Chapter

Implementation of SPC-EPC Scheme to Lessen and Control Production Disruptions in Chlor-Alkali Industry

Walid Smew, Bader Al-Mutawa and Ali Issawy

Abstract

The quality of products in the industry can be improved by monitoring the manufacturing process and adjusting/optimizing the process input variables based on the output deviation from the target. SPC stands for statistical process control, and it is used to monitor processes in order to identify any assignable causes of variation. EPC stands for engineering process control, and it is concerned with adjusting systems inputs to keep the system output on target using different types of controllers such as integral controllers and PID controllers. Combining SPC and EPC as a unified framework proved to be effective in reducing production disruption in manufacturing industries. The main objective of this project is to redesign the production and quality control system in a chemical batch processing company, anonymous company, by developing an engineering process controller (EPC) in order to adjust the chemical process inputs to keep the output chemical concentration on best optimized target while monitoring the system using the sensitive time weighted control charts (SPC), in order to eliminate the process assignable causes of variation, improve system elements life, and reduce overall system wide costs.

Keywords: batch processing, production disruptions, engineering process control (EPC), integral controller, statistical process control (SPC), time weighted control charts

1. Introduction

Statistical process control (SPC) and engineering process control (EPC) are two very different approaches to improve the process efficiency by reducing the process disturbances or variability and achieving a much better product quality which will lead to customer satisfaction and increase in sales [1]. SPC works by monitoring the process by utilizing different types of control charts and tries to identify any points located outside the control limits [2, 3]. Points located outside the control limits are commonly referred as assignable causes which mean there is a specific cause that caused the point to be out of the control limits [4]. It is sometimes difficult to differentiate between common cause and assignable cause, furthermore just because the points are within the control limits, it does not mean the process is under control [5]. The points sometimes generate a suspicious pattern which will indicate there's something wrong in the process and must be fixed. Now for the EPC it's a continuous process of manipulating the process input controls in order to keep the output on target [6]. EPC utilizes different types of controllers that work by feedback adjustment such as the integral controller and the PID controller [2, 6]. These controllers will work in conjunction with a certain type of control chart where if a point falls outside the control limits then it will automatically trigger the controller to take corrective actions to bring the process back in control. The SPC and EPC unified framework has been proven to be very effective at significantly reducing the process variation and drastically improving the product quality. Aljebory and Alshebeb [7] presented how effective to combine both techniques and implemented a unified framework of SPC and EPC into a chemical manufacturing industry and managed to reduce the process standard deviation by 30%. Out of the many types of statistical control charts, the cumulative sum control chart (CUSUM) and the exponentially weighted moving average control chart (EWMA) are very good at detecting small mean shifts in many quality characteristics and can easily be devolved and analyzed using software such as Minitab. In order to develop an engineering controller, one must first mathematically model the process and identify the important inputs, outputs, flow rates ...etc. and then translate them into programming code to be run and analyzed using software such as MATLAB.

This work considers three research parts: chemical batch processing monitoring and control, integration of SPC and EPC, and a case study to demonstrate the unified scheme to lessen and control the production disruptions in Chlor-Alkali industry. This book chapter is organized as follows: Sections 2–4 illustrate the theoretical background and derivation of the basic relations from literature for integrated SPC-EPC systems. Next, Sections 5–7 describe and explain the case system, key input variables, the problem, and the proposed unified SPC-EPC scheme implemented in Chlor-Alkali industry. Finally, Sections 8 and 9 present the results, findings and conclusions of this research work.

2. Statistical process control (SPC)

The idea of statistical control charts is that a reference distribution that can be attained by simply combining observations from rational subgroups where they are taken over short periods of time in which that the process is considered to be stable [8]. A continuous comparison of the current process observations will be compared to the control limits that is calculated based on the reference distribution can lead to a detection of assignable causes such as out of control points and patterns.

In order to implement a control chart successfully, a practitioner will ask three main questions [8]:

- Is the control chart an important tool for this application?
- Which type of control charts must be used?
- Where should be the control limits be placed?

To develop a statistical control chart, it all depends on whether or not a reference distribution exists. If a reference distribution does not exist then an effective alternative approach would be plotting individual data subgroup means or variances onto run charts and those run charts must be presented clearly to the individuals that are responsible for the process. Control limits will not be used, however if the process means exhibits a drifting behavior then an Engineering process control strategy should be implemented in order to reduce process variation [8].

The answer of questions two and three depends on why the charts will be used. There are three main uses for a statistical control chart: (1) real time process monitoring, (2) problem solving, and (3) assessment of process stability. Uses 2 and 3 are more important than 1. Long-term process improvement is way more important than just process monitoring and detecting [8].

After determining the main use for a control chart, a specific and suitable control chart must be chosen to monitor the process. If the process noise is white noise and the objective is to detect a spike, then a Shewhart chart should be used; if a step change, then a cumulative sum (CUSUM) should be used; and if an exponential change or increase, then an exponentially weighted averaged should be used [8]. CUSUM and EWMA control charts provide faster detection in small shifts in the process mean where the regular unmodified Shewhart control charts might fail to detect small step changes in the process which would result in a higher process variation [8].

2.1 Time weighted control charts

All control charts have the same basic format with a center line, an upper control limit, and a lower control limit however, time weighted control charts uses weighted averages as a performance measure, where they take in consideration the current and the previous process observations in order to make the control chart more sensitive to small process shifts especially in phase II process monitoring [9]. They can be used as an excellent alternative to the Shewhart control charts which uses only the information contained in the last sample observation. There are three types of time weighted control charts; the exponentially weighted moving average control chart, the cumulative sum control chart and the moving average control chart [10].

2.1.1 Exponential weighted moving average (EWMA)

The exponentially weighted moving average control chart is a time weighted control chart which uses the weighted average Z_i, as the chart statistic rather than the sample number i [2, 11]. The weighted average can be calculated by using the following equation:

$$EWMA_i = Z_i = \lambda X_i + (1-\lambda)Z_{i-1} \tag{1}$$

The EWMA control chart control limits can be calculated by using the following equation:

$$UCL = \mu_0 + L_\sigma \sqrt{\frac{\lambda}{(2-\lambda)}\left(1-(1-\lambda)^{2i}\right)} \tag{2}$$

$$CL = \mu_0; UCL = \mu_0 + L_\sigma \sqrt{\frac{\lambda}{(2-\lambda)}\left(1-(1-\lambda)^{2i}\right)} \tag{3}$$

The factor L, that is shown in Eqs. (2) and (3), is called the width of the control limit and the λ is called the weighting factor. The common values of λ ranges from $0.05 \leq \lambda \leq 0.25$ [6]. Generally, using a smaller weight would be better at detecting small shifts in the process mean. The boundary value L is usually determined from an engineering decision based on the costs of being off target and the costs of making the adjustment [7]. Montgomery proposed the following equation (Eq. (4)) to estimate $\sigma EWMA$ [2, 11].

$$\hat{\sigma}EWMA = \sqrt{\frac{\lambda}{2-\lambda}}\hat{\sigma} \tag{4}$$

3. Engineering process control (EPC)

Quality control engineers frequently need to adjust different processes. Control charts such as Shewhart control charts are inefficient and inappropriate in adjusting processes. Simple principles provided by EPC could be easily put to use [12]. Principles such as feedback adjustment using a discrete proportional integral (PI) control can be easily implemented and understood [8]. PI controllers are not only simple and effective, but it's also very robust and versatile, which means it could be implemented in different industries [13]. Discrete PI controllers can easily replace, much more complicated control schemes with only a slight loss of efficiency [14].

When adjustments cannot be done automatically, there usually a cost factor that goes with every process adjustment that is done [15]. The fixed cost that goes with every feedback adjustment is often not economical to make adjustment at every opportunity [8]. However, in cases like this, using and EWMA control chart that uses bounded adjustment could give minimum cost in feedback adjustments, where the adjustment is only made when the process observation exceeds the upper or lower boundary [16]. Appropriate tuning can be done on the bounded adjustment scheme where it would minimize three main costs:

1. Cost of being off target

2. Costs of adjusting

3. Cost of sampling and testing

EPC will use feedback adjustment to remove any assignable cause that the SPC approach failed to remove [2]. The Integral control approach works by adjusting the process input variables based on the error that started to accumulate over a certain period of time. Usually, integral controls are used in conjunction with a proportional controller which is responsible for making corrective adjustments to the proportion of error in the input, so it can adjust faster and more accurate [6]. The combination of the integral controller and proportional controller is referred as the PI controller where they use feedback adjustment to reduce the deviation from the target [2].

3.1 Process control by feedback adjustment: integral control

The main objective in feedback adjustment is to make the output as close to the desired target as possible. Let us say the process at period time t has an output of y_t and a singular input process variable of x, so changing x will affect the output y. $y_{t+1} - T = gx_t$, where T is the desired target and g is a constant called the process gain. The process gain is basically relating to the magnitude of change in x_t to the magnitude of change in y_t. It basically acts like a regression coefficient [2, 6]. In any process, there will most likely be some disturbances, we will denote the disturbance in the process with N, so $y_{t+1} - T = N_{t+1} + gx_t$. This equation shows that at period $t + 1$, the output deviation $y_{t+1} - T$ will depend on the disturbance in period $t + 1$ plus the input variable x_t which is our chosen set point. By forecasting the disturbance, we would know the optimal set point to cancel out the disturbance [17].

$$x_t = \sum_{j=1}^{t} \left(x_j + x_{j-1}\right) = -\frac{\lambda}{g} \sum_{j=1}^{t} e_j \tag{5}$$

The actual set point for variable x_t at the end period t is the sum of all adjustments through time t, where λ is the weight and is e are the predicted error [2]. This type of process adjustment scheme is called the integral control, where it uses feedback control to manipulate the variable input x_t, to reduce the process deviation from the target.

3.2 Process control by feedback adjustment: proportional integral derivative controller (PID) controller

A PID controller has the optimum control dynamics as it has zero steady state error and would eliminate the overshoot and oscillations of the output [6]. Moreover, it has a quicker response time compared to the integral controller or the proportional integral controller. Choosing the manipulative variable for a PID controller is calculated as shown below:

$$x_t = k_p e_t + k_i \sum_{i=1}^{t} e_i + k_D(e_t - e_{t-1}) \tag{6}$$

k and c are constants that are chosen based on the tuning of the controller [6].

3.3 The adjusting chart

Most feedback adjustment schemes adjust the process automatically, utilizing many different combinations of sensors and computers and finally actuators to physically implement the adjustment [2]. When the feedback adjustment adjusts the process automatically, it is called the automatic process control. In some processes, the feedback adjustment is done manually by the operators, where the process deviations are routinely observed to know how much adjustment needed to keep the output closer to the target.

4. Integrated SPC and EPC systems

SPC works by continuously plotting and comparing a statistical measure of certain variable with a user generated control limit [18]. If the plotted statistic exceeds the upper or lower control limit, then the process is considered to be out of statistical control. Corrective action is then applied to the process in order to eliminate the assignable cause thus reducing process variation [18]. Matos et al. [19] integrated SPC and EPC into a unified framework and investigated a pulp and paper industry through three phases and found that:

- Phase 1: fitting several single input and single output (SISO) transfer function models in order to identify any possible relationships between the input and output variables.

- Phase 2: merging of three data sets in order to achieve the main goal which is obtaining a better profile of the bleach pulp process; phase 1 was then repeated.

- Phase 3: a multiple input single output (MISO) transfer function will be developed based on the results obtained in phase 2.

However, using this type of integration has two big concerns. The first concern is that the identified input and output variables must be monitored. The second concern is that a decision must be made on which type of controller should be used, whether an automatic controller or a manual controller. The decision will be made based on the adjustment costs and type of adjustment [19].

SPC and EPC are two techniques that complete each other as they both work together to reduce the process disturbances and improve the product quality. There is a relationship between the EWMA predictor and the integral controller, they both work hand in hand in order to make predictions. Using EWMA control charts in conjunction with integral controllers are frequently used because of their simplicity and efficiency. Jiang and Farr [20] proposed four different categories of the application of the two different quality control approaches, which are going to be illustrated:

1. The EPC scheme is not needed if the data is not correlated. The SPC will be used to monitor the process and identify any assignable causes.

2. The EPC control scheme should be examined if the data is correlated. The SPC control charts should be brought up to monitor the autocorrelation if no possible EPC control scheme exists.

3. Even though the EPC control scheme can compensate some auto correlation disturbances, however a single EPC control scheme will not be able to compensate all the different kind of variations.

4. The diagnostic process of the SPC will be used in conjunction with the feedback adjustment of the EPC control scheme, where the SPC will detect any sudden shift in the process mean and the EPC will take corrective actions based on the deviation from the target.

SPC and EPC originated in different industries, the parts industry and the process industry, and both approaches have been developed independently and they have they are on controversies, since the word control has different meanings depending on the approach. The word 'control' in SPC means process monitoring, while the word 'control' in EPC process regulation. SPC and EPC strategies are considered as two complimentary strategies for quality improvement [18]. There are three types of SPC and EPC unified frameworks: The Algorithmic SPC, Active SPC and the Run-to-Run.

4.1 Algorithmic SPC (ASPC)

ASPC is proactive approach to quality improvement that uses feedback and feedforward adjustments to reduce predictable variations [18]. This approach aims to reduce both short term and long-term variations by using a new discipline that replaces the traditional discipline 'monitor, then adjust when out of control' with 'adjust optimally and monitor [21].

4.2 Active SPC

Active SPC are statistical models that are used to define the control limits and develop control laws that suggest the exact adjustment needed to maintain the process under statistical control [18]. Thus, using this strategy would eliminate the need for an algorithmic automatic controller. As a result, active SPC would result in a saving in raw materials and utilities.

4.3 Run-to-Run (RTR)

RTR is a process control technique where a run is represented by a batch or any other type of grouping [18]. In an RTR process, control actions are only made or implemented between runs instead of during runs. The SPC acts as a supervisor [18] where it triggers the adjustments whenever needed.

5. Case study

Anonymous company is a locally based Chlor-Alkali chemical manufacturing company that was listed in Kuwait stock exchange in the year 2002 and is focused on continual growth and optimization. The anonymous company complies with many international standards such as ISO 9001: 2008 quality management systems, ISO 14001: 2004 environmental management systems and OSHA 18001: Occupational health and safety management. The anonymous company has a total equity of approximately $107,000,000, produces and exports many kinds of salt-based products such as sodium chloride, sodium hypochlorite, sodium hydroxide, hydrogen and chlorine. These products have many uses in industrial sectors as they play an important role in the chemical manufacturing industry and the oil and gas industry. The anonymous company suffers from production disruptions and is unable to keep the feed brine concentration on target. The production disruptions are causing the cell membranes lifecycle to decrease due to the high variability in the feed brine concentration. The cell membranes main function is to prevent any unwanted reaction to occur in the electrolysis chamber. The anonymous company has a total of 120 cell membranes with a total cost of approximately $600,000.

As in **Figure 1**, the current control system that the anonymous company follows to regulate the salt levels can be described as: firstly, sensors such as the hydrometer and the 2-wire conductivity transmitter will start measuring the acidity and the concentration of the feed brine solution in Tk102 and inputs them into a regression model in order to predict what the feed brine concentration will be in Tk151. The values of the feed brine concentration will be plotted on IMR—control charts, as in **Figure 2**, so the control engineer can monitor the process. If there is an out of control point then an alarm will sound in the control room and the control engineer will then manually manipulate the salt levels to bring the process back in control.

This current control system has many problems. First, the anonymous company uses IMR-control charts (which has low sensitivity and is unable to detect small shifts in the process mean. Second, the IMR-control chart lacks the ability to predict the next error, which is a big problem since predicting error is essential in control engineering. The third problem is that the adjustments are done manually by the control engineers in the control room. Now manually adjusting the process comes with many drawbacks. First, the control engineers may not input the exact adjustment. Secondly the control engineer must always be present and alert at all times, and that would cause cognitive fatigue whereby human error is more likely to occur.

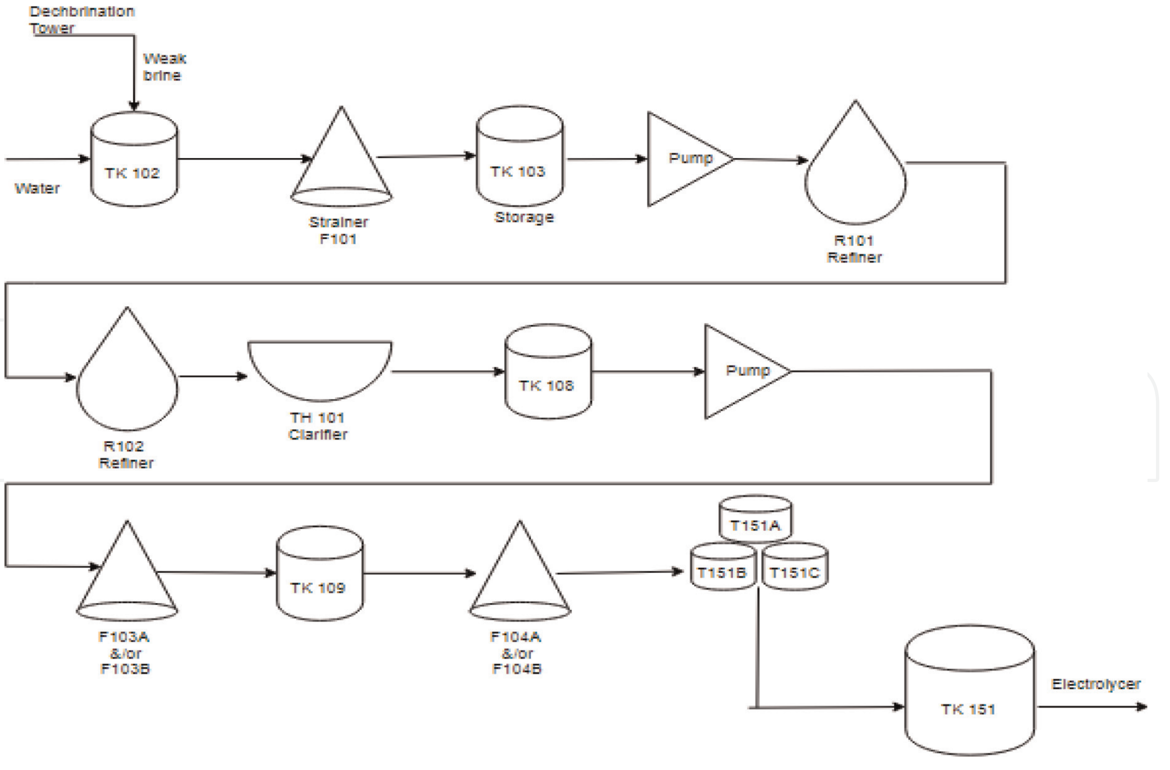

Figure 1.
Ferric treatment tank.

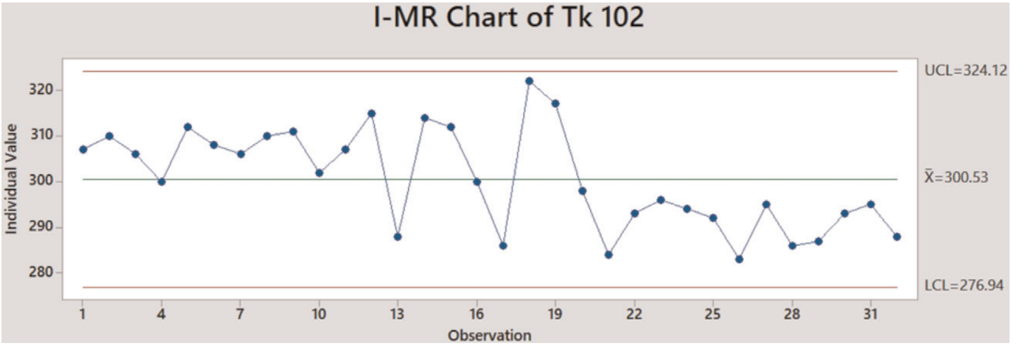

Figure 2.
I-MR control chart.

It's believed that by developing an integrated/unified SPC-EPC framework into the anonymous company Chlor-Alkali processing, it would drastically reduce the variation in the feed brine concentration and as a result would increase the cell membranes lifecycle.

6. Integrated SPC and EPC unified framework

The integration of SPC and EPC will be done in three phases which are the offline monitoring phase, the online measuring and detecting phase, and the integrated SPC and EPC phase. The offline monitoring phase focuses on analyzing the process flowchart, identifying key input variables, identifying critical to quality, collecting historical data and checking them for normality and autocorrelation. The online measuring and detecting phases focuses on generating control charts ensure all points are within the limits and there's no pattern present in the data. Also, the analysis of the current control system happens in this phase. The integrated SPC and EPC phase focuses on the implementation of the Concept of this research work.

Beginning with the offline monitoring phase and according to the process flowchart shown in **Figure 3**, the key process variables and the critical to quality will be identified. It can be seen that the he process starts by pumping in Sea Water which is then undergoes many multiple filtration steps to remove varies types of impurities that may be present due to sea pollution. The sea water will eventually be evaporated away until only purified salt will be left behind and it will be stored into super purified salt storage tanks. The salt will be mixed with purified water in the ferric treatment tank and it undergoes further filtration and re-saturation until we get super purified brine (pure salt dissolved in water). The purified brine then enters the Electrolysis Chamber shown in **Figure 4**, where the solution will breakdown into its elements to make hydrogen, chlorine and sodium hydroxide. These chemicals will then undergo further processing until they get their final product which is hydrochloric acid, sodium hypochlorite and sodium hydroxide. Finally, some of the feed brine will be recycled back into the treatment tank for re-saturation.

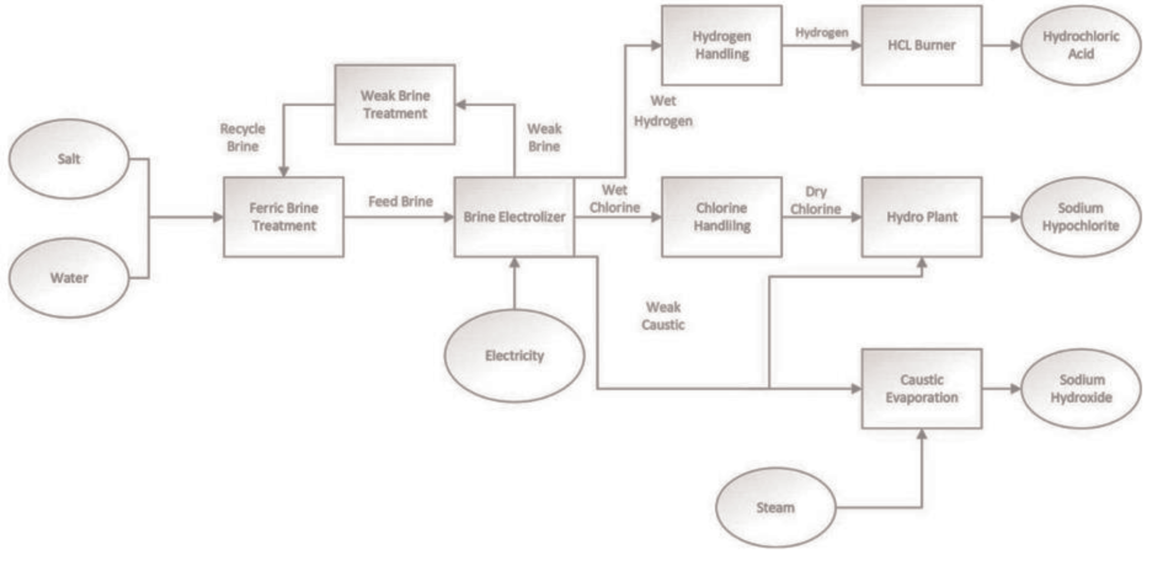

Figure 3.
Process flowchart.

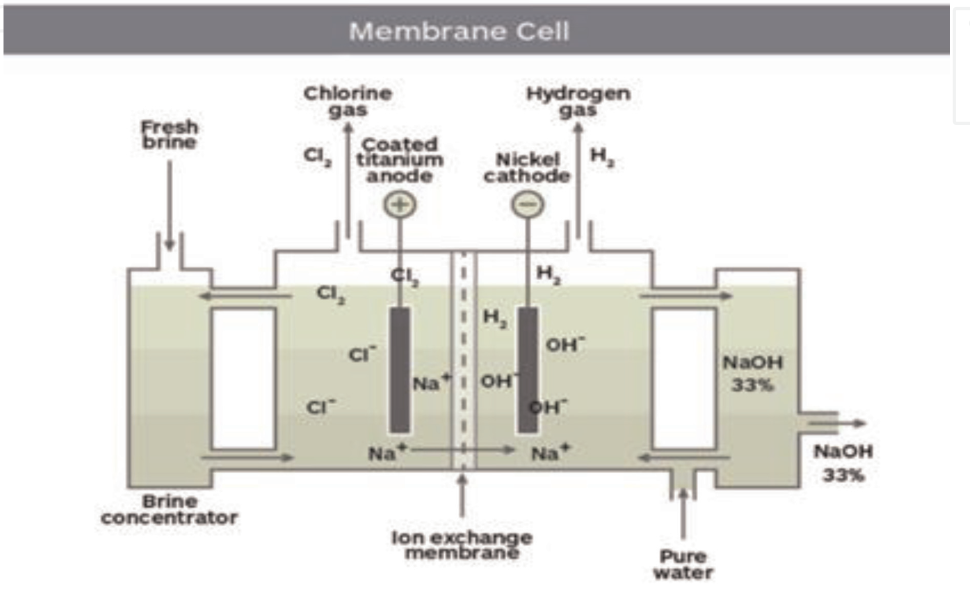

Figure 4.
Electrolysis chamber (electrolizer and cell membrane).

Varies things happens in the electrolysis chamber. First, when the feed brine enters the electrolizer, then the NaCl (salt) and the H_2O (water) will breakdown into their elements where chlorine ions will go to the positive electrode (anode) and sodium ions and hydroxide ions will go to the negative electrode (cathode) and hydrogen gas will also be formed. Both electrodes are separated by a cell membrane where it helps with ion exchange and also prevents any unwanted reaction to occur in the electrolizer.

Recall that the main purpose of the ferric treatment tank shown in **Figure 1** is to re-saturate the brine solution to the optimum concentration to make sure it does not affect the cell membrane located in the electrolizer. The treatment tank begins with the input tank Tk102 then brine goes through varies filtration steps until it reaches the refiner R101 where caustic soda and soda ash is added to the brine solution to remove impurities such as calcium and magnesium. The brine will then keep going through varies filtration stages in the treatment tank until it reaches the final tank which is Tk151 which is where the super purified feed brine is stored with a target concentration of 306 gpl. The feed brine will then exit the treatment tank and enter the electrolizer.

It has been found out that the cell membrane located in the electrolizer is very sensitive to the feed brine concentration and needs to be replaced every three to 4 years. The cell membrane has a current Lifecyle of 3–4 years, each cell membrane costs around $5000 and the company have 120 membranes with a total cost of nearly $600,000. Our objective is to increase the cell membranes life cycle to 6–8 years by reducing the variation in the feed brine concentration.

7. Framework demo

Our research Concept is proposing the use of the sensitive EWMA control chart in conjunction with the Integral Controller where we will have two arrays, one is the EWMA points and the other is the process observation. The Integral Controller will keep checking the EWMA points and once it exceeds the boundary limits then the integral controller would formulate an adjustment and send it to the process. **Figure 5** is a visual representation of the concept, where array 1 is the weighted averages and array 2 is the actual measured process values.

The boundary limit is an engineering decision that can be calculated based on equation (Eq. (4)). MATLAB have been used to develop a code that will continually

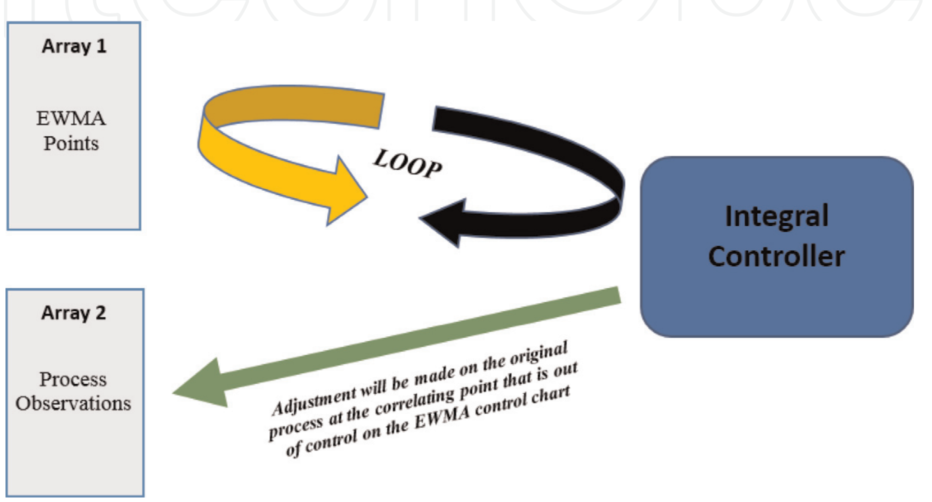

Figure 5.
Research concept.

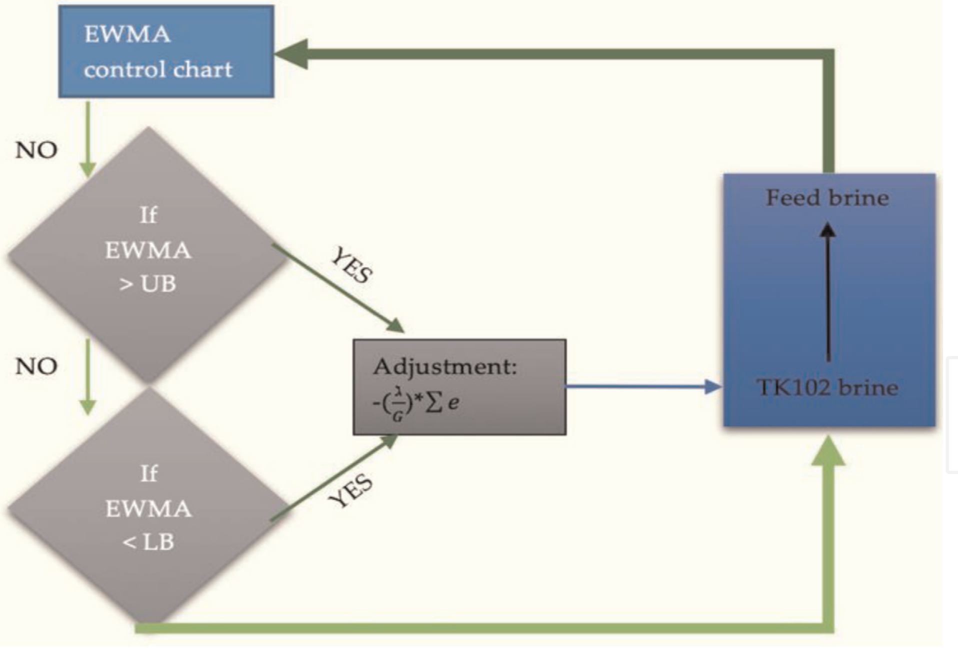

Figure 6.
Concept logic.

check the EWMA values in array 1 using MATLAB for-loops. When a point exceeds the upper or lower boundary, the Integral Controller will calculate the required adjustment (Eq. (5)) to keep the process on target and send the adjustment to the actual process as shown in the Concept logic, **Figure 6**.

A fitted regression model will be developed to understand the relationship and brine concentration levels in the output tank (Tk151) and input tank (Tk102). Also help to estimate the process gain (G) to be used in calculating the adjustment in the integral controller. The weight λ will be tested at different values ranging from 0.1 to 0.5 to find the best target with the minimum variation.

8. Results and findings

The upper boundary (UB) is equal to 311.78 gpl and the lower boundary (LB) is equal to 300.22 gpl. The weight value of λ was selected to be 0.3 which resulted in a process gain of 0.9795. A fitted regression model was developed as below:

$$\text{Tk151} = 6.31 + 0.9795\ \text{Tk102} \tag{7}$$

Figure 7 shows the fitted regression model plot between the brine concentration levels in the output tank (Tk151) and the input tank (Tk102).

The EWMA control chart will plot the feed brine concentration which is located in Tk151, and then the integral controller would continuously check whether or not the observation exceeds the upper or lower bound. In an event where the feed brine concentration exceeds the bounded limits, an adjustment will be formulated and sent to the input tank Tk102. **Figure 8** shows the EWMA control chart for the input tank Tk102 and **Figure 9** shows the EWMA control chart for the output tank Tk151 where bounded control limits are used. The control scheme will be using this control chart to formulate its adjustments. **Figure 9** shows 11 out of control points, each out of control point will trigger the integral controller to formulate the exact adjustment needed to bring the process back in control.

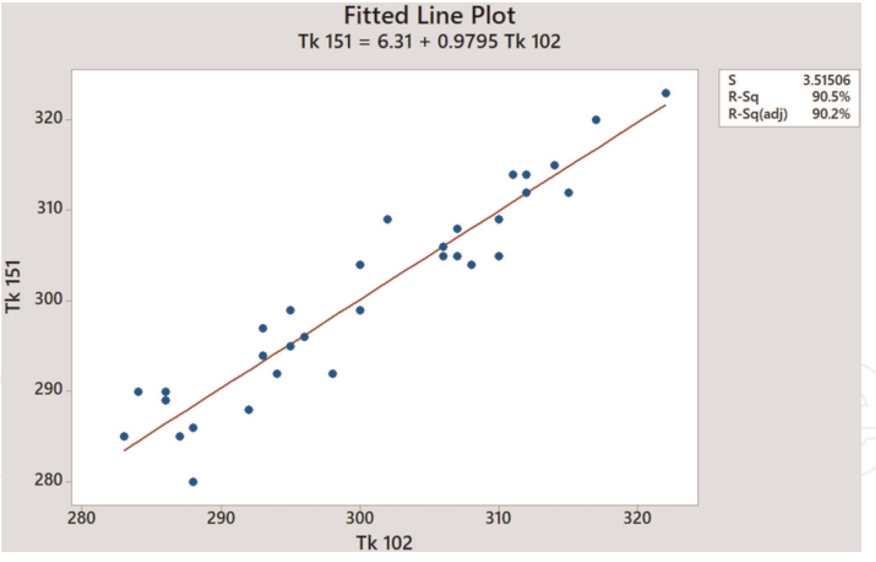

Figure 7.
Fitted line plot for Tk102 and Tk151.

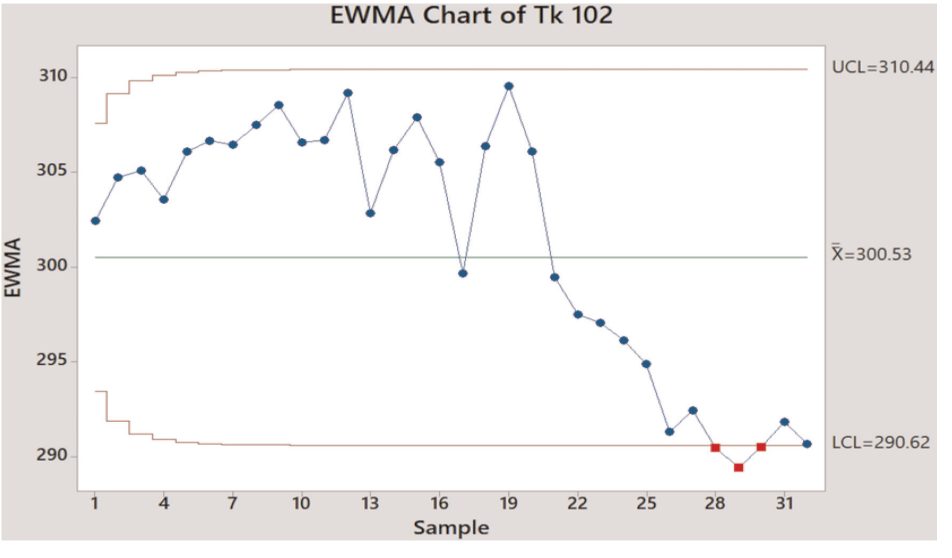

Figure 8.
EWMA chart for Tk102.

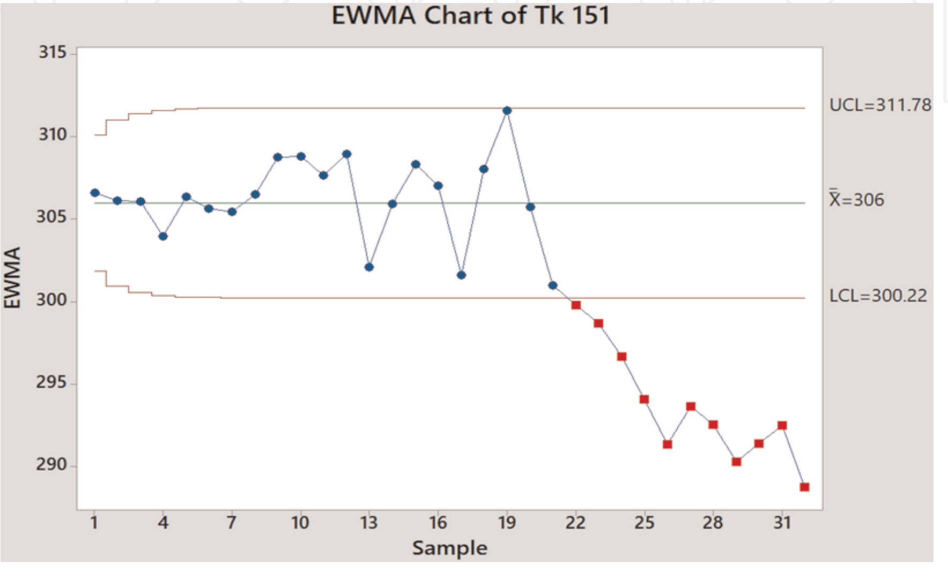

Figure 9.
EWMA chart for Tk151.

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	Tk 102	Adjusted Tk 102	EWMA	Adjustments	Setpoints
1	307	307.00	306.60	0	0
2	310	310.00	306.12	0	0
3	306	306.00	306.08	0	0
4	300	300.00	303.96	0	0
5	312	312.00	306.37	0	0
6	308	308.00	305.66	0	0
7	306	306.00	305.46	0	0
20	298	298.00	305.74	0	0
21	284	284.00	301.02	0	0
22	293	293.00	299.81	3.98	3.98

Table 1.
Process data before and after adjustment.

	Before adjustment	After adjustment				
		$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$
Target g/lit	300.30	302.12	303.02	304.10	304.07	303.98
Variance	119.16	95.91	90.97	80.07	82.84	86.13
St Dev	10.92	9.79	9.54	8.95	9.10	9.28

Table 2.
Optimum λ.

Table 1 shows the adjusted and unadjusted values for brine concentration in Tk102. The third column in is setpoints and it's the cumulative adjustments done to the process. The first adjustment was made at observation 22 which exceeds the lower boundary and the integral controller calculated the required adjustment of 3.98 to bring the process back on target and reduce the deviation of the output from the target. The control scheme will continue this way where the integral controller will continuously calculate the required adjustments to bring the process under control and keep it within the boundaries.

After integrating the EWMA control chart in conjunction with the integral controller in the ferric treatment tank, the framework implementation managed significantly to reduce the process variation by 32.8% and reduced the standard deviation by 18%. By reducing the process variation and standard deviation, the process becomes continuously under control and the cell membranes lifecycle increased successfully. As in **Table 2**, different λ weight values have been tested in order to find the optimum that gives the least variation for after adjustment.

The high sensitivity of the EWMA control chart can be seen when compared to the I-MR control chart. It can be seen how the EWMA control chart was able to detect out of control points that I-MR control chart missed. **Figure 2** is showing that all points are under control however, the same points are out of control when plotted on the EWMA control chart as seen in **Figure 8**.

9. Conclusion

Many schemes of SPC and EPC integration had been proposed in literature with a view to complement each other's insufficiency [7, 12, 18–21]. While intensive work has been focused on developing various efficient and robust EPC controllers, some emphasized the crucial task of monitoring auto correlated processes and EPC systems. In this research work the objective was to create a concept in which we used the EWMA control chart in conjunction with the integral controller to keep the feed brine concentration on target in order to increase the cell membranes life cycle.

SPC and EPC integration approach was done in three phases; offline monitoring phase, online measuring and detecting phase and finally the integrated SPC-EPC phase. The first phase was about analyzing the process, identifying the critical to quality characteristic, identifying the key input variables and understating the process flow chart. The second phase involves analyzing the current control system. The third and final phase is where we introduce the concept which is the EWMA control chart in conjunction with the integral controller.

According to the proposed scheme and results and with the cooperation of the anonymous company, by keeping the feed brine concentration on target the Chlor-Alkali process variation is reduced, the cell membrane lifecycle is expected to be doubled, and monthly cost is minimized by 50%. The implementations of our effective concept drastically improved the product quality and reduce cost. The concept is versatile and applicable to different industries.

SPC and EPC unified framework has been proven to be very effective at reducing process variation and improving the product quality.

EWMA control charts are very effective and sensitive in detecting small processes means shifts and ability to forecast the next processes error which is essential in control engineering.

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