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DEVELOPING QUALITY CONTROL CHARTS FOR THE CONTROL POINTS OF A FOOD PRODUCT

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Abstract

Monitoring the production process is a critical issue for improving the quality of product and for reducing the costs regarding external failures. Quality control charts are often used to visualize measurements on the process during the monitoring activities. This paper presents a case study based on the use of advanced charts, Cumulative Summation (CUSUM) and Estimated Weighted Moving Average (EWMA) charts, for visualizing the control points of a particular chicken product in fast-food industry. Furthermore, GM (1,1) and GM (1,1) Markov models were built to generate predictions to see the trends and future values to maintain a follow-up procedure for the fluctuations in the process performance. In this context, three control points are considered that are weight of the chicken wings, sterilizer temperature, and grid-pan temperature. The findings provide a significant feedback for the efficiency of the corresponding processes. Results show that the methodology selected to develop these charts has an important impact on creating an effective quality control process.

Keywords: *Quality Control Charts*, *Food Chain*, *CUSUM, EWMA, Grey Model.*

1. Introduction

Quality has become a concept that can indicate different meanings for people. In general, quality can be considered as all of the characteristics of goods and services that meet the needs of internal and

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external customers (Reeves and Bednar, 1994). This concept is used in every area of life as well as life quality, service quality, and product quality. In every sense, quality is tried to be standardized. Achieving the standardization results in the existence and development of the quality.

In 1924, Walter Shewhart introduced a statistical quality or process control (SPC) concept for economical control of quality in the mass production environment by considering the concept of quality control in the form of processes, programs and methods. Feigenbaum (1999) broadly defined the concept as the planning and coordination of contributions to the organization of departments such as R&D, production, sales and after-sales service at a certain quality level.

The process variability has become more observable, and it has become easier to take action. In this context, statistical process or quality control charts are the most common techniques that are used to visualize, monitor and improve the process requirements helping managers to maintain particular standards (Vaughn, 1990). Quality control charts have a common use due to their predictability and process monitoring ease. Montgomery (1996) pointed out the important features of control charts regarding reducing the waste in processes; preventing errors; providing relevant information about process capacities. Shewhart charts emerged as the starting point for SPC methods. This method of industrial production that aimed at measuring the production process has perhaps been the most discussed method over time and has never lost its value.

In this context, the objective of this study is to build an efficient process monitoring model for a particular chicken product used in the fast-food industry. For this purpose, CUSUM and EWMA control charts were developed to visualize the control points, and then GM (1,1) and GM (1,1) Markov models were built to generate predictions to see the trends and future values to maintain a monitoring procedure for the fluctuations in the process performance. In this context, three control points are considered: the weight of the chicken wings, sterilizer temperature, and grid-pan temperature.

The rest of the paper is organized as follows: the second section of the paper continues describing the current literature on the use and the development of these charts to emphasize their advantages, and then the third section presents the findings of the implementation carried out in the company; the paper concludes with the performances of the control charts included in the study are discussed, and suggestions are emphasized based on the evaluations.

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2. Literature Review

CUSUM is a method proposed by Page (1954) for process management after Shewhart. CUSUM is developed as an alternative to this graphic because of the small but continuous slip sensitivity of Shewart control charts in the sample averages. Page was intended to keep the defective products under control during the quality control process. Unlike Shewhart, it is used to detect small shifts in the process. CUSUM is not only a snapshot of the moment, but it also allows detecting minor changes to account for recent observations. However, CUSUM control charts are also a significant drawback. If observations show periodic fluctuations, they may be inadequate to make accurate decisions about the process.

EWMA control charts were originally introduced in Robert's (1956) work with the name Geometric Moving Average. EWMA is particularly suited for individual chart types arranged in small subgroup sizes. EWMA control charts are also frequently used in the analysis of time series and estimates other than process control. EWMA can be thought of as the weighted average of all past and present observations. Therefore, it is insensitive to normality hypothesis and is ideal for cases where the sub-sample volume is equal.

After the introduction of CUSUM chart by Page (1954), many authors have performed the chart in various areas and made many developments. Bissel (1969) noted that the CUSUM method is suitable for quality control. Woodall (1985) used this technique to observe whether variables are in or out of control, so the statistical performance of control chart has been projected. In recent years it has been seen that different branches of science have been used in different applications.

Bakker et al. (2014) used CUSUM control charts as a monitoring method to prevent the explosion of drinking-water pipes. Shams et al. (2011) used a cumulative total-based statistical surveillance scheme to track out failures that could not be detected or diagnosed correctly. Besides, Chan et al. (2010) utilized the CUSUM technique to estimate the weight of the year as variable in the estimation of tourism data. Chen (2016) applied CUSUM charts in online service processes to track customer request changes. CUSUM control chart was also used to determine the learning curves in anesthesia, surgical interventions, plastic surgery, and in other processes of medicine (Segna et al., 2017; Collmann-Camiora et al., 2017; Kwak et al., 2014; Parikh et al., 2014.)

EWMA control chart has frequently been used in many different areas like CUSUM chart. EWMA chart was compared by Hunter (1986) to CUSUM and Shewhart control charts. In this study, it was demonstrated that these three control charts produce the weight of the data they use in the production process. Lucas and Casucci (1990) compared the EWMA and CUSUM control charts in their studies and demonstrated the positive aspects of EWMA. Woodall and Maragh (1990) pointed out that EWMA may be later than CUSUM control charts in some cases. Vargas et al. (2004) presented a comparison for the performance of CUSUM and EWMA control schemes. The purpose of this study is to demonstrate when the CUSUM and EWMA control charts can achieve the best control region to detect small changes in the process average. In another study, Fleischer et al. (2008) compared EWMA type control charts with traditional control charts in micro-manufacturing processes that have a unique structure with high process variability and measurement uncertainty associated with their narrow tolerance properties.

Şentürk et al. (2014) developed EWMA control charts for uni-variate data in fuzzy environments. They recommend fuzzy EWMA control chart. It provides flexibility in control limits and reduces the number of false judgments by detecting small shifts on the rim represented by fuzzy numbers. Harrou et al. (2015) used partial least squares (PLS) and EWMA methods to improve error detection strategies for process monitoring. It is stated that EWMA succeeded in detecting small errors, but only in small variables. For this purpose, a combined method with PLS method was proposed. Adegoke et al. (2017) investigated the performance of classical EWMA control charts using the information associated with process variables. The EWMA type control charts are based on a product estimator in which are tracked using an auxiliary variable of the progressive position parameter.

In this paper, CUSUM and EWMA charts were comparatively used to develop a quality monitoring process for chicken wings by considering the critical specifications of this product. In different conditions, especially when analysts come up with a small-size data, grey model is often suggested. This trend has resulted in the development of grey control charts. Guo and Dunne (2006) analyzed and compared Gray predictable Shewhart and CUSUM control chart, and proposed a grey-fuzzy predictive control scheme then demonstrated the use of the grey systematic equation system for process control forecasting charts. In addition to this work, Chou et al. (2000) and Chen et al. (2002) proposed grey fuzzy control schemes to control the turning operation under various cutting conditions. Karmakar and Mujumdar (2006) developed a grey-fuzzy optimization model for water quality management of the river system. Proposed model has the ambiguity to fix the membership

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functions for the Pollution Control Agency (PCA) and the different targets of the discharge devices.

Similar to the abovementioned studies concerning grey-fuzzy control charts, grey prediction model for one variable, GM(1,1), was utilized as a supportive technique to be able to develop a predictive controlling scheme for the selected product.

3. Methodology

The data set provided by the company was collected within the time interval of 16.02.2017-08.03.2017. Three quality control points were effective on the product regarding meeting the customers' expectations: the weight of the chicken wings, sterilizer temperature, and grid-pan temperature. Characteristics of the collected data were compatible with CUSUM, EWMA charts. Thus these selected chart types were used to develop the required visualizations for process monitoring.

3.1. CUSUM quality control chart

CUSUM quality control charts are beneficial for understanding the small shifts in a production process (Wu et al., 2017, 80). Following steps can explain how to build CUSUM charts (Vargas et al., 2004, 711).

1. Calculate sample means;
2. Find the difference between the sample mean and the target process mean;
3. List the cumulative sums of the difference between sample mean, and the process mean;
4. Calculate the standard deviation of the process or the standard deviation of the sample; these values are used to determine the upper and the lower control limits;
5. If the difference between sample mean and the process mean is greater than upper control limit, or the difference between sample mean and the process mean is lower than the lower control limit, then the production process is said to be out of control. Otherwise, the production process is said to be in control.

3.2. EWMA quality control chart

EWMA quality control chart needs target mean and standard deviation as well, besides, EWMA quality control chart also needs additional value called weight value defined on the interval [0, 1]. The mainframe of these two quality control charts are almost same. Thus the similar steps also work for the basic methodology of EWMA quality control charts (Vargas et al., 2004, 712-713).

The first step of this quality control chart type is to determine the target mean. The desired process mean value or the average of preliminary data can be used as the target mean. Then the standard deviation value should be found for the quality control chart. The desired process standard deviation or the standard deviation value of the preliminary data can be used as the standard deviation. Next step is to determine the weighted value (smoothing constant). Smaller values of the smoothing constant can detect smaller shifts in the process mean.

3.3. GM (1,1) and GM (1,1) Markov Models

Grey System Theory (Deng, 1989) concerns the incompleteness, uncertainty, and poverty in information. GM (*m*, *n*) is a well-known prediction model in Grey System Theory that is developed for predicting future values of series data (Chen *et al*., 2015). Among subsets of GM (*m,n*), GM (1,1) has been recently used for many business problems such as discovering economic trends, financial issues, and solving many other prediction problems from various industries. The general prediction model based on GM (1,1) can be described in the following equation:

$$\hat{x}^{(1)}(k+1) = \left[x^{(1)}(1) - \frac{\hat{u}}{\hat{a}}\right] e^{-\hat{a}k} + \frac{\hat{u}}{\hat{a}}$$

Where $\hat{u}$ and $\hat{a}$ are parameters that are obtained from the solution of differential equations, and k is the number of the period.

Especially for fluctuating datasets, GM(1,1) may result in high relative errors., Markov chain is integrated to classify errors and calculate the probabilities between the error class transitions to overcome this issue. These transitions are then used to predict a new value (Li *et al*., 2007; Onalan, 2014; Juan *et al*., 2012; Ozdemir & Ozdagoglu, 2017). In this study, GM (1,1) and GM(1,1) Markov models were performed to develop a predictive model and to find out the trends of the undesired fluctuations in the process.

4. Findings

This section presents the findings based three control points regarding the results that were obtained from the calculations for the selected control charts, CUSUM, EWMA, and Grey Model, respectively.

4.1. Control Point -1: The Weights of the Chicken Wings

Based on the observed values of the wing weights, the calculations were performed on the inputs as explained in Table 1, and the chart presented in Figure 1 was obtained to monitor the current performance of the corresponding process.

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Table 1. CUSUM Quality Control Chart Values for the Wing Weights

Sample	Average	Average – Process Mean	CUSUM	Result
1	51.3750	1.1381	1.1381	in Control
2	51.1000	0.8631	2.0012	in Control
3	50.3250	0.0881	2.0893	in Control
4	48.5750	-1.6619	0.4274	in Control
5	49.3750	-0.8619	-0.4345	in Control
6	50.5250	0.2881	-0.1464	in Control
7	49.9250	-0.3119	-0.4583	in Control
8	50.5113	0.2743	-0.1840	in Control
9	49.9500	-0.2869	-0.4709	in Control
10	52.3750	2.1381	1.6672	in Control
11	51.1556	0.9186	2.5858	in Control
12	51.3750	1.1381	3.7239	Out of Control
13	50.9275	0.6906	4.4145	Out of Control
14	51.5250	1.2881	5.7026	Out of Control
15	48.4000	-1.8369	3.8657	Out of Control
16	48.4000	-1.8369	2.0288	In Control
17	48.7500	-1.4869	0.5419	In Control
18	49.6950	-0.5419	0.0000	In Control
Center Line	**Sigma Level**	**Standard Deviation**	**UCL**	**LCL**
50.2369	3	1.1879	3.5638	-3.5638

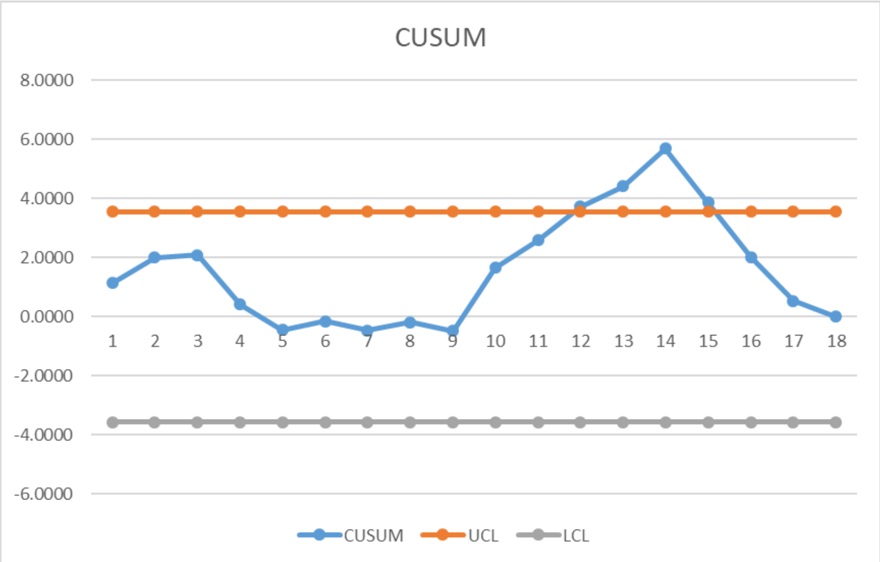

Figure 1. CUSUM Quality Control Chart for the Chicken Wings

The CUSUM chart in Figure 1 indicates that the samples go out of the upper control limits at four consecutive points.

EWMA control chart also points out a similar alert for the weights of the wings, but the distribution and direction of the out-of-control limits are completely different. As depicted in Table 2, there exists a new couple of lower and upper control limits to use as a comparative value for the corresponding sample. According to the results in Table 2 and Figure 2, there are five out-of-control points, but only two of them consecutives.

Table 2. EWMA Quality Control Chart Values for the Chicken Wings

Sample	Sample Value	UCL	LCL	RESULT
1	51.3750	51.3061	49.1678	Out of control
2	51.1000	51.5420	48.9318	In Control
3	50.3250	51.6432	48.8306	In Control
4	48.5750	51.6902	48.7836	Out of Control
5	49.3750	51.7127	48.7611	In Control
6	50.5250	51.7236	48.7502	In Control
7	49.9250	51.7289	48.7449	In Control
8	50.5113	51.7315	48.7423	In Control
9	49.9500	51.7328	48.7410	In Control
10	52.3750	51.7334	48.7404	Out of control
11	51.1556	51.7337	48.7401	In Control
12	51.3750	51.7339	48.7399	In Control
13	50.9275	51.7339	48.7399	In Control
14	51.5250	51.7340	48.7398	In Control
15	48.4000	51.7340	48.7398	Out of Control
16	48.4000	51.7340	48.7398	Out of Control
17	48.7500	51.7340	48.7398	In Control
18	49.6950	51.7340	48.7398	In Control

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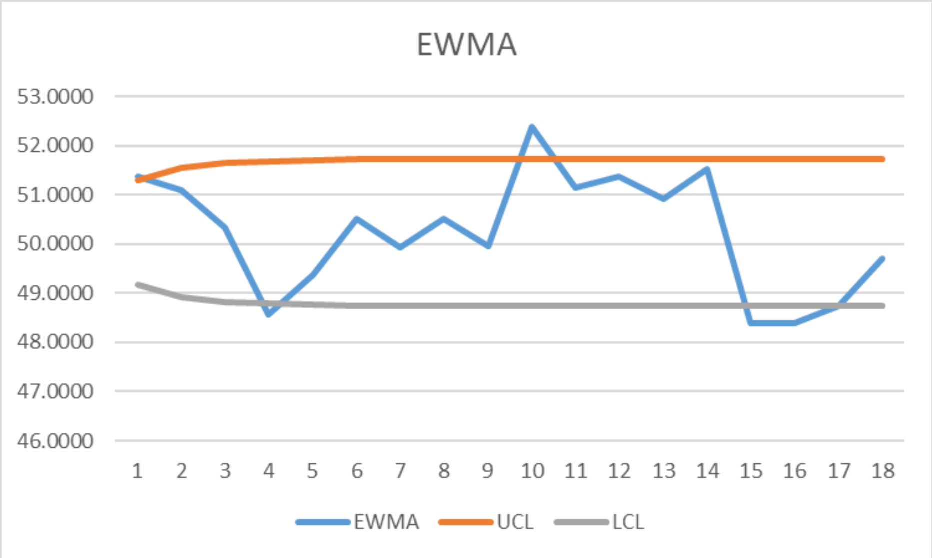

Figure 2. EWMA Quality Control Chart for the Chicken Wings

Therefore, these charts reveals that remedial actions should be taken to assure a stable process.

GM (1,1) and GM(1,1) Markov Model for Predicting Future Values

A prediction model can be developed to foresee the future values of the product characteristics. However, most of the statistical techniques require large amount of data for developing the models. One of the alternative models that can be performed with small-size data is a grey prediction model. Then, the fluctuations can be traced by predicting the future values continuously, and the required actions can be planned proactively before the values go beyond the limits. Since the dataset includes only one variable, a well-known grey model, GM (1,1), was developed initially, $x^{(0)}, x^{(1)}, z^{(1)}, -z^{(1)}$ series for the weight of the chicken wings are constructed, and predictions were developed. As seen in Table 3, relatively high error measures were obtained, thus, to improve the model and reduce the errors, a Grey-Markov model based on GM (1,1) was applied for predicting the trends in the production process.

The residual errors of the GM (1,1) model ranging within [-1.8108, 2.2377] were divided into five states, and the first-order transition probability matrix of the Markov chain is constructed:

P	1	2	3	4	5
1	0.6667	0.3333	0.0000	0.0000	0.0000
2	0.0000	0.0000	0.6667	0.0000	0.3333
3	0.2500	0.5000	0.0000	0.2500	0.0000
4	0.0000	0.0000	0.2500	0.5000	0.2500
5	0.5000	0.0000	0.0000	0.5000	0.0000

The predicted values of the GM (1,1)-Markov model were calculated by revising the predicted values of GM (1,1) with the residuals computed using the medians of state intervals.

Table 3. Series of the Weight of the Chicken Wings for GM (1,1)

$x^{(0)}$	$x^{(1)}$	$z^{(1)}$	$-z^{(1)}$	$x^{(0)}$ **Prediction GM (1,1)**	$x^{(0)}$ **Prediction GM (1,1) Markov**
51.3750	51.3750			51.3750	51.5885
51.1000	102.4750	76.9250	-76.9250	50.4690	51.4921
50.3250	152.8000	127.6375	-127.6375	50.4274	50.6408
48.5750	201.3750	177.0875	-177.0875	50.3858	48.9799
49.3750	250.7500	226.0625	-226.0625	50.3443	49.7481
50.5250	301.2750	276.0125	-276.0125	50.3028	50.5163
49.9250	351.2000	326.2375	-326.2375	50.2614	49.6651
50.5113	401.7113	376.4556	-376.4556	50.2200	50.4334
49.9500	451.6613	426.6863	-426.6863	50.1786	49.5823
52.3750	504.0363	477.8488	-477.8488	50.1373	52.7799
51.1556	555.1918	529.6140	-529.6140	50.0959	51.1191
51.3750	606.5668	580.8793	-580.8793	50.0547	51.0778
50.9275	657.4943	632.0306	-632.0306	50.0134	51.0366
51.5250	709.0193	683.2568	-683.2568	49.9722	51.8051
48.4000	757.4193	733.2193	-733.2193	49.9310	48.5251
48.4000	805.8193	781.6193	-781.6193	49.8899	48.4839
48.7500	854.5693	830.1943	-830.1943	49.8488	48.4428
	GM(1,1)			**GM(1,1)-Markov**	
MAD	**MAPE**	**MSE**	**MAD**	**MAPE**	**MSE**
0.9292	0.0185	1.2834	0.2387	0.0047	0.0748

Actual and predicted values according to GM (1,1) and GM (1,1) Markov models for the weight of the chicken wings can be compared through **Figure 3 and Figure 4**.

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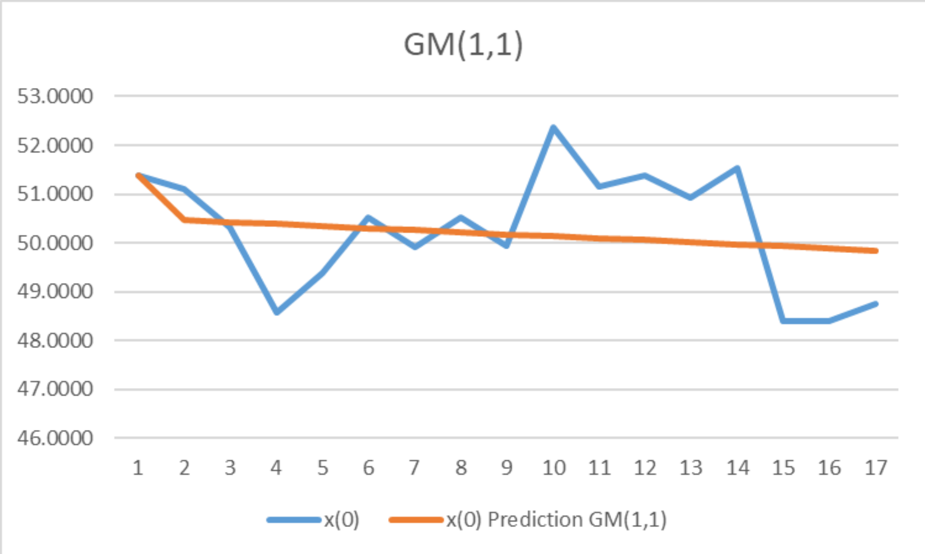

Figure 3. Actual and Predicted Values According To GM(1,1) Model For The Chicken Wings

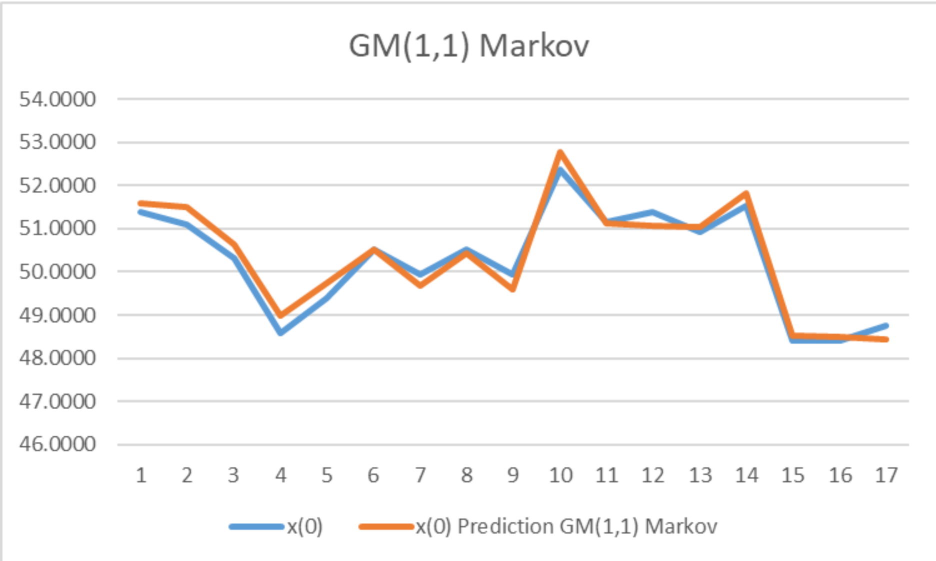

Figure 4. Actual and Predicted Values According To GM (1,1) Markov Model For The Chicken Wings

Figure 3 shows that GM (1,1) model does not fit well on the fluctuations in the dataset. Thus the predicted values over this model may not give ups and downs on the graph properly. Instead, a Markov chain integration was used as explained in Section 3.2, and better results were obtained as shown in **Table 3** and Figure 4.

4.2. Control Point -2: The Sterilizer Temperature

Based on the observed values of the sterilizer temperature, the calculations were performed on the inputs as explained in Table 4, and the chart presented in Figure 5 was obtained to monitor the current performance of the corresponding process.

Table 4. CUSUM Quality Control Chart Values for the Sterilizer Temperature

Sample	Average	Average – Process Mean	CUSUM	Result
1	84.1667	0.1491	0.1491	in Control
2	84.2500	0.2325	0.3816	in Control
3	84.3667	0.3491	0.7307	in Control
4	83.9143	-0.1032	0.6275	in Control
5	84.7000	0.6825	1.3100	in Control
6	83.4111	-0.6064	0.7035	in Control
7	83.4000	-0.6175	0.0860	in Control
8	84.6000	0.5825	0.6685	in Control
9	84.1667	0.1491	0.8176	in Control
10	83.2143	-0.8032	0.0144	in Control
11	84.1500	0.1325	0.1468	in Control
12	84.3667	0.3491	0.4960	in Control
13	83.7667	-0.2509	0.2451	in Control
14	84.3333	0.3158	0.5609	in Control
15	82.9250	-1.0925	-0.5316	in Control
16	84.3000	0.2825	-0.2491	in Control
17	84.2667	0.2491	0.0000	in Control
Center Line	**Sigma Level**	**Standard Deviation**	**UCL**	**LCL**
84.0175	3	0.5042	1.5127	-1.5127

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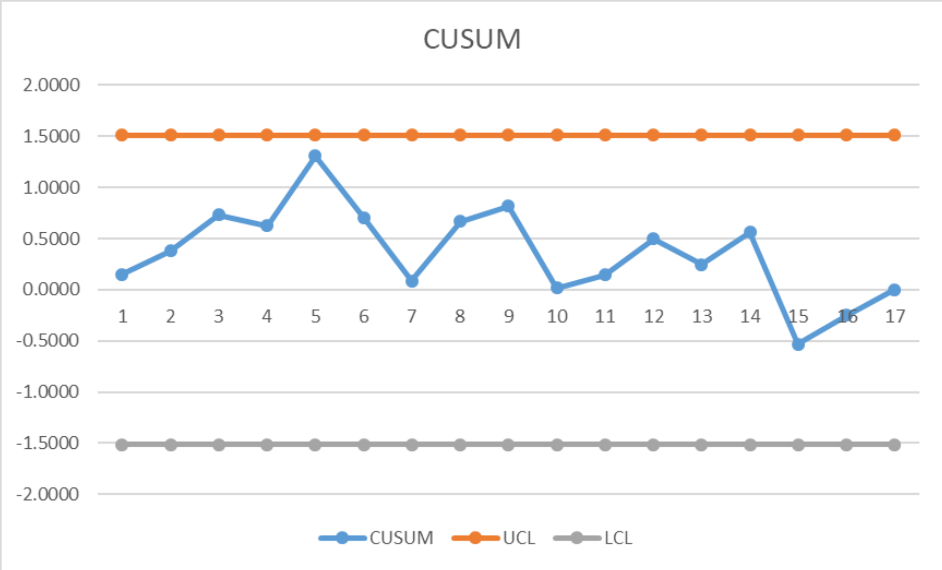

Figure 5. CUSUM Quality Control Chart for the Sterilizer Temperature

The CUSUM chart in Figure 5 indicates that all samples are between the upper control limits and the lower control limits.

On the other hand, EWMA control chart indicated alerts for the sterilizer temperature, so the distribution and direction of the values are completely different. As indicated in Table 4, there exists a new couple of lower and upper control limits to use as a comparative value for the corresponding sample. According to the results in Table 5 and Figure 6, there are three out-of-control points, but none of them consecutives.

Table 5. EWMA Quality Control Chart Values for the Sterilizer Temperature

Sample	Sample Value	UCL	LCL	RESULT
1	84.1667	84.4713	83.5637	In Control
2	84.2500	84.5715	83.4636	In Control
3	84.3667	84.6144	83.4206	In Control
4	83.9143	84.6344	83.4007	In Control
5	84.7000	84.6440	83.3911	Out of control
6	83.4111	84.6486	83.3865	In Control
7	83.4000	84.6508	83.3842	In Control
8	84.6000	84.6519	83.3831	In Control
9	84.1667	84.6525	83.3826	In Control
10	83.2143	84.6527	83.3823	Out of Control

11	84.1500	84.6529	83.3822	In Control
12	84.3667	84.6529	83.3821	In Control
13	83.7667	84.6530	83.3821	In Control
14	84.3333	84.6530	83.3821	In Control
15	82.9250	84.6530	83.3821	Out of Control
16	84.3000	84.6530	83.3821	In Control
17	84.2667	84.6530	83.3821	In Control

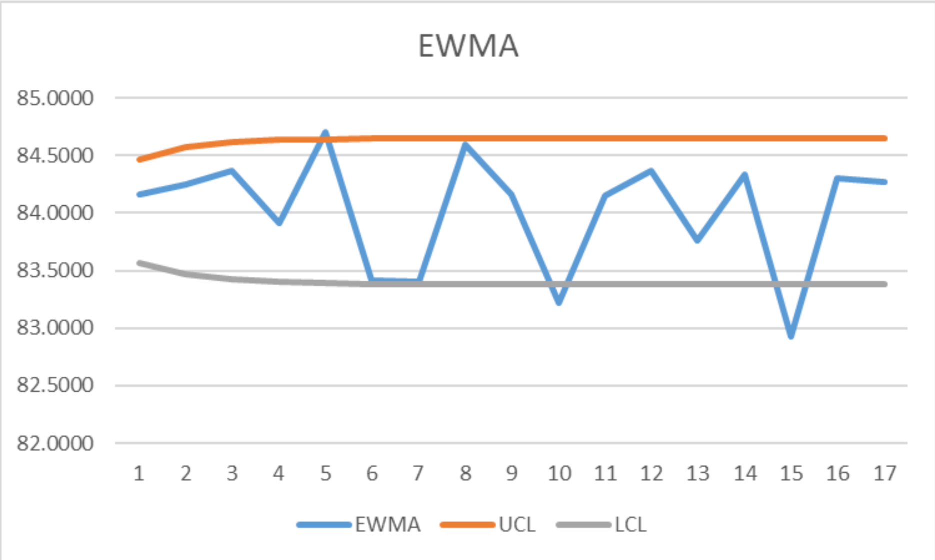

Figure 6. EWMA Quality Control Chart for the Sterilizer Temperature

Therefore, these charts reveals that remedial actions should be taken to assure a stable process.

GM (1,1) and GM(1,1) Markov Model for Predicting Future Values

A prediction model can be developed to foresee the future values of the product characteristics. However, most of the statistical techniques require large amount of data for developing the models. One of the alternative models that can be performed with small-size data is a grey prediction model. Then, the fluctuations can be traced by predicting the future values continuously, and the required actions can be planned proactively before the values go beyond the limits. Since the dataset includes only one variable, a well-known grey model, GM (1,1), was developed initially, $x^{(0)}, x^{(1)}, z^{(1)}, -z^{(1)}$ series for the sterilizer temperature are constructed, and predictions were developed. As seen in

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Table 6, relatively high error measures were obtained, thus, to improve the model and reduce the errors, a Grey-Markov model based on GM (1,1) was applied for predicting the trends in the production process.

The residual errors of the GM (1,1) model ranging within [-0.8921, 0.6345] were divided into five states, and the first-order transition probability matrix of the Markov chain is constructed:

P	1	2	3	4	5
1	0.2500	0.0000	0.0000	0.2500	0.5000
2	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!	#DIV/0!
3	0.0000	0.0000	0.0000	0.3333	0.6667
4	0.2500	0.0000	0.2500	0.2500	0.2500
5	0.5000	0.0000	0.2500	0.2500	0.0000

The predicted values of the GM (1,1)-Markov model were calculated by revising the predicted values of GM (1,1) with the residuals computed using the medians of state intervals.

Table 6. Series of the Sterilizer Temperature for GM (1,1)

$x^{(0)}$	$x^{(1)}$	$z^{(1)}$	$-z^{(1)}$	$x^{(0)}$ Prediction GM (1,1)	$x^{(0)}$ Prediction GM (1,1) Markov
84.1667	84.1667			84.1667	84.0379
84.2500	168.4167	126.2917	-126.2917	84.1402	84.3167
84.3667	252.7833	210.6000	-210.6000	84.1153	84.2918
83.9143	336.6976	294.7405	-294.7405	84.0904	83.9616
84.7000	421.3976	379.0476	-379.0476	84.0655	84.5473
83.4111	504.8087	463.1032	-463.1032	84.0406	83.3012
83.4000	588.2087	546.5087	-546.5087	84.0158	83.2764
84.6000	672.8087	630.5087	-630.5087	83.9909	84.4727
84.1667	756.9754	714.8921	-714.8921	83.9661	84.1426
83.2143	840.1897	798.5825	-798.5825	83.9412	83.2018
84.1500	924.3397	882.2647	-882.2647	83.9164	84.0929
84.3667	1008.7063	966.5230	-966.5230	83.8915	84.3733
83.7667	1092.4730	1050.5897	-1050.5897	83.8667	83.7379
84.3333	1176.8063	1134.6397	-1134.6397	83.8419	84.3237
82.9250	1259.7313	1218.2688	-1218.2688	83.8171	83.0777
84.3000	1344.0313	1301.8813	-1301.8813	83.7923	84.2741
	GM(1,1)			**GM(1,1)-Markov**	
MAD	**MAPE**	**MSE**	**MAD**	**MAPE**	**MSE**
0.4159	0.0050	0.2381	0.0718	0.0009	0.0078

Actual and predicted values according to GM (1,1) and GM (1,1) Markov models for the sterilizer temperature can be compared through **Figure 7 and Figure 8**.

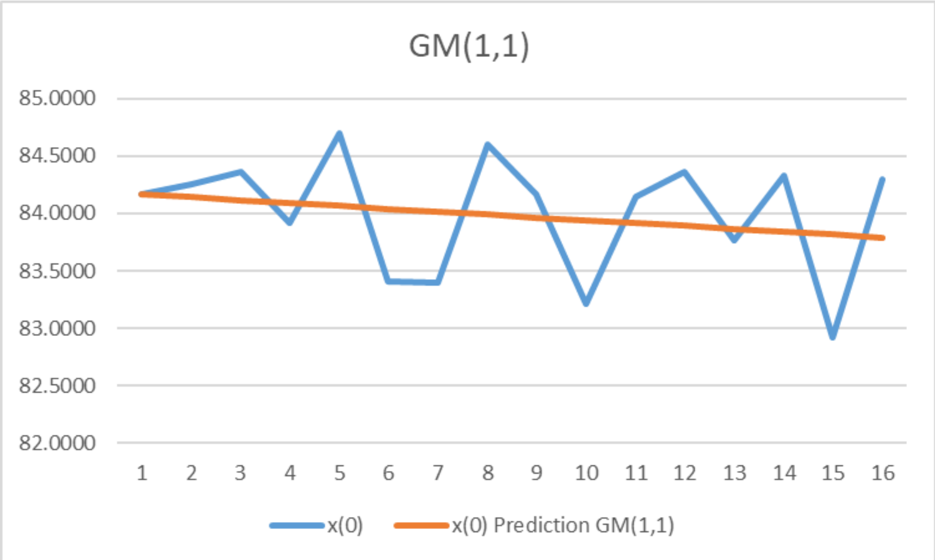

Figure 7. Actual and Predicted Values According To GM(1,1) Model For The Sterilizer Temperature

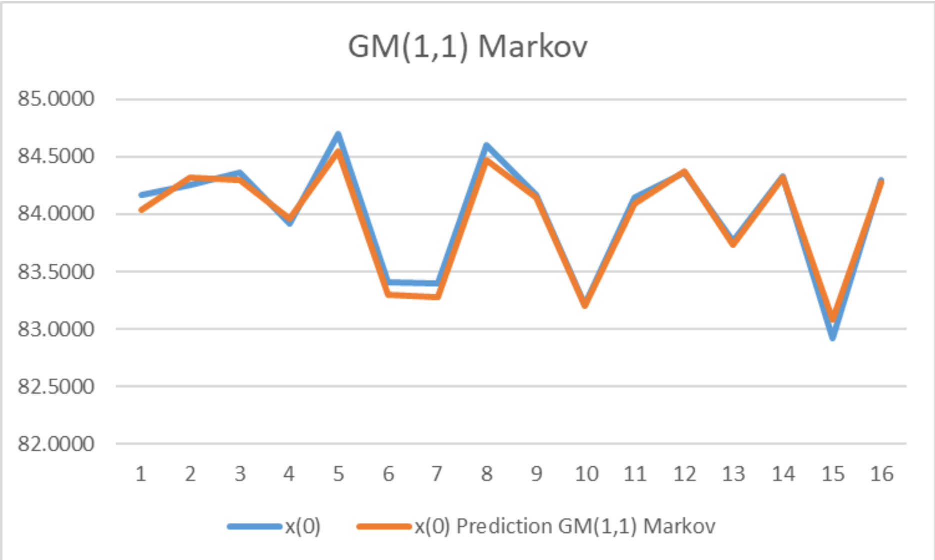

Figure 8. Actual and Predicted Values According To GM (1,1) Markov Model For The Sterilizer Temperature

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Figure 8 shows a better fit on the data set with the help of Markov Chain integration when compared to Figure 7. Table 6 shows the details about the comparison.

4.3. Control Point -3: The Grid-Pan Temperature

Based on the observed values of the grid-pan temperature, the calculations were performed on the inputs as explained in Table 7, and the chart presented in Figure 9 was obtained to monitor the current performance of the corresponding process.

Table 7. CUSUM Quality Control Chart Values for the Grid-Pan Temperature

Sample	Average	Average – Process Mean	CUSUM	Result
1	3.3460	-0.1732	-0.1732	in Control
2	3.3877	-0.1315	-0.3047	in Control
3	3.4267	-0.0925	-0.3973	in Control
4	3.4655	-0.0538	-0.4510	in Control
5	3.3740	-0.1452	-0.5962	Out of Control
6	3.5354	0.0162	-0.5801	Out of Control
7	3.6033	0.0841	-0.4960	Out of Control
8	3.6644	0.1452	-0.3507	in Control
9	3.3000	-0.2192	-0.5699	Out of Control
10	3.4378	-0.0814	-0.6514	Out of Control
11	3.3418	-0.1774	-0.8288	Out of Control
12	3.5978	0.0786	-0.7502	Out of Control
13	3.5743	0.0551	-0.6951	Out of Control
14	3.4075	-0.1117	-0.8068	Out of Control
15	3.6883	0.1691	-0.6377	Out of Control
16	3.8250	0.3058	-0.3319	in Control
17	3.6075	0.0883	-0.2436	in Control
18	3.7629	0.2436	0.0000	in Control
Center Line	**Sigma Level**	**Standard Deviation**	**UCL**	**LCL**
3.5192	3	0.1544	0.4633	-0.4633

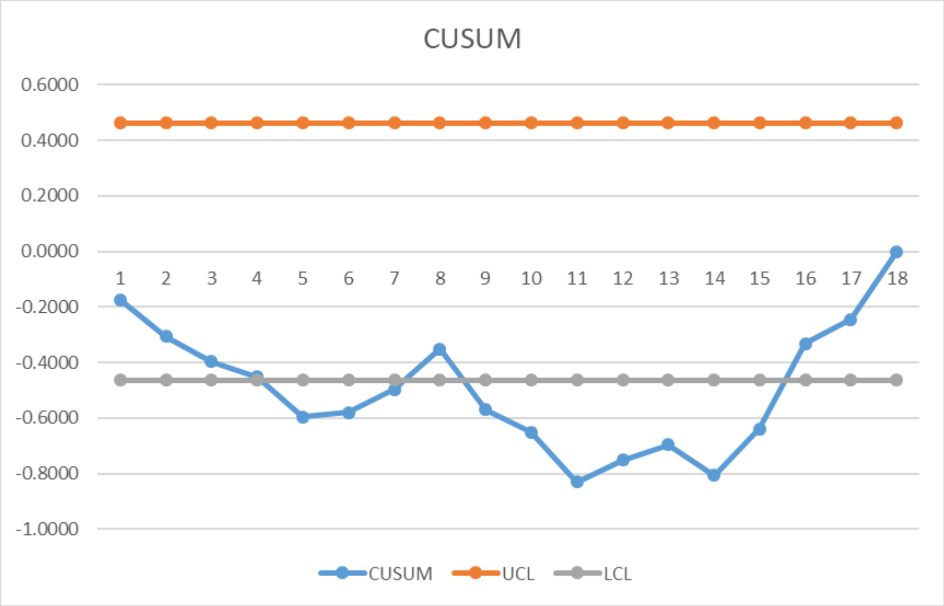

Figure 9. CUSUM Quality Control Chart for the Grid-Pan Temperature

The CUSUM chart in Figure 9 indicates that many different samples are out of control limits and seven of them consecutives.

On the other hand, there are only four out of control points in EWMA control chart for the grid-pan temperature, so the distribution and direction of the values are completely different. As indicated in Table 8, there exists a new couple of lower and upper control limits to use as a comparative value for the corresponding sample. According to the results in Table 8 and Figure 10, there are three out-of-control points, but none of them consecutives.

Table 8. EWMA Quality Control Chart Values for the Grid-Pan Temperature

Sample	Sample Value	UCL	LCL	RESULT
1	3.3460	3.6582	3.3802	Out of Control
2	3.3877	3.6889	3.3496	In Control
3	3.4267	3.7020	3.3364	In Control
4	3.4655	3.7081	3.3303	In Control
5	3.3740	3.7111	3.3274	In Control
6	3.5354	3.7125	3.3260	In Control
7	3.6033	3.7132	3.3253	In Control
8	3.6644	3.7135	3.3249	In Control
9	3.3000	3.7137	3.3248	Out of Control

10	3.4378	3.7137	3.3247	In Control
11	3.3418	3.7138	3.3246	In Control
12	3.5978	3.7138	3.3246	In Control
13	3.5743	3.7138	3.3246	In Control
14	3.4075	3.7138	3.3246	In Control
15	3.6883	3.7138	3.3246	In Control
16	3.8250	3.7138	3.3246	Out of control
17	3.6075	3.7138	3.3246	In Control
18	3.7629	3.7138	3.3246	Out of control

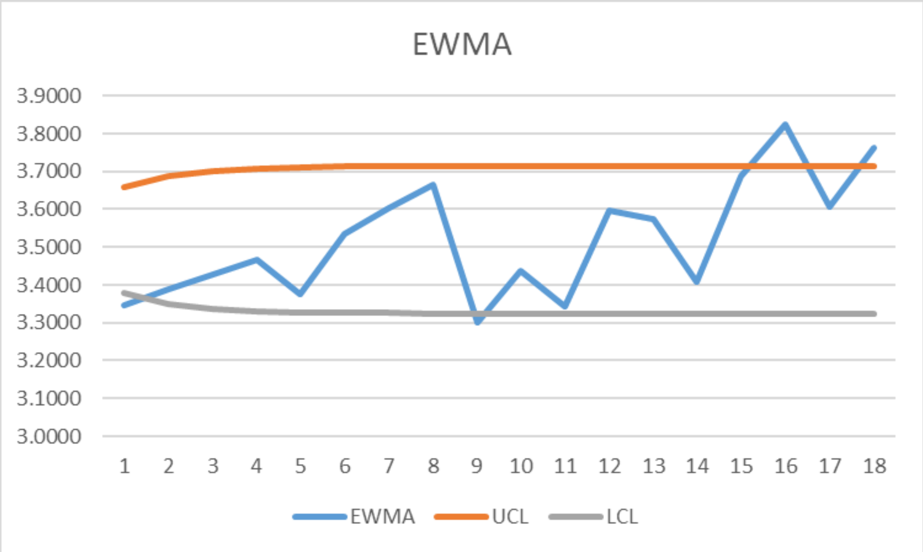

Figure 10. EWMA Quality Control Chart for the Grid-Pan Temperature

Therefore, these charts reveal that remedial actions should be taken to assure a stable process.

GM (1,1) and GM(1,1) Markov Model for Predicting Future Values

A prediction model can be developed to foresee the future values of the product characteristics. However, most of the statistical techniques require large amount of data for developing the models. One of the alternative models that can be performed with small-size data is a grey prediction model. Then, the fluctuations can be traced by predicting the future values continuously, and the required actions can be planned proactively before the values go beyond the limits. Since the dataset includes only one variable, a well-known grey model, GM (1,1), was developed initially, $x^{(0)}, x^{(1)}, z^{(1)}, -z^{(1)}$ series for the grid-pan temperature are constructed, and predictions were developed. As seen in Table 9, relatively high error measures were obtained, thus, to improve the model and reduce the errors, a Grey-Markov model based on GM (1,1) was applied for predicting the trends in the production process.

The residual errors of the GM (1,1) model ranging within [-0.2219, 0.1908] were divided into five states, and the first-order transition probability matrix of the Markov chain is constructed:

P	1	2	3	4	5
1	0.0000	0.3333	0.0000	0.6667	0.0000
2	0.5000	0.0000	0.0000	0.5000	0.0000
3	0.2000	0.2000	0.6000	0.0000	0.0000
4	0.0000	0.0000	0.3333	0.0000	0.6667
5	0.3333	0.0000	0.3333	0.0000	0.3333

The predicted values of the GM (1,1)-Markov model were calculated by revising the predicted values of GM (1,1) with the residuals computed using the medians of state intervals.

Table 9. Series of the Grid-Pan Temperature for GM (1,1)

$x^{(0)}$	$x^{(1)}$	$z^{(1)}$	$-z^{(1)}$	$x^{(0)}$ **Prediction GM (1,1)**	$x^{(0)}$ **Prediction GM (1,1) Markov**
3.3460	3.3460			3.3460	3.3304
3.3877	6.7337	5.0398	-5.0398	3.4131	3.3976
3.4267	10.1604	8.4470	-8.4470	3.4285	3.4129
3.4655	13.6258	11.8931	-11.8931	3.4439	3.4283
3.3740	16.9998	15.3128	-15.3128	3.4593	3.3612
3.5354	20.5352	18.7675	-18.7675	3.4749	3.5419
3.6033	24.1385	22.3369	-22.3369	3.4905	3.6400
3.6644	27.8030	25.9708	-25.9708	3.5062	3.6557
3.3000	31.1030	29.4530	-29.4530	3.5219	3.3413
3.4378	34.5408	32.8219	-32.8219	3.5378	3.4396
3.3418	37.8826	36.2117	-36.2117	3.5536	3.3730
3.5978	41.4803	39.6815	-39.6815	3.5696	3.6366
3.5743	45.0546	43.2675	-43.2675	3.5857	3.5701
3.4075	48.4621	46.7584	-46.7584	3.6018	3.4211
3.6883	52.1505	50.3063	-50.3063	3.6179	3.6849
3.8250	55.9755	54.0630	-54.0630	3.6342	3.7837
3.6075	59.5830	57.7792	-57.7792	3.6505	3.6350
	GM(1,1)			**GM(1,1)-Markov**	
MAD	**MAPE**	**MSE**	**MAD**	**MAPE**	**MSE**
0.0904	0.0259	0.0139	0.0202	0.0058	0.0006

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Actual and predicted values according to GM (1,1) and GM (1,1) Markov models for the grid-pan temperature can be compared through **Figure 11 and Figure 12**.

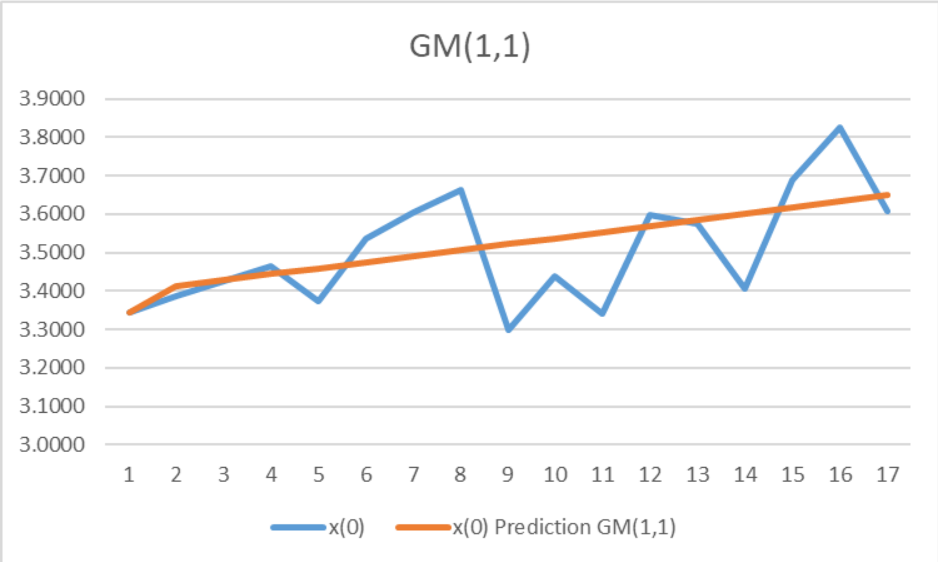

Figure 11. Actual and Predicted Values According To GM(1,1) Model For The Grid-Pan Temperature

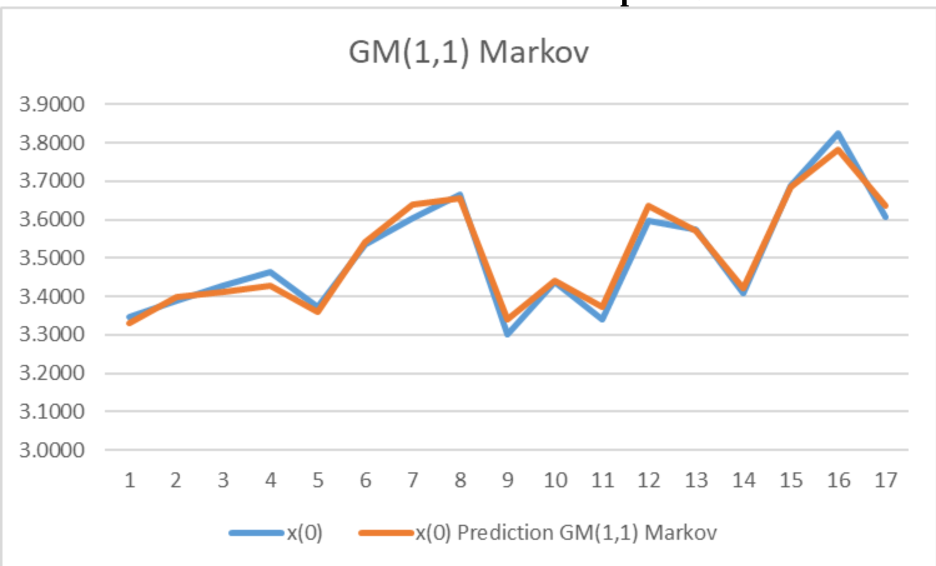

Figure 12. Actual and Predicted Values According To GM (1,1) Markov Model For The Grid-Pan Temperature

As explained in the previous findings, Markov Chain integration resulted in better predictions as shown in **Table 9** and Figure 12.

5. Conclusion

Selecting and controlling the quality of a product is an important issue to reveal the desired product both by meeting the customer expectations and by maintaining efficient production and service processes. In this context, this paper presented a case study at a food company for which a process control procedures are tried to be developed over the particular quality control points. The company processes chicken products for fast-food chains and quality of the product is tracked over the points such as weight of the chicken wings, sterilizer temperature, and grid-pan temperature.

The study aimed at developing a control framework to as a monitoring methodology for the particular product. For this purpose, quality control charts were constructed through CUSUM and EWMA techniques. These charts visualized the spread of the observations between or out of the lower and upper limits. Then a prediction model was necessary to predict the future values in details and to see if the fluctuations will continue to go beyond the limits. Hence, initially, GM(1,1) model was build, and relative errors were calculated. At that point, we came up with high relative error rates. Then Markov chain components were developed to obtain a GM (1,1)-Markov model with better prediction performance. The results revealed whether the sudden fluctuations are randomly occurred or the result of a problem within the process workflow.

These kind of procedures or techniques can also be suggested for any product or service providers whose products are very sensitive to the input characteristics and environmental factors and whose process problems should be resolved immediately and proactively.

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