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EWMA Control Chart Using Repetitive Sampling for Monitoring Blood Glucose Levels in Type-II Diabetes Patients

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Abstract: In this paper, we discuss the application of the exponentially weighted moving average (EWMA) control chart for the monitoring blood glucose in type-II diabetes patients. We present tables for the practical use in healthcare. From the simulation results and a real example, the efficiency of the proposed chart in detecting a shift in diabetic level is compared with the existing chart. It is found that the proposed chart provides a strict method to monitor the diabetic levels in diabetes patients. From the simulation results and a real example, it is concluded that the use of the proposed chart in health care issues may reduce the risk of heart disease by monitoring diabetic levels in an effective way.

Keywords: exponentially weighted moving average chart; repetitive sampling; diabetes monitoring; statistical process monitoring

1. Introduction

Nowadays, control charts have many applications in public health and healthcare monitoring in hospitals and the improvement of hospital performance. The quality parameters in health care, such as the time for the examination of the patient, the number of surgical failures, the utilization of health services, and the cost of treatment and management. One of the most important procedures in statistical process control methods are control chart techniques, which are useful to improve the quality improvement in surveillance of an in-control process in health care. For example, the traditional quality aspects, like quality planning, quality improvement, and quality control, have been widely used throughout many applications (for more details see [1]).

Shewhart [2] originally proposed that control charts can also be used to understand present process performance and variation, to help achieve and confirm when a state of statistical control or the desired quality level has been reached, and to verify an improved process. The main objective to use the control charts and related methods are for understanding current process performance, achieving a consistent level of process quality and performance, monitoring for process deterioration, and reducing the amount of process variation (see [1]). The purpose of control charts is to identify the assignable causes of variation or unnatural sources of variation and remove from the process in an attempt to bring the process into statistical control. The most important purpose of statistical process control (SPC) is that the use control charts is used to initiate and evaluate quality improvement activities. According to Montgomery [3], a condition of using Shewhart control charts is that they

are constructed according to specific methodological criteria to generate valid warning signals. The detailed information on control charts, formulas, and implementation mostly related to industrial applications can be found in Aslam et al. [4]. A more detailed study about the application of the control chart can be seen in [3]. The importance of SPC in the healthcare perspective has been addressed by different authors; for example, [1] proposed control chart for the infection monitoring, and [3,5,6] discussed the applications of the various control charts in healthcare improvement. Noyez [7] proposed the cumulative sum control (CUSUM) charts for the improved monitoring of health-related issues; Woodall [3] used the control chart for the monitoring of public health issues; control charts for the monitoring of the cardiac results were applied by [7,8]; reference [9] used the control chart tools for healthcare regulation; and Steiner et al. [1] evaluated the surgical performance using risk-adjusted cumulative sum control charts. SPC applications in healthcare are focused in several books, for example, references [10–15]; and methodological interpretation for attribute data and comparison of control charts for monitoring clinical performance using binary data are given by [16–18]. Cappon [19] also discussed the monitoring of the glucose level. Diabetes is a metabolic disease in which the blood glucose or blood sugar levels are too high, either because insulin production is insufficient, or because the body's cells do not respond properly to insulin, or both (see [19]]). As mentioned by [1], glucose comes from the diet that we eat regularly. Insulin is a hormone that helps the glucose gets into your cells to give them energy. With type 1 diabetes (T1D), that body does not make insulin. With type 2 diabetes (T2D), the more common type, the body does not make or use insulin well. Without enough insulin, the glucose stays in your blood.

The exponentially weighted moving average (EWMA) control charts are more "sensitive" to detect a small shift in the process, (see [2]). The EWMA control charts have had many applications in healthcare: in cardiac surgery [8]; reference [20] used an EWMA chart for the early detection of abnormal patient arrivals at hospital emergency department; reference [21] developed the repetitive sampling plan; worked on the modification of the EWMA chart [22]; reference [23] worked on X-bar chart using the repetitive sampling; reference [24] designed t-chart using the repetitive sampling; reference [25] worked on sign chart using the repetitive sampling. The details about repetitive group sampling plans can be seen in [20–25].

In this paper, we discuss the application of the EWMA control chart for the repetitive using the symmetry property of the normal distribution for the monitoring of blood glucose in type-II diabetes patients. We will compare the efficiency of the proposed chart with the existing control chart in terms of average run length. We presented some tables for the practical use in healthcare.

2. Methodology

Let us assume that the quality characteristic of interest, blood glucose level, in mg/dL is denoted by X_t; $t = 1, 2, \ldots$, which follows the normal distribution with mean μ and variance σ^2. Based on this assumption, we propose the following steps in the repetitive sampling EWMA chart [25]:

Step 1: Select a sample of size n and compute the following statistics at each time t, where λ is smoothing constant:

$$EWMA_t = \lambda \overline{X}_t + (1 - \lambda) EWMA_{t-1} \quad (1)$$

where $\overline{X}_t$ is the sample mean at the time tand $EWMA_{t-1}$ is EWMA calculated at time $t - 1$.

Step 2: Declare the process is stated as out-of-control if $EWMA_t \geq UCL_1$ or $EWMA_t \leq LCL_1$. Declare the process as in-control if $LCL_2 \leq EWMA_t \leq UCL_2$. Otherwise, go to Step 1 and repeat the process.

Note here that the operational process of the EWMA chart using the repetitive sampling is same as in sequential sampling. In sequential sampling, the process continues to select a sample until the final decision about the state of the process. In the repetitive sampling, we repeat the process when in-decision at first sample. For the in-decision case, the process is repeated and a new sample is selected to make a decision about the state of the process.

The proposed repetitive sampling EWMA control chart has two pairs of control limits UCL_1, UCL_2 and LCL_1, LCL_2 are given as:

$$LCL_1 = \overline{X} - k_1 \frac{s}{\sqrt{n}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{2}$$

$$LCL_2 = \overline{X} - k_2 \frac{s}{\sqrt{n}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{3}$$

$$UCL_1 = \overline{X} + k_1 \frac{s}{\sqrt{n}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{4}$$

$$UCL_2 = \overline{X} + k_2 \frac{s}{\sqrt{n}} \sqrt{\frac{\lambda}{2-\lambda}} \tag{5}$$

where k_1 and k_2 are control chart coefficients, $\overline{X}$ is the sample mean, and s is the sample standard deviation.

Under single sampling, the probability that the process is in out-of-control the repetition and out of control (P^0) from [25]:

$$P^0 = P(EWMA_t > UCL_1) + P(EWMA_t < LCL_1) \tag{6}$$

The probability of repetition $\left(P_{rep0}\right)$ for the proposed control chart is given as follows [25].

$$P^0_{rep} = P(LCL_1 < EWMA_t < LCL_2) + P(UCL_2 < EWMA_t < UCL_1) \tag{7}$$

Hence, the probability of the process being declared to be out of control $\left(P^0_{out}\right)$ for the proposed control chart under repetitive sampling is given as follows (see [4,25]):

$$P^0_{out} = \frac{P^0}{1 - P^0_{rep}} \tag{8}$$

The in-control ARL (ARL_0) is given by Equation (9), which is the expected number of subgroups to be examined until the process is declared to be out of control when the process is truly in control:

$$ARL_0 = \frac{1}{P^0_{out}} \tag{9}$$

Suppose now that the process parameter μ is shifted to $\mu_1 = \mu + c\sigma$, where c is the shift constant. Then, the probability of the process being declared to be out-of-control based on a single sample when the process is shifted is:

$$\mathrm{P}^1 = P(EWMA_t > UCL_1) + P(EWMA_t < LCL_1) \tag{10}$$

The probability of repetition $\left(P^1_{rep}\right)$ for the proposed control chart when the process is shifted is given as follows (see [4,25]):

$$P^1_{rep} = P(LCL_1 < EWMA_t < LCL_2) + P(\mathrm{UCL}_2 < EWMA_t < UCL_1) \tag{11}$$

Hence, the probability of the process being declared to be out of control $\left(P^1_{out}\right)$ for the proposed control chart under repetitive sampling when the process is given as follows (see [4,25]):

$$P^1_{out} = \frac{\mathrm{P}^1}{1 - P^1_{rep}} \tag{12}$$

The out-of-control *ARL* (ARL_1) is obtained as follows:

$$ARL_1 = \frac{1}{P_{out}^1} \tag{13}$$

Usually, the practitioners have the information about the parameters of the normal distribution. If parameters are unknown, they can estimate from the data.

Let r_0 be the assumed in-control *ARL*. We estimated the control constants k_1 and k_2 using Monte Carlo simulation such that $ARL_0 \geq r_0$. We noted first out-of-control (run length) and repeated the process 10,000 times. We developed programming to obtain the estimates of control constants. The program is available with authors upon request. Then using Equation (13), we obtain ARL_1 based on the determined values of k_1 and k_2 for various shift values of $\mu_1 = \mu + c\sigma$. From Tables 1–3, wherein the ARL for r_0 = 370, c = 0 to 1.0, and λ = 0.10, 0.20, and 0.30, respectively, we observe the following behavior of ARL_1:

1. The case of $\mu = 0$, $\sigma = 1$, that is when the process is in-control, ARL value obtained is very close to the target r_0 values.
2. As the shift c increases (i.e., the process mean increases), the out-of-control ARLs decrease rapidly. A similar trend can be observed from Tables 2 and 3 whereas decreasing speed seems to get faster after c = 0.1. When sample size increases, the values of ARL_1 decrease. It means that at the large sample size, we have a quick indication about the shift in the sugar level (see Figure 1).

Table 1. Estimated ARLs when $r_0 = 370$ and $\lambda = 0.10$.

c	k_1 = 3.0066; k_2 = 2.2356					
	n					
	5	10	20	30	50	100
	ARL_1					
0	370.00	370.00	370.00	370.00	370.00	370.00
0.01	353.12	337.55	309.80	285.82	246.48	180.10
0.02	309.80	264.89	202.54	161.53	111.35	56.53
0.03	255.40	190.77	121.26	85.18	49.32	19.43
0.05	157.38	91.57	43.43	25.36	11.59	3.56
0.08	71.94	31.58	11.15	5.60	2.39	1.15
0.1	43.43	16.54	5.22	2.64	1.37	1.02
0.15	13.75	4.26	1.53	1.12	1.01	1.00
0.2	5.22	1.75	1.06	1.01	1.00	1.00
0.25	2.48	1.17	1.00	1.00	1.00	1.00
0.3	1.53	1.03	1.00	1.00	1.00	1.00
0.4	1.06	1.00	1.00	1.00	1.00	1.00
0.5	1.00	1.00	1.00	1.00	1.00	1.00

Table 2. Estimated ARLs when $r_0 = 370$ and $\lambda = 0.20$.

c	k_1 = 3.0134; k_2 = 1.9885					
	n					
	5	10	20	30	50	100
	ARL_1					
0	370.00	370.00	370.00	370.00	370.00	370.00
0.01	369.06	368.13	366.28	364.45	360.83	352.05
0.02	366.28	362.63	355.52	348.65	335.58	306.40
0.03	361.73	353.78	338.77	324.84	299.79	249.85
0.05	347.81	327.85	293.42	264.81	220.03	150.24
0.08	317.53	276.78	217.76	177.24	125.62	66.17
0.1	293.42	240.66	173.06	131.95	85.20	38.94
0.15	229.96	160.99	94.11	62.43	33.31	11.56
0.2	173.06	104.58	51.38	30.48	14.06	4.19
0.25	127.94	67.88	28.79	15.61	6.52	2.00

Table 2. *Cont.*

c	k_1 = 3.0134; k_2 = 1.9885					
	n					
	5	10	20	30	50	100
	ARL_1					
0.3	94.11	44.52	16.66	8.44	3.40	1.32
0.4	51.38	20.02	6.25	3.04	1.47	1.03
0.5	28.79	9.65	2.84	1.58	1.09	1.00
0.6	16.66	5.06	1.66	1.16	1.01	1.00
0.7	10.00	2.94	1.23	1.04	1.00	1.00
0.8	6.25	1.94	1.08	1.01	1.00	1.00
0.9	4.10	1.45	1.02	1.00	1.00	1.00
1	2.84	1.22	1.01	1.00	1.00	1.00

Table 3. Estimated ARLs when $r_0 = 370$ and $\lambda = 0.30$.

c	k_1 = 3.0105; k_2 = 2.0796					
	n					
	5	10	20	30	50	100
	ARL_1					
0	370.00	370.00	370.00	370.00	370.00	370.00
0.01	361.77	353.86	338.92	325.05	300.11	250.36
0.02	338.92	312.15	268.43	234.28	184.55	115.17
0.03	306.03	259.12	195.20	153.91	104.29	51.39
0.05	230.54	161.76	94.95	63.23	33.98	11.98
0.08	136.81	74.79	32.92	18.30	7.87	2.38
0.1	94.95	45.26	17.17	8.80	3.59	1.36
0.15	39.02	14.24	4.31	2.20	1.24	1.01
0.2	17.17	5.31	1.73	1.19	1.02	1.00
0.25	8.20	2.47	1.16	1.02	1.00	1.00
0.3	4.31	1.51	1.03	1.00	1.00	1.00
0.4	1.73	1.06	1.00	1.00	1.00	1.00
0.5	1.16	1.00	1.00	1.00	1.00	1.00
0.6	1.03	1.00	1.00	1.00	1.00	1.00

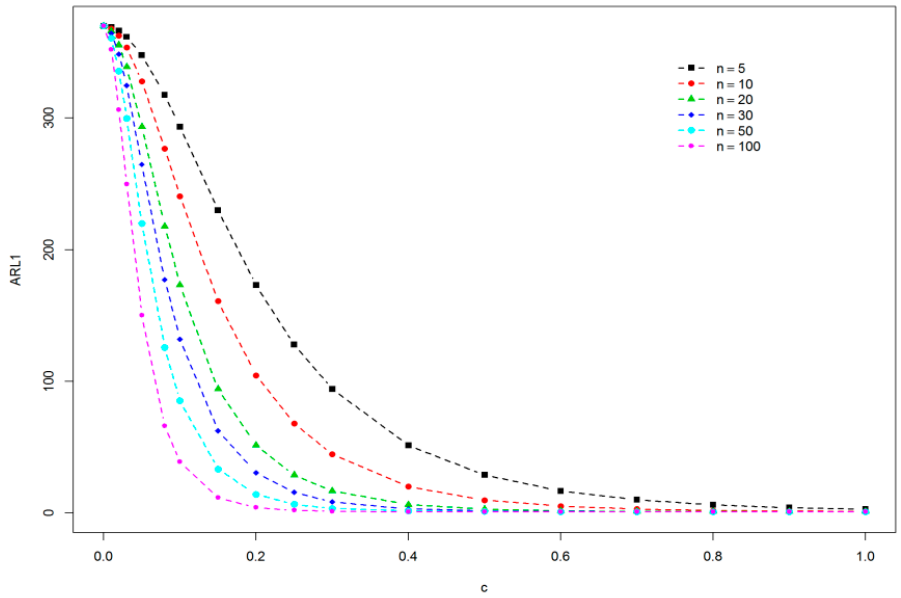

Figure 1. The proposed chart ARL1 performance for different values of n at λ = 0.10 and $r_0 = 370$.

3. Case Study Results

The diabetic health issue is a long-believed disease with major significance to world health and is now considered one of the foremost threats to human health in Saudi Arabia (see [26]). The worldwide epidemic of people with type II diabetes is mostly related to a place of living, food habits, ageing, the obesity and physical inactivity. The World Health Organization (WHO) defines diabetes as a metabolic disorder of multiple etiologies characterized by chronic hyperglycemia with disturbances of carbohydrate, fat, and protein metabolism that results from defects in insulin secretion, insulin action, or both. Rathmann and Giani [27] studied that the total number of people worldwide with type II diabetes was expected to increase from 171 million in 2000 to 366 million in 2030. A study carried out by [28] on Saudi women from Al-Khobar with the aim of examining their behaviors of eating and physical activity as well as their perceptions of body size, accepted the hypothesis that obesity is related to eating and exercise behaviors. Al-Nuaim et al. [26] confirmed that the prevalence of obesity and overweight was attributed to regional differences. Al-Baghli et al. [29] studied overweight and obesity in the eastern province of Saudi Arabia, less educated women was more subjected to obesity. Glycemic control is one of the important strategies for the management of diabetic levels as regarded by the American Diabetes Association (ADA) (see [30]). Diabetic has become one of the most common public health issues in Saudi Arabia.

As the global average prevalence of diabetes is around 10%. A study of [31], reveals that the gulf countries appear to have a higher prevalence of diabetes than the global average. The recent rapid socio-economic development of these countries has been associated with this rising prevalence. Based on a study in 2009, the overall prevalence of Type 2 diabetes in the Kingdom of Saudi Arabia (KSA) was 30%. This article is designed to study the rate of glycemic control of diabetic care hospital with type 2 diabetes in KSA. The data was collected from five patients that constitute the case study. The blood sugar level mg/dL of each patient is checked and reported in Table 4. A drug Glucophage 500 mg was given twice a day in first 20 weeks, 500 mg in a day for weeks 21–30 and then 250 mg for a day for the weeks 31–40. Using Table 4, we constructed the Shewhart control and repetitive sampling EWMA chart to monitor the variations in the blood sugar level of patients.

Table 4. Blood sugar level (mg/dL) of patients in 2016.

Week	Blood Sugar Level (mg/dL)					$\overline{X}$	$EWMA_t$	Week	Blood Sugar Level (mg/dL)					$\overline{X}$	$EWMA_t$
1	370	175	193	192	197	225.4	197.6	21	149	157	126	160	137	145.8	174.0
2	313	255	170	294	203	247.0	207.5	22	132	203	229	184	123	174.2	174.0
3	270	205	190	203	194	212.4	208.5	23	126	190	237	187	139	175.8	174.4
4	190	221	177	173	171	186.4	204.1	24	143	204	200	245	187	195.8	178.6
5	185	242	278	202	189	219.2	207.1	25	117	219	170	197	158	172.2	177.4
6	190	228	184	165	268	207.0	207.1	26	114	201	264	169	178	185.2	178.9
7	177	166	173	224	234	194.8	204.6	27	122	179	235	167	226	185.8	180.3
8	175	239	268	198	176	211.2	205.9	28	134	213	182	137	269	187.0	181.6
9	165	176	196	201	246	196.8	204.1	29	132	284	180	207	235	207.6	186.8
10	183	150	243	188	172	187.2	200.7	30	110	246	110	272	117	171.0	183.7
11	185	165	164	188	231	186.6	197.9	31	107	234	212	201	141	179.0	182.7
12	177	189	178	186	186	183.2	195.0	32	125	220	225	113	214	179.4	182.1
13	165	274	248	183	179	209.8	197.9	33	105	190	196	187	252	186.0	182.9
14	169	177	159	269	207	196.2	197.6	34	107	232	209	257	225	206.0	187.5
15	170	218	197	140	186	182.2	194.5	35	116	234	241	214	182	197.4	189.5
16	155	170	206	155	176	172.4	190.1	36	118	189	194	183	164	169.6	185.5
17	160	231	228	220	241	216.0	195.3	37	116	207	271	213	219	205.2	189.4
18	152	161	179	162	168	164.4	189.1	38	105	173	179	226	165	169.6	185.5
19	162	173	111	153	200	159.8	183.2	39	108	215	246	259	236	212.8	190.9
20	165	196	173	168	158	172.0	181.0	40	109	281	134	200	232	191.2	191.0

We have taken an average of five patients as our quality characteristic. Thus, in Figures 2 and 3, an average quality characteristic has been used. Figure 2 shows the traditional control chart for monitoring of glucose levels in type II diabetic patients and Figure 3 shows the same data using the proposed control chart. From Figure 2, it can be seen that the traditional Shewhart control chart shows

that patients sugar levels are in-control state while Figure 3 shows that the diabetic level of patients has been gone out-of-control in several occasions. We also noted some points in the in-decision area which clearly indicates the advisor to select another sample from the patient to reach on the specific decision (e.g., at 3, 4, 6, 7, 8, 9, 10, 22, 23, and 24).

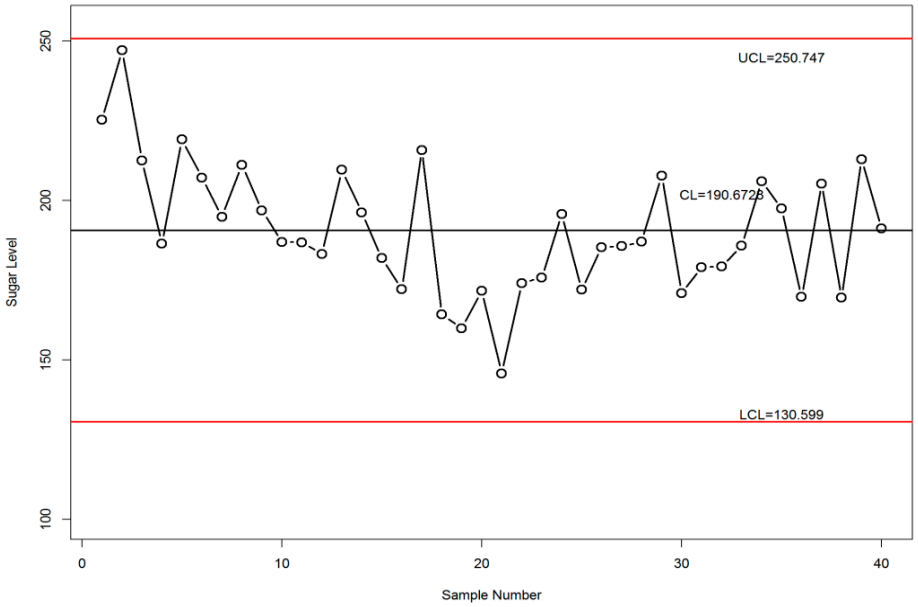

Figure 2. The Shewhart mean control chart for the glucose levels in type II diabetic patients.

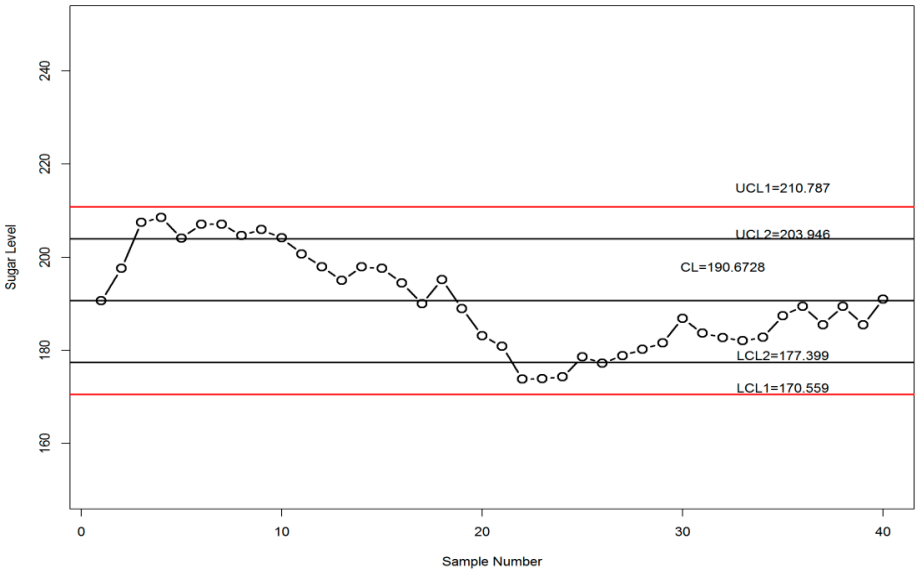

Figure 3. The proposed control chart for the glucose levels in type II diabetic patients.

The performance of the proposed control chart for the monitoring diabetic levels is also discussed with the help of simulated data. Diabetics should aim for an SD of one-third of their mean blood sugar. Therefore, if your mean blood sugar were 120 mg/dL, you would want your standard deviation to be no more than 40 mg/dL, or one-third of the mean (for more information, (see [32]). In simulation study first 20 observation each of size 10 is generated from in control process with mean 120 and standard deviation of 40 and next 20 are generated with a shift in mean as 120 + c SD, where c = 0.10. The sugar levels of 40 patients of size 10 are plotted in Figures 4 and 5. From Figure 5, it can be noted that the proposed chart clearly indicates that sugar level of the patient has been shifted and out-of-control

while Figure 4, which is traditional Shewhart chart, shows that sugar level is in control and the medical advisor should take no action.

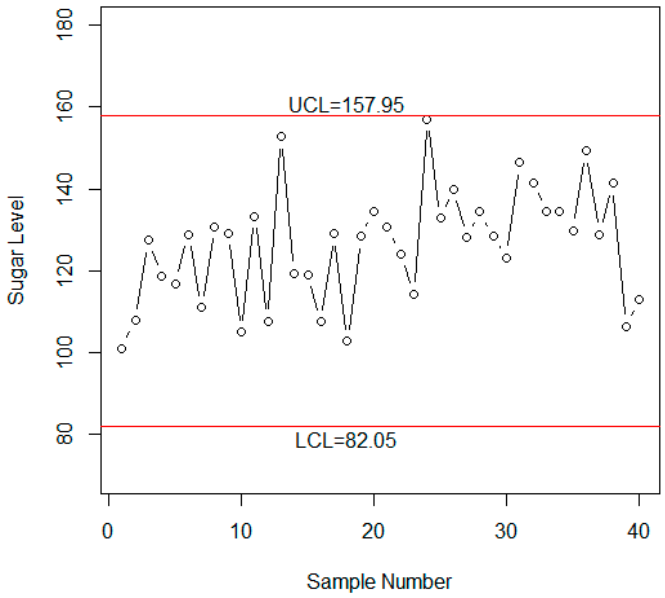

Figure 4. The Shewhart chart for simulated data.

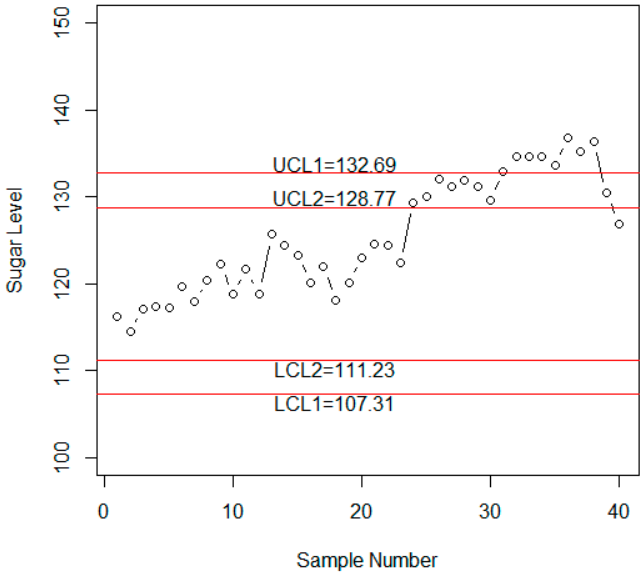

Figure 5. The proposed chart for simulated data when $\lambda = 0.20$.

4. Conclusions and Recommendations

The monitoring of glucose levels in type II diabetic patients through the traditional Shewhart control chart is unable to detect a shift in the sugar level, which may cause of series diseases associated with sugar such as damage of kidneys, heart attack, and blood pressure. The proposed control chart was able to diagnose the shift in sugar level of patients as compared to Shewhart control chart and, thus, help the medical advisor to take on-time action to bring back the sugar level to the normal range. Therefore, the use of the proposed control chart in the healthcare issues will be helpful for strict monitoring of glucose levels in type II diabetic patients as compared to existing charts. The proposed control chart also directs the medical advisor to take another blood sample from the patient, in case a using single blood sample information.

Author Contributions: Conceived and designed the experiments: M.A., G.S.R., N.K. and F.A.A.-A.; performed the experiments: M.A., G.S.R. and N.K.; analyzed the data: M.A., G.S.R. and N.K.; contributed reagents/materials/analysis tools: M.A.; wrote the paper: M.A. and G.S.R.

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