots, k. \tag{7}$$

$$w_{11} = \frac{S}{[J+K+\dots+L]},\quad J = e^{-\left(\frac{x_{11}-x_{11}}{b_{11}}\right)^2} e^{-\left(\frac{x_{12}-x_{12}}{b_{12}}\right)^2} \dots e^{-\left(\frac{x_{1k}-x_{1k}}{b_{1k}}\right)^2},$$

$$K = e^{-\left(\frac{x_{21}-x_{11}}{b_{21}}\right)^2} e^{-\left(\frac{x_{22}-x_{12}}{b_{22}}\right)^2} \dots e^{-\left(\frac{x_{2k}-x_{1k}}{b_{2k}}\right)^2}$$

and $L = e^{-\left(\frac{x_{n1}-x_{11}}{b_{n1}}\right)^2} e^{-\left(\frac{x_{n2}-x_{12}}{b_{n2}}\right)^2} \dots e^{-\left(\frac{x_{nk}-x_{1k}}{b_{nk}}\right)^2}$

$$w_{12} = \frac{\prod_{j=1}^{k} K\left(\frac{x_{2j}-x_{1j}}{b_{2j}}\right)}{\sum_{p=1}^{n}\prod_{j=1}^{k} K\left(\frac{x_{pj}-x_{1j}}{pj}\right)},$$

$$p = 1, 2, \dots, n; j = 1, 2, \dots, k. \tag{8}$$

$$w_{12} = \frac{V}{[W+R+\dots+Q]},$$

$R = e^{-\left(\frac{x_{21}-x_{11}}{b_{21}}\right)^2} e^{-\left(\frac{x_{22}-x_{12}}{b_{22}}\right)^2} \dots e^{-\left(\frac{x_{2k}-x_{1k}}{b_{2k}}\right)^2}$, $W = e^{-\left(\frac{x_{11}-x_{11}}{b_{11}}\right)^2} e^{-\left(\frac{x_{12}-x_{12}}{b_{12}}\right)^2} \dots e^{-\left(\frac{x_{1k}-x_{1k}}{b_{1k}}\right)^2}$

and $Q = e^{-\left(\frac{x_{n1}-x_{11}}{b_{n1}}\right)^2} e^{-\left(\frac{x_{n2}-x_{12}}{b_{n2}}\right)^2} \dots e^{-\left(\frac{x_{nk}-x_{1k}}{b_{nk}}\right)^2}$

$$w_{1n} = \frac{\prod_{j=1}^{k} K\left(\frac{x_{nj}-x_{1j}}{b_{nj}}\right)}{\sum_{p=1}^{n}\prod_{j=1}^{k} K\left(\frac{x_{pj}-x_{1j}}{b_{pj}}\right)},$$

$$p = 1, 2, \dots, n; j = 1, 2, \dots, k. \tag{9}$$

$$w_{1n} = \frac{R}{[G+H+\dots+T]} \tag{10}$$

$T = e^{-\left(\frac{x_{n1}-x_{11}}{b_{n1}}\right)^2} e^{-\left(\frac{x_{n2}-x_{12}}{b_{n2}}\right)^2} \dots e^{-\left(\frac{x_{nk}-x_{1k}}{b_{nk}}\right)^2}$,

$H = e^{-\left(\frac{x_{21}-x_{11}}{b_{21}}\right)^2} e^{-\left(\frac{x_{22}-x_{12}}{b_{22}}\right)^2} \dots e^{-\left(\frac{x_{2k}-x_{1k}}{b_{2k}}\right)^2}$

and $G = e^{-\left(\frac{x_{11}-x_{11}}{b_{11}}\right)^2} e^{-\left(\frac{x_{12}-x_{12}}{b_{12}}\right)^2} \dots e^{-\left(\frac{x_{1k}-x_{1k}}{b_{1k}}\right)^2}$

Experimental design

In RSM, the numbers of factors are usually more than one. Hence, if the number of factors is too large, it may directly affect the response (Received signal strength) of interest, and since not all factors are desirable to be included in the experimental design for reason due to cost implication, it required the use of factor screening approach or two-level full factorial design to identify the variables with main effects (Nair *et al*., (2014); Eguasa *et al*., 2022; Akhideno and Eguasa, 2022).

The Experimental Design phase allows for a suitable design that can provide acceptable and significant estimation relationship between the response and one or more factors. Generally applied DOEs in RSM include: 2^k full factorial design, 3^k full factorial design, BBD and the Central Composite Design (CCD). In this paper, we shall employ the CCD and BBD for comparative analysis on the adaptive local linear regression to justify the better design as it relates to WSN.

This analysis was chosen essentially for the battery powered and energy gathering based nodes that rarely transmit data packets. Input factors as shown in Table 1. According to Hovat *et al*., (2013) described the factors as:

T_{SP} - Cyclic Sleep period: This value controls how long the end device will sleep at a time, up to 28 seconds. On the parent node, this value controls how lengthy the parent will cushion a message for the sleeping end device. It must be set at least equal to the lengthiest SP time of any child end device.

T_{PO} - Polling rate: Set/Read the end device poll rate. Adaptive polling may permit the end device to poll more quickly for a short time when receiving RF data.

T_{ST} - Time before sleep: Sets the time before sleep timer on an end device. The timer is reset each time serial or RF data is received. Once the timer expires, an end device may enter low power process.

Table 1: BBD coded stages and range for the design of experiments (Hovat *et al*., 2013)

Factors or Input parameters	-1(Low)	0(Medium)	1(High)
T_{ST}	500	2750	5000
T_{PO}	20	460	900
T_{SP}	320	1160	2000

Table 2: CCCD coded stages and range for the design of experiments

Factors or Input parameters	$-\alpha$	-1(Low)	0(Medium)	1(High)	$+\alpha$
T_{ST}	250	500	2750	5000	5250
T_{PO}	10	20	460	900	910
T_{SP}	200	320	1160	2000	2120

The Box – Behnken design (BBD)

A BBD permits for the design of the second-order regression model in a given response that is frequently used for process optimization (Hovat *et al*., 2013). The BBD comprises three types of trials namely; two levels (2^k) full factorial designs, $2k$ axial (star) points and C_p, p^{th} central points (Bezerra *et al*., 2008).

The mathematical expression for the BBD is given as:

$$BBD = 2k^2 - 2k + C_p \tag{11}$$

where $2k^2$ is the factorial portion, $2k$ is the axial or star points and C_p is at least pth central points utilized in the design. In this design $k = 3$ and $C_p = 5$ which from equation (11) sum up to 17 experimental run.

The Circumscribed Central Composite Design (CCCD)

In this study, the CCCD has been utilized because it is cost efficient, maintain rotatability and accommodates small number of experimental runs in the design.

The mathematical expression for the CCCD is given as:

$$CCCD = 2^k + 2k + k_c \tag{12}$$

where 2^k is the factorial portion, $2k$ is the axial or star points and k_c is at least kth central points utilized in the design. In this design $k = 3$ and $k_c = 3$ which from equation (12) sum up to 17 experimental run.

Table 3: Experimental coded level for RSM data (Hovat *et al*., 2013)

Exptal. Run	Coded Time Before Sleep	Coded Poll Rate	Coded Cyclic sleep period	$T_{Delay}(ms)$	$P_{Idle}(mW)$	$T_{Trans}(ms)$
1	0	1	1	1971	5.26	12753
2	0	-1	1	2110	5.23	14050
3	-1	0	-1	689	12.94	2098
4	0	-1	-1	297	14.29	2003
5	0	0	0	923	6.20	7108
6	1	1	0	1162	6.13	6452
7	0	0	0	1297	6.09	8839
8	0	1	-1	1242	12.50	2349
9	0	0	0	1190	6.47	5403

10	0	0	0	1397	6.14	7989
11	-1	1	0	1316	5.88	8129
12	1	0	1	2071	5.27	13783
13	-1	-1	0	1228	6.24	8330
14	1	-1	0	1080	6.08	6654
15	1	0	-1	484	13.13	1908
16	0	0	0	1085	6.28	8429
17	-1	0	1	2104	5.28	12874

Table 4 : CCCD Experimental coded level for RSM data

i	CODED LEVELS			$y_1 = T_{Delay}(ms)$	$y_2 = P_{Idle}(mW)$	$y_3 = T_{Trans}(ms)$
	x_1	x_2	x_3			
1	-1	-1	-1	1971	5.26	12753
2	1	-1	-1	2110	5.23	14050
3	-1	1	-1	689	12.94	2098
4	1	1	-1	297	14.29	2003
5	-1	-1	1	923	6.20	7108
6	1	-1	1	1162	6.13	6452
7	-1	1	1	1297	6.09	8839
8	1	1	1	1242	12.50	2349
9	-1.682	0	0	1190	6.47	5403
10	1.682	0	0	1397	6.14	7989
11	0	-1.682	0	1316	5.88	8129
12	0	1.682	0	2071	5.27	13783
13	0	0	-1.682	1228	6.24	8330
14	0	0	1.682	1080	6.08	6654
15	0	0	0	484	13.13	1908
16	0	0	0	1085	6.28	8429
17	0	0	0	2104	5.28	12874

Data transformation to RSM data

The values of the explanatory variables are coded between 0 and 1. The data collected through a BBD is transformed by a mathematical relation:

$$x_{NEW} = \frac{Min(x_{OLD}) - x_0}{(Min(x_{OLD}) - Max(x_{OLD}))} \tag{13}$$

where x_{NEW} is the transformed value, x_0 is the target value that needed to be transformed in the vector containing the old coded value represented as x_{OLD}, $\mathrm{Min}(x_{OLD})$ and $Max(x_{OLD})$ are the minimum and maximum values in the vector x_{OLD} respectively, (Eguasa *et al.*, 2022). The natural or coded variables in Table 2 can be transformed to explanatory variables in Table 4 using Equation (13).

Target points needed to be transformed for location 3 under the coded variables are given below:

Target points $x_0: -1, 0, -1$; $Min(x_{OLD}): -1, -1, -1$; $Max(x_{OLD}): 1, 1, 1$

$$x_{NEW} = \frac{Min(x_{OLD}) - x_0}{(Min(x_{OLD}) - Max(x_{OLD}))}$$

$$Explanatory\ variable\ x_1 : x_{31} = \frac{-1 - (-1)}{((-1) - (1))} = 0.0000$$

$$Explanatory\ variable\ x_2 : x_{32} = \frac{-1 - (0)}{((-1) - (1))} = 0.5000$$

$$Explanatory\ variable\ x_3:\ x_{33} = \frac{-1-(-1)}{((-1)-(1))} = 0.0000$$

where $x_1 = Coded\ Time\ Before\ Sleep\ (T_{ST}),\ x_2 = Coded\ Poll\ Rate\ (T_{PO}),$
$x_3 = Coded\ Cyclic\ sleep\ period\ (T_{SP})$

Table 5: Experimental BBD for the transformed RSM data that are coded btw 0 and 1

Exp. Run	Coded Time Before Sleep	Coded Poll Rate	Coded Cyclic sleep period	$T_{Delay}(ms)$	$P_{Idle}(mW)$	$T_{Trans}(ms)$
1	0.5000	1.0000	1.0000	1971	5.26	12753
2	0.5000	0.0000	1.0000	2110	5.23	14050
3	**0.0000**	**0.5000**	**0.0000**	689	12.94	2098
4	0.5000	0.0000	0.0000	297	14.29	2003
5	0.5000	0.5000	0.5000	923	6.20	7108
6	1.0000	1.0000	0.5000	1162	6.13	6452
7	0.5000	0.5000	0.5000	1297	6.09	8839
8	0.5000	1.0000	0.0000	1242	12.50	2349
9	0.5000	0.5000	0.5000	1190	6.47	5403
10	0.5000	0.5000	0.5000	1397	6.14	7989
11	0.0000	1.0000	0.5000	1316	5.88	8129
12	1.0000	0.5000	1.0000	2071	5.27	13783
13	0.0000	0.0000	0.5000	1228	6.24	8330
14	1.0000	0.0000	0.5000	1080	6.08	6654
15	1.0000	0.5000	0.0000	484	13.13	1908
16	0.5000	0.5000	0.5000	1085	6.28	8429
17	0.0000	0.5000	1.0000	2104	5.28	12874

Table 6: Experimental BBD for the transformed RSM data that are coded between 0 and 1

Exp. Run	x_1	x_2	x_3	$y_1\ (T_{Delay})$ (ms)	$y_2(P_{Idle})$ (mW)	$y_3(T_{Trans})$ (ms)
1	0.5000	1.0000	1.0000	1971	5.26	12753
2	0.5000	0.0000	1.0000	2110	5.23	14050
3	0.0000	0.5000	0.0000	689	12.94	2098
4	0.5000	0.0000	0.0000	297	14.29	2003
5	0.5000	0.5000	0.5000	923	6.20	7108
6	1.0000	1.0000	0.5000	1162	6.13	6452
7	0.5000	0.5000	0.5000	1297	6.09	8839
8	0.5000	1.0000	0.0000	1242	12.50	2349
9	0.5000	0.5000	0.5000	1190	6.47	5403
10	0.5000	0.5000	0.5000	1397	6.14	7989
11	0.0000	1.0000	0.5000	1316	5.88	8129
12	1.0000	0.5000	1.0000	2071	5.27	13783
13	0.0000	0.0000	0.5000	1228	6.24	8330
14	1.0000	0.0000	0.5000	1080	6.08	6654
15	1.0000	0.5000	0.0000	484	13.13	1908
16	0.5000	0.5000	0.5000	1085	6.28	8429
17	0.0000	0.5000	1.0000	2104	5.28	12874

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Table 7: The transformed CCCD for WSN

i	x_1	x_2	x_3	$y_1 = T_{Delay}(ms)$	$y_2 = P_{Idle}(mW)$	$y_3 = T_{Trans}(ms)$
1	0.2030	0.2030	0.2030	1971	5.26	12753
2	0.7970	0.2030	0.2030	2110	5.23	14050
3	0.2030	0.7970	0.2030	689	12.94	2098
4	0.7970	0.7970	0.2030	297	14.29	2003
5	0.2030	0.2030	0.7970	923	6.20	7108
6	0.7970	0.2030	0.7970	1162	6.13	6452
7	0.2030	0.7970	0.7970	1297	6.09	8839
8	0.7970	0.7970	0.7970	1242	12.50	2349
9	0.0000	0.5000	0.5000	1190	6.47	5403
10	1.0000	0.5000	0.5000	1397	6.14	7989
11	0.5000	0.0000	0.5000	1316	5.88	8129
12	0.5000	1.0000	0.5000	2071	5.27	13783
13	0.5000	0.5000	0.0000	1228	6.24	8330
14	0.5000	0.5000	1.0000	1080	6.08	6654
15	0.5000	0.5000	0.5000	484	13.13	1908
16	0.5000	0.5000	0.5000	1085	6.28	8429
17	0.5000	0.5000	0.5000	2104	5.28	12874

Results and Discussion

In Table 8 is the estimated responses for y_1 (T_{Delay}), y_2 (P_{Idle}) and y_3 (T_{Trans}) were obtained via genetic algorithm tool in Matlab and it is only applicable to local linear regression model, since it accommodates the diagonal weight matrix as given in equation (4). Whereas, Table 9 is the goodness-of-fit statistics showing the predictive power of the design on the regression model.

Table 8: Experimental BBD for the transformed RSM data that are coded between 0 and 1

Exp. Run	$CCCD\ y_1$	$CCCDy_2$	$CCCDy_3$	y_1 (T_{Delay}) (ms)	$BBD\ y_1$	$y_2(P_{Idle})$ (mW)	$BBD\ y_2$	$y_3(T_{Trans})$ (ms)	$BBD\ y_3$
1	1699.4	5.2600	12753	1971	1971.0	5.26	5.2600	12753	12753
2	1776	5.2300	14050	2110	2082.7	5.23	5.2757	14050	14050
3	661	12.9400	2098	689	689.0	12.94	2.9400	2098	2098
4	297	14.2900	2003	297	297.0	14.29	4.2900	2003	2003
5	947.4	5.8921	7598	923	1178.4	6.20	.2360	7108	7554
6	1162	6.0237	6766	1162	1162.0	6.13	6.1300	6452	6452
7	1294.5	6.0900	8839	1297	1178.4	6.09	6.2360	8839	7554
8	1242	12.5000	2349	1242	1242.0	12.50	2.5000	2349	2349
9	1190	6.4700	5403	1190	1178.4	6.47	6.2360	5403	7554
10	1397	6.1400	7989	1397	1178.4	6.14	.2360	7989	7554
11	1242.7	5.8800	8129	1316	1316.0	5.88	.8800	8129	8129
12	2039.7	5.2700	13783	2071	2071.0	5.27	.2700	13783	13783
13	1228.2	6.2422	8328	1228	1228.0	6.24	.2400	8330	8330
14	1079.8	6.2617	6680	1080	1080.0	6.08	.0800	6654	6654
15	1265.8	8.2229	7744	484	484.0	13.13	3.1300	1908	1908
16	1265.8	8.2229	7744	1085	1178.4	6.28	.2360	8429	7554
17	1265.8	8.2229	7744	2104	2104.0	5.28	.2800	12874	2874

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Table 9: Model goodness-of-fits statistics for power consumption

Response	Model	*DF*	*PRESS***	*PRESS*	*SSE*	*MSE*	R^2(%)
$y_1\ (T_{Delay})$	*CCCD*	2.8326	5.6866e+005	4.1700e+008	1.5395e+006	5.4350e+005	0.6701
	BBD	4.0252	**2.0931e+005**	**3.0075e+006**	**1.3668e+005**	**3.3957e+004**	**0.9707**
$y_2\ (P_{Idle})$	*CCCD*	2.1250	**108.5621**	**1.2307e+003**	36.6543	17.2494	0.7824
	BBD	4.0252	279.4508	4.7497e+003	**0.0906**	**0.0225**	**0.9995**
$y_3\ (T_{Trans})$	*CCCD*	2.1250	1.4018e+008	1.6604e+009	6.1184e+007	2.8793e+007	0.7702
	BBD	4.0000	**2.3282e+006**	**1.8883e+007**	**7.4318e+006**	**1.8579e+006**	**0.9721**

Figures 1, 2 and 3 are the CCCD LLR AB surface plots minimum Transmission Delay (297 ms), minimum Average Idle Power Consumption (5.23 mW) and maximum Transition Time (14050 ms).

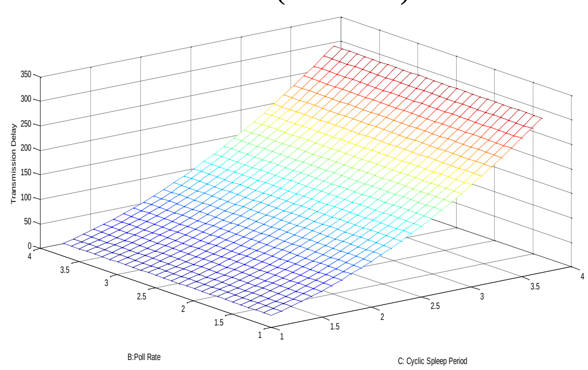

Fig. 1: CCCD surface plot for minimum Transmission Delay (297 ms)

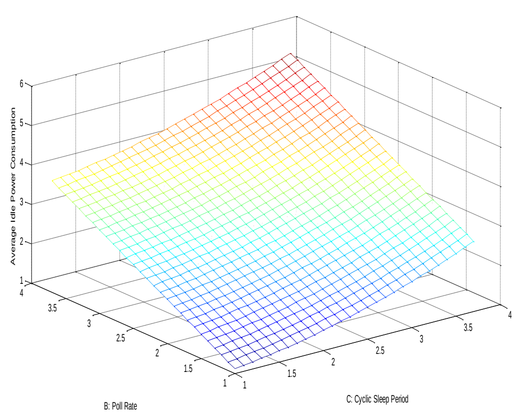

Fig. 2: CCCD surface plot for minimum Average Idle Power Consumption (5.23 mW)

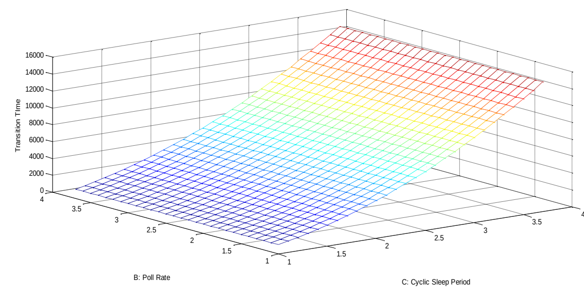

Fig. 3: CCCD surface plot for maximum Transition Time (14050 ms)

The results obtained from Tables 9 and 10, clearly shows that LLR_{AB} that uses BBD from the respective response gave the better performance statistic as compared with LLR_{AB} that uses CCCD, for the multi-response problem. For $y_1\ (T_{Delay})$, $y_2\ (P_{Idle})$, $y_3\ (T_{Trans})$ the BBD for adaptive bandwidths outperformed the CCCD in terms PRESS**, PRESS, SSE, MSE, R^2 and R^2Adj and gives a better predictive power.

Conclusion: In this study, we presented a BBD in other to address rotatability and curvature in the data, a LLR_{FB} for adequate fitting of the data, (T_{Delay}), $y_2\ (P_{Idle})$ and $y_3\ (T_{Trans})$ respectively. The performance statistics carried out is a clear indication that the LLR_{AB} that uses BBD outperformed the LLR_{AB} that uses CCCD for $y_1\ (T_{Delay})$ (PRESS**= 209310, PRESS = 3007500, SSE = 136680, MSE = 33957, R^2= 97.07% and R^2Adj = 88.36%) as against LLR_{AB} that uses CCCD with R^2= 67.01%; $y_2\ (P_{Idle})$ with (PRESS**= 279.4508, PRESS = 4749.7, SSE = 0.0906, MSE = 0.0225, R^2=99.95% and R^2Adj = 99.79%) as against LLR_{AB} that uses CCCD with R^2=78.24% and $y_3\ (T_{Trans})$ with (PRESS**= 2328200, PRESS = 18883000, SSE = 7431800, MSE = 1857900, R^2= 97.21% and R^2Adj = 88.83%) as against LLR_{AB} that uses CCCD with, R^2=77.02% for WSN communication technologies and also provided minimum residual plots for their respective network.

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