

# Integration of Statistical and Engineering Process Control for Quality Improvement

(A Case Study: Chemical Industry - National Chlorine Industries)

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## Abstract

The quality of product in industrial process can be improved by on-line monitoring, regulating and correcting actions. There are two approaches addressing this problem: (1) Statistical Process Control (SPC), which focuses on identifying assignable causes that can be removed, leads to permanent process improvement or reduction in variability; and (2) Engineering Process Control (EPC), based on adjusting the process variables to get less deviation from target (often called feedback adjustment). Feedback adjustment regulates the process to account for sources of variability that cannot be removed by the SPC approach.

Integrating SPC/EPC is a very effective way in quality control, since features from both SPC and EPC could give a complementary performance. This work introduces a framework that integrates SPC and EPC in one methodology; SPC control limits for critical key variables are developed depending on information from the historical reference of past successful processes. While the EPC algorithm is derived of a progressive set of knowledge-based rules. The approach is applied to data collected from chlorine industry, as a case study. This is poorly automated, subject to several disturbances, monitored by measuring the feed brine solution concentration and the acidity index of samples from the ferric brine treatment tank. The experimental results proved that, when the production process is affected by certain disruptions, the process engineers have a decision making tool, by on-line monitoring and regulating the process key variables. Furthermore, by implementing proper adjustment strategies, the stability of the process can be better maintained, and significant economic benefits will be achieved.

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## 1. Introduction

Product quality is becoming the most critical objective in various industries. So, innovative monitoring and control techniques of the process operations are strongly needed in the process control field. Generally, batch processes exhibit some batch-to-batch variation arising from such things as deviations of the process variables from their specified trajectories, errors in the charging of the recipe of materials, and disturbances arising from variations in impurities. These abnormal conditions can lead to the production of at least one batch or a whole sequence of batches with poor-quality product if the problem is not detected and remedied. Most industrial batch processes are run without any effective form of real-time, on-line monitoring to ensure that the batch is

progressing in a manner that will lead to a high-quality product or to detect and indicate faults that can be corrected prior to the completion of the batch or can be corrected in subsequent batches.

Statistical Process Control (SPC) and Engineering Process Control (EPC) are two techniques that are used for improving process productivity and product quality by reducing the variability of process from target while keeping it stable and under control. SPC, a widely used technique, is an effective monitoring technique as far as the process variables can be stated by independently observed statistical variables whose values fall in the vicinity of deterministic values. On the contrary, EPC is a continuous procedure that adjusts the process manipulatable variable in order to keep the output on set point or target [14].

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Most of the literature on integrated SPC and EPC systems is focused on continuous process mainly with Algorithmic SPC. The integrated SPC/EPC systems in batch process control have not received the same degree of attention. There are numerous related studies in production process control, the first attempts to integrate EPC and SPC appeared long time ago, with the work of Barnard [7] in 1959. Using the machine-tool case study, the author demonstrated that automatic control and statistical control can be used in parallel. Box and Kramer [4] proposed the idea of using feedback control to compensate disturbances estimated by statistical forecasting, while SPC was deployed to monitor the process output after the adjustment in order to detect an assignable cause which cannot be compensated by the controller. Montgomery *et al.* [15] supported the claim that SPC can detect an assignable cause from the output rapidly, while EPC can effectively keep a process on target. Hoerl and Snee [8] proposed the term statistical engineering, defined as the study of how to best use statistical concepts, methods and tools, and integrated them with information technology and other relevant sciences to generate improved results. Box and Luceno [5] suggested using EPC activities as process adjustment and to SPC activities as process monitoring. While the two approaches have been applied independently in different areas for decades, the relationship between them has not yet been clearly explored. Nembhard and Mastrangelo [17] stated that a shift in this process can occur as the result of assignable causes (e.g., machine shutdown, or changes in raw materials, equipment or products) and during the transient state (production startup), which results in abundant loss in the process. The transient phase is induced by the dynamic behavior of the process, which causes the output to lag behind input before reaching a steady state. The dynamic behavior of processes can be modeled by deploying continuous state space equations (control theory). The integration between SPC and APC provides the opportunity to perform an adjustment, which can significantly decrease the transient-period as well as the variation of processes. Vander Wiel *et al.* [25] proposed the Algorithmic Statistical Process Control (ASPC) as a method of reducing predictable variation; ASPC employs both feedback and feed forward control, and then monitors the system to detect and remove the assignable causes of disturbances. Hunter [9] and Montgomery and Mastrangelo [17] reported that the Exponentially Weighted Moving Average (EWMA) approach is equivalent to the Proportional-Integral-Differential (PID) control technique. However, MacGregor [12] contended that the EWMA approach and PID control differ substantially. Tucker [24] also argued that control rules will compensate for assignable variation if assignable cause variation could be predictable; when assignable cause variation is unpredictable, a search for assignable causes must be made. Alwan and Roberts [1] and Montgomery and Mastrangelo [17] have all recommended that whenever observations are autocorrelated, an appropriate time series model should be fitted to these observations and control charts then applied to the residuals of the model. Montgomery *et al.* [15] examined the benefits of combining SPC and EPC techniques. Their simulations demonstrated the superiority of integrated use of SPC and

EPC to the use of EPC alone. But while their simulations employed the Shewhart, CUSUM and EWMA control charts. From this short review of literature, we conclude that none of the studies was found to be dynamic on-line model to integrate SPC/EPC in chlorine process industry for quality improvements.

This paper considers three research areas: batch processes monitoring and control, integration of SPC and EPC, and case study: Chlorine production industry (Chemical Industry- National Chlorine Industries). The objectives of this study are: (a) to detail a literature review of SPC/EPC integration, (b) to establish an integrated SPC/EPC methodology for a batch process, and (c) to investigate the proposed approach with an application of the analysis and monitoring of an industrial batch Chlorine production. The remainder of the article is organized as follows. Sections 2-4 illustrate the theoretical background and derivation of the basic relations from literature for integrated SPC/EPC systems. Following this, Section 5 and 6 describe the proposed integrated SPC/EPC approach control scheme and the results of adopting it in Chlorine production. Finally, Section 7 presents the concluding remarks and future work.

## 2. Statistical Process Control (SPC)

The SPC is a binary view of the state of a process, i.e., whether it is running satisfactorily or not. As developed by Shewhart [21], the two states are classified as having a common cause of variations, from the management point of view, this kind is inherent in the process and difficult to eliminate or assign special cause of variations, should be identified and removed at the root.

Basics: Let  $x$  be a sample statistic that measures some quality characteristic of interest, and suppose that the mean of  $x$  is  $\mu_x$  and the standard deviation of  $x$  is  $\sigma_x$ . Then the center line and control limits become:

$$\begin{aligned} UCL &= \mu_x + L\sigma_x \\ CL &= \mu_x \\ LCL &= \mu_x - L\sigma_x \end{aligned} \quad (1)$$

where  $L$  is the "distance" of the control limits from the center line, expressed in standard deviation unit, (a common choice is  $L=3$ ). Dr. Walter A. Shewhart first proposed this general theory of control charts.

### 2.1. Control Charts for Individual Measurements

The control chart for individuals uses the moving range of successive observations to estimate the process variability. The moving range at time  $t$  is defined as  $MR_t = |X_t - X_{t-1}|$ . Letting  $\overline{MR}$  be the average of the moving ranges, an estimate of  $\sigma$  is

$$\hat{\sigma} = \frac{\overline{MR}}{d_2} = \frac{\overline{MR}}{1.128} \quad (2)$$

$d_2$  is constant that depends on the size of the sample, values of  $d_2$  for sample sizes ( $2 \leq n \leq 25$ ) are given in (Montgomery,2013), noting that( $d_2 = 1.128$ ) when two consecutive observations are used to calculate a moving range ( $n =2$ ). Then the control chart for individual measurements is:

$$\begin{aligned}
 UCL &= \mu_x + 3 \frac{\overline{MR}}{d_2} \\
 CL &= \mu_x \\
 LCL &= \mu_x - 3 \frac{\overline{MR}}{d_2}
 \end{aligned}
 \tag{3}$$

2.2. The Cumulative Sum Control Chart (CUSUM)

CUSUM chart was developed by Page (1954). This technique plots the cumulative sums of deviations of the sample values of a quality characteristic from a target value against time. The tabular CUSUM works by accumulating derivations from  $\mu_o$  that are above target with one statistic  $C^+$  and accumulating derivations from  $\mu_o$  that are below target with another statistic  $C^-$ . The statistics  $C^+$  and  $C^-$  are called one-sided upper and lower CUSUM, respectively. They are computed as follows:

$$C_t^+ = \max \left[ 0, x_t - (\mu_o + K) + C_{t-1}^+ \right] \tag{4}$$

$$C_t^- = \max \left[ 0, (\mu_o - K) - x_t + C_{t-1}^- \right] \tag{5}$$

And the starting values are  $C_0^+ = C_0^- = 0$ .

In equations (4) and (5),  $K$  is called the reference value and it is often chosen about halfway between the target  $\mu_o$  and the out of control value of the mean  $\mu_I$  that we are interested in detecting quickly, using ( $K=0.5$ ) usually provide a good results. Note that  $C_t^+$  and  $C_t^-$  accumulate deviations from the target value  $\mu_o$  that are greater than  $K$ , with both quantities reset to zero on becoming negative. If either  $C_t^+$  or  $C_t^-$  exceeds the decision interval  $H$ , the process is considered to be out of control, a reasonable value for  $H$  is five times the process standard deviation  $\sigma$  and (Montgomery, 2013) [16].

2.3. The Exponentially Weighted Moving Average Control Chart (EWMA)

The EWMA control chart was introduced by Roberts [20, 3]. The performance of the EWMA control chart is approximately equivalent to that of the CUSUM control chart, and in some ways it is easier to set up and operate. As with the CUSUM, the EWMA is typically used with individual observations, EWMA technique has been widely used in order to monitor the process mean, since it weighs the average of all past and present observations. In the EWMA, the predicted value of process mean at  $z_t$  time  $t$ , is defined as

$$z_t = \lambda x_t + (1 - \lambda) z_{t-1} \tag{6}$$

where ( $0 < \lambda \leq 1$ ) is a constant factor, and  $x_t$  is the observed value of process mean at time  $t$ , the starting value required with the first sample at ( $t = 1$ ) is the process target, so that ( $z_o = \mu_o$ ).

The EWMA control chart would be constructed by plotting  $z_t$  versus the sample number or time ( $t$ ). The center line and control limits for the EWMA control chart are as follows:

$$UCL = \mu_o + L\sigma \sqrt{\frac{\lambda}{(2-\lambda)} \left[ 1 - (1-\lambda)^{2t} \right]} \tag{7}$$

$$CL = \mu_o$$

$$LCL = \mu_o - L\sigma \sqrt{\frac{\lambda}{(2-\lambda)} \left[ 1 - (1-\lambda)^{2t} \right]} \tag{8}$$

In equations (7) and (8) above, the factor  $L$  is the width of the control limits.

3. Engineering Process Control (EPC)

Engineering Process Control (EPC) is a popular strategy for process optimization and improvement. It describes the manufacturing process as an input-output system where the input variables (recipes) can be manipulated (or adjusted) to counteract the uncontrollable disturbances to maintain the process target. The output of the process can be measurements of the final product or critical in-process variables that need to be controlled.

3.1. Process Control by Feedback Adjustment: Integral Control

Let the process output characteristic of interest at time period  $t$  is  $y_t$ , and we wish to keep  $y_t$  as close as possible to a target  $T$ . This process has a manipulatable variable  $x$ , and a change in  $x$  will produce all of its effect on  $y$  within one period, that is,

$$y_t - T = g x_t \tag{9}$$

where  $g$  is a constant called the process gain that relates the magnitude of a change in  $x_t$  to a change in  $y_t$ . Now, if no adjustment is made, the process drifts away from the target according to a disturbance  $N_{t+1}$

$$y_{t+1} - T = N_{t+1} \tag{10}$$

Suppose that the disturbance can be predicted adequately using EWMA which is shown in Section 2.3.

$$\hat{N}_{t+1} = \hat{N}_t + \lambda \left( N_t - \hat{N}_t \right) = \hat{N}_t + \lambda e_t \tag{11}$$

where  $e_t = (N_t - \hat{N}_t)$  is the prediction error at time period  $t$  and ( $0 < \lambda \leq 1$ ) is the weighting factor for the EWMA. Therefore, the adjustment to be made to the manipulatable variable at time period  $t$

$$x_t - x_{t-1} = -\frac{\lambda}{g} (y_t - T) = -\frac{\lambda}{g} e_t \tag{12}$$

The actual **set point** for the manipulatable variable at the end of period  $t$  is simply the sum of all the adjustments through time  $t$ , or

$$x_t = \sum_{j=1}^t (x_j - x_{j-1}) = -\frac{\lambda}{g} \sum_{j=1}^t e_j \tag{13}$$

This type of process adjustment scheme is called **integral control (I)**. It is a pure feedback control scheme that sets the level of the manipulatable variable equal to a weighted sum of all current and previous process deviations from target.

### 3.2. The Adjustment Chart

The feedback adjustment scheme based on integral control (Section 3.1) can be implemented so that the adjustments are made automatically. This involves some combination of sensors or measuring devices, a logic device or computer, and actuators to make the adjustments of the variable  $x$ . When EPC adjustment is implemented in this manner, it is often called Automatic Process Control (APC).

In many processes, feedback adjustments can be made manually by observing the current output deviation from target, compute the amount of adjustment to apply using equation (12), and then bring  $X_t$  to its new set point. When adjustments are made manually, a variation called the manual adjustment chart is very useful.

### 3.3. Bounded Adjustment Chart

The adjustment procedures in Sections (3.1) and (3.2) are very straightforward to implement, but they require an adjustment to be made to the process after each observation. In feedback adjustment applications, in chemical and process industries, this is not a serious issue because the major cost is the cost of being off target, and the adjustments themselves are made with either no or very little cost. Indeed, they are often made automatically.

There are several ways to do this. One of these ways is the bounded adjustment chart, a variation of the procedure (Section 3.2) in which an adjustment will be made only in periods for which the EWMA forecast is outside one of the bounds given by  $(\pm L)$ . The boundary value  $L$  is usually determined from engineering judgment, taking the costs of being off target and the cost of making the adjustment into account. Montgomery [16] proposed the following relation to estimate  $\hat{\sigma}_{EWMA}$ .

$$\hat{\sigma}_{EWMA} = \sqrt{\frac{\lambda}{2-\lambda}} \hat{\sigma}_{unadjusted\_process} \quad (14)$$

Note that, if the standard deviation of the unadjusted process is known, so the standard deviation of EWMA is approximately. Noting that we often use control limits on a EWMA that are slightly less than three-sigma.

## 4. Integration of SPC/EPC Methods

SPC and EPC are two complementary strategies developed for quality improvement. There is a corresponding relationship between them through prediction. EWMA predictor, which corresponds to the integral (I) control, is one of the most frequently used

prediction methods in business and industry, mainly because of its simplicity and efficiency. Wei Jiang and John V. Farr [27] proposed four categories of ongoing research and application of the two quality-control approaches as shown in Figure 1:

- If a process is not correlated, there is no need to employ EPC schemes. Traditional SPC control charts should be used for identifying assignable cause variations.
- When data are correlated, the possibility of employing EPC scheme should be examined. SPC control charts are invoked to monitor auto correlated processes if no feasible EPC controller exists.
- If appropriate controller is available, EPC control scheme can be employed to compensate the auto correlated disturbance. However, no single EPC controller can compensate all kinds of variations.
- To identify and understand the cause of process changes, a unified control framework should be applied to regulate a process using feedback control, while using the diagnostic capability of SPC to detect sudden shift disturbances to the process.

The integration of SPC/EPC looks for the best opportunities of quality improvement by integrating/combining the strengths of SPC and EPC in various levels of control that may be incorporated into a manufacturing system. According to literature review there are four types of integration, conventional SPC, algorithmic SPC, Active SPC, and Run-to-Run.

## 5. The Proposed SPC/EPC Integration Approach

Based on the theoretical development of SPC/EPC integration approaches, we construct an integrated approach guideline so as to fill up the gap and implement SPC/EPC integration into practice. The theoretical and practical concerns that we have discovered will be incorporated in this guideline. As shown in Figure 2 the proposed SPC/EPC integration approach is conducted in three phases; off-line monitoring, on-line measuring and detecting, and integrating SPC/EPC phase.

## 6. Case Study

A real case from a chlorine industry has been studied. In this section, we will discuss the application of the proposed approach to data collected from this process. This industrial process is poorly automated, subject to several disturbances. We used the method of feedback integral adjustment to show how this technique can be easily implemented in process where there is a manipulatable variable that affects the process output.

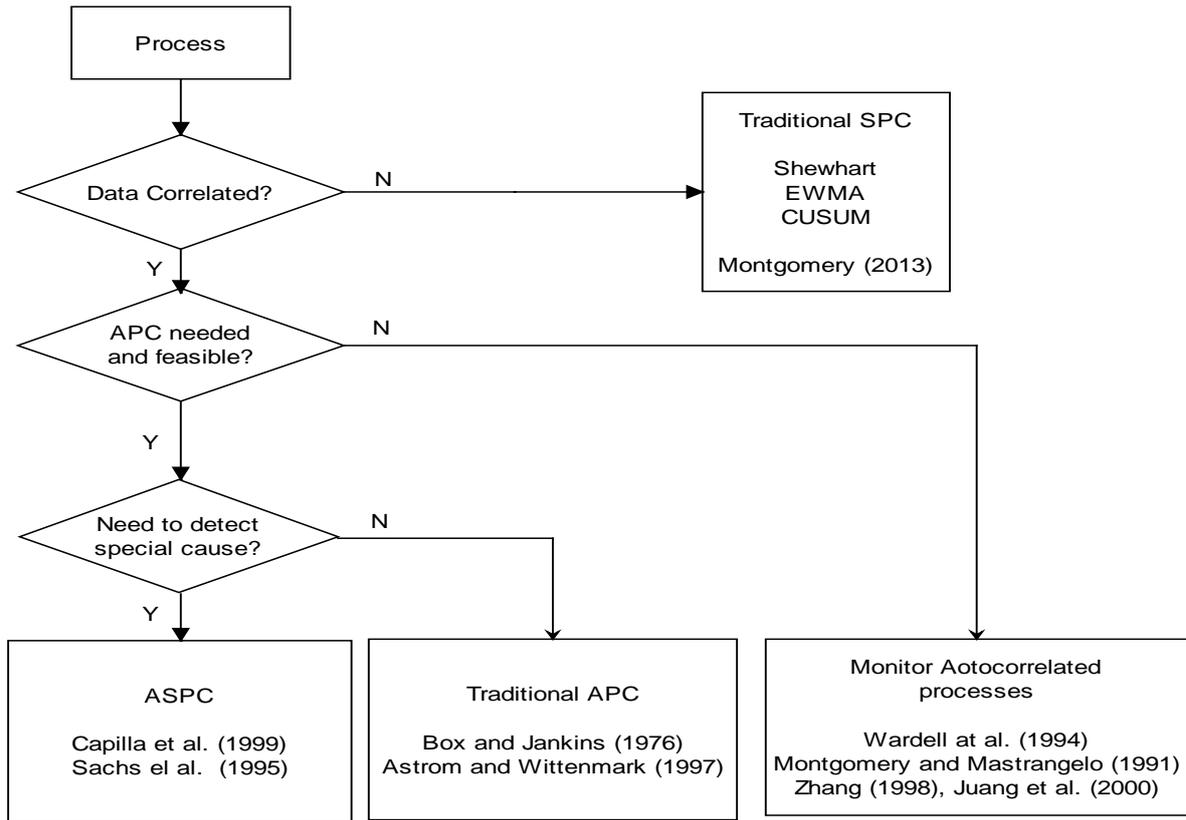


Figure 1. Control scheme select of SPC and APC methods

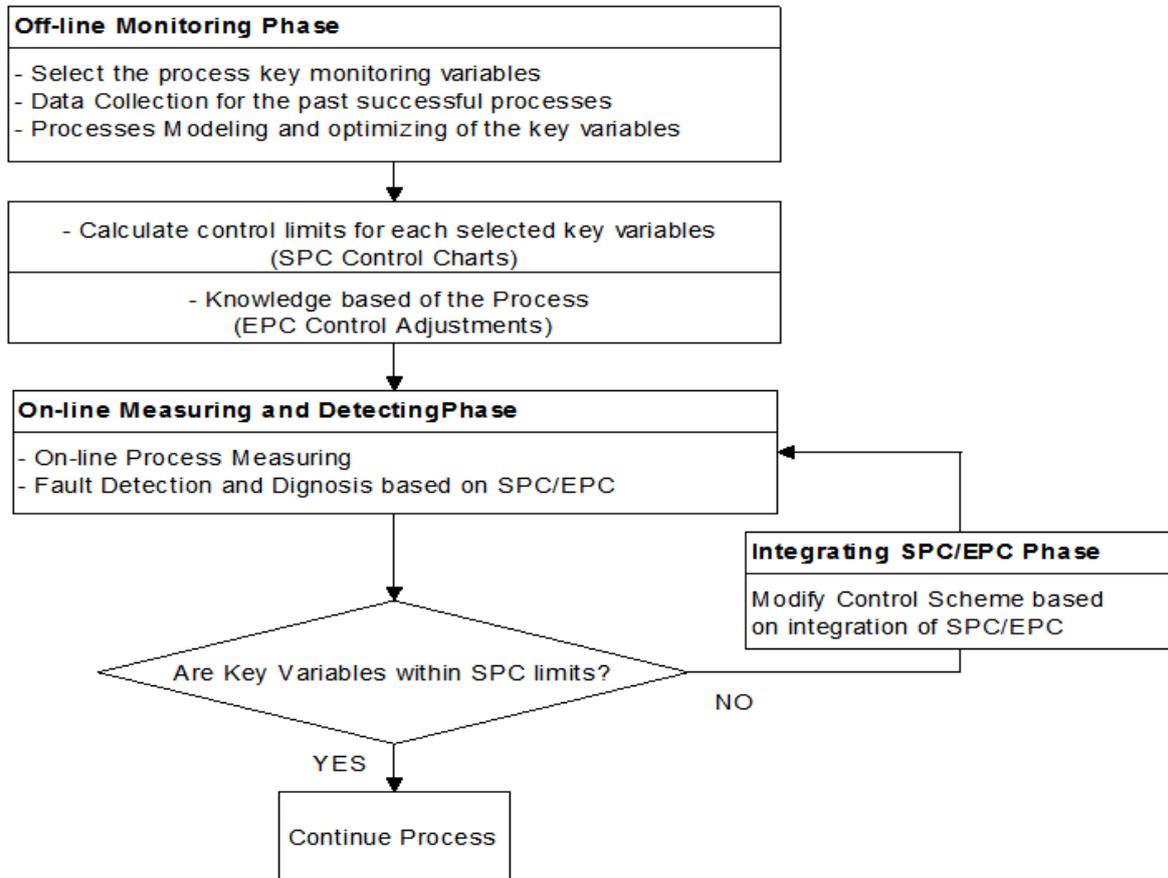


Figure 2. The Guiding flowchart for the proposed SPC/EPC integration approach

**Case Briefing**

The case for practical study is a process from a chlorine factory, as depicted in Figure 3. Chlorine is produced by passing an electric current through a solution of brine (salt dissolved in water). This process is called electrolysis. There are three main technologies of producing chlorine: (1) the membrane cell process, nowadays most widely used in Europe, (2) the mercury cell process, being phased out worldwide because of the toxic character of mercury, and (3) the diaphragm cell process. Our study was conducted in a factory using membrane process to produce chlorine products, so that we will focus only on this process.

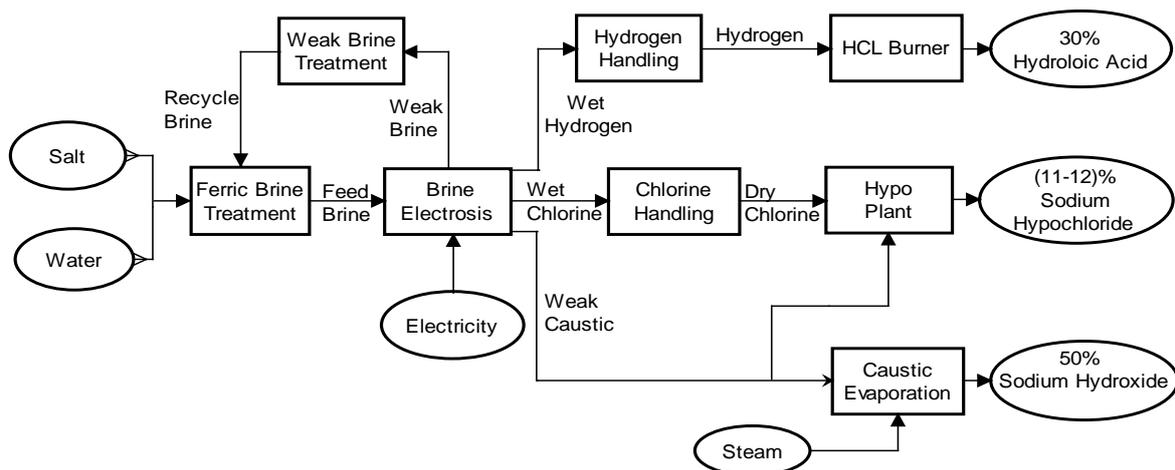
The two electric connection points of each chlorine production cell, the anode and the cathode, are separated by an ion-exchange membrane. Only sodium ions and a little water pass through the membrane. The brine is dechlorinated and re-circulated. Solid salt is usually needed to re-saturate the brine. After purification by precipitation-filtration, the brine is further purified with an ion-exchanger. The caustic solution leaves the cell with about 30% concentration and, at a later stage in the process, is usually concentrated to 50%.

**6.1. Off-line Monitoring Phase**

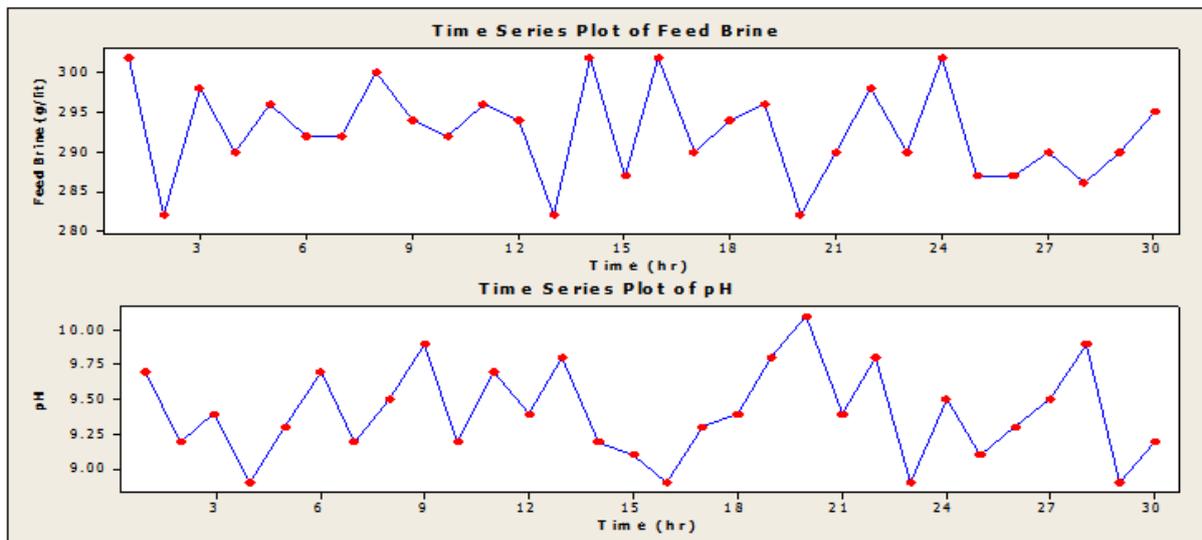
The first step in the real case study is process analysis, which is called off-line monitoring. The purpose of the process analysis is: (1) to understand the entire process, including the critical relations between the quality requirements and the performance metrics of both input and output conditions, and (2) the selection of key variables that could reduce inefficiencies in the process.

**Select the Process Critical Monitoring Variables**

For demonstration, we selected only one production line from the process. In this production line, sodium hypochlorite ( $NaOCl$ ) is the output that required to achieve a certain target specification value of about (11-12) %. Based on consultations, we define critical-to-quality input key variables, in the selected production line. The key variables, at different process time, were used to determine the advance and the final product quality. These variables are feed brine solution concentration ( $NaCl$ ) and acidity index ( $pH$ ) in ferric brine treatment tank as shown in Figure 3. Variable monitoring is done each one hour sampling times. Figure 4 shows the fluctuation of selected key variables with time.



**Figure 3.** Factory Process Activity Flowchart



**Figure 4.** Feed Brine concentration and Acidity Index fluctuations with time

Quality measurements are only available off-line; the operating procedure for a process progress through a nominal recipe, which is subject to several online adjustments made by the factory personnel depending on the actual progression of the process, as it is monitored by the quality measurements.

#### Data Collection of the Past Successful Processes

Based on the analysis of historical database using Minitab program and interviews with technical experts of the factory, four inputs key variables were selected as critical to monitor the process and one final output. The variables selection is based on historical production reports. These variables are: the value of *NaCl* measured at times 800, 1600 and 2200 hours during production day denoted by *NaCl 800*, *NaCl 1600* and *NaCl 2200*, respectively, and the value of *pH* measured at time 00 which denoted by *pH 00*. Each one of these critical variables is selected from past thirty successful processes. These key variables and final product output of *NaOCl* Sodium were presented in Table 1.

#### Processes Modelling and optimizing

In this phase, the selected key variables are modelled in order to apply SPC tools, the standard assumptions that are usually cited in justifying the use of control charts are that the data generated by the process when in control are normal (i.e., the data have a normal probability density function) and independent of observations (i.e., value is not influenced by its past value and will not affect future values) distributed with mean  $\mu$  and standard deviation  $\sigma$ .

The test of normality and the test of independence of each selected key variable are applied as shown in Figure 5; this figure approved standard assumptions, that the data generated by the process are in control, are normally distributed and independent. In order to predict *NaOCl* for a new process, we used Minitab to model the output of *NaOCl* as a linear regression with the four selected input key variables. The use of Minitab confirmed the following equation with a regression square (R-Sq) coefficient equal to 84%.

$$NaOCl = 28.2 - 0.0192NaCl800 - 0.0281NaCl1600 + 0.00034NaCl2200 - 0.325pH00 \quad (15)$$

**Table 1.** Measurements of key critical variables for thirty successful processes

Exp.	NaCl 800 (g/lit)	NaCl 1600 (g/lit)	NaCl 2200 (g/lit)	pH 00	NaOCl
1	275	295	293	9.3	11.66
2	304	287	285	8.7	11.63
3	300	294	306	9.4	11.15
4	292	294	298	9.2	11.19
5	300	287	296	9.2	11.41
6	295	297	300	9.8	11.0
7	287	291	300	9.3	11.56
8	293	296	306	9.4	11.27
9	295	296	293	9.2	11.15
10	291	291	300	9.5	11.41
11	295	287	298	9.4	11.51
12	313	291	302	9.4	11.0
13	300	292	295	8.9	11.41
14	294	294	289	9.2	11.29
15	315	289	297	9.6	11.0
16	287	288	278	9.9	11.41
17	283	288	290	9.3	11.78
18	279	295	290	9.2	11.72
19	306	297	302	9	11.09
20	312	297	304	9.7	11.29
21	284	290	290	8.8	11.92
22	298	297	295	9.4	11.09
23	286	297	298	9.3	11.48
24	276	298	302	8.7	11.75
25	297	303	301	9.4	11.05
26	289	292	305	9.3	11.48
27	285	291	296	8.7	11.85
28	314	290	290	9.4	11.05
29	295	299	300	9.2	11.09
30	279	286	293	9	12

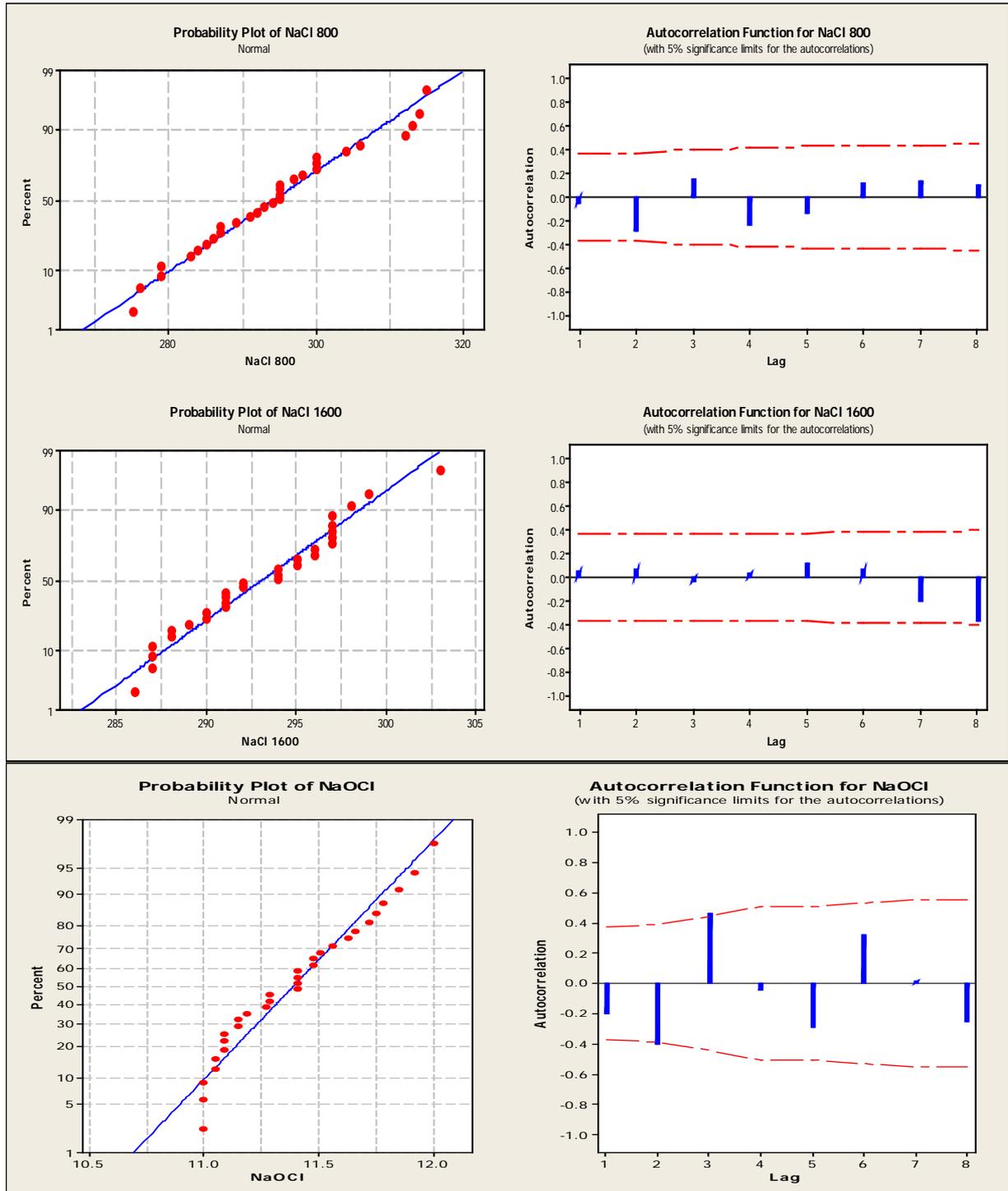


Figure 5. Normal Probability and Autocorrelation (independent) tests for key variables

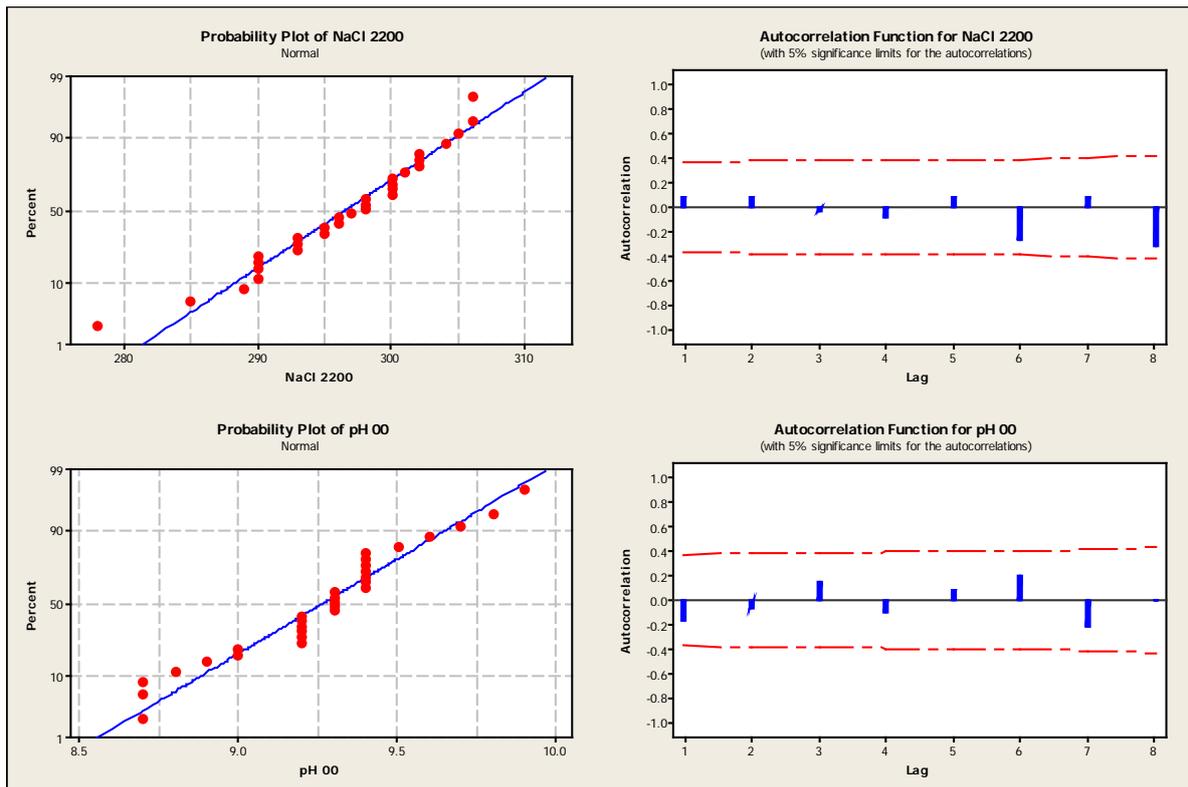


Figure 5. (continue) Normal Probability and Autocorrelation (independent) tests for key var

### 6.2. On-line Measuring and Detecting Phase

The key to a successful operation is efficient on-line process monitoring, which enables the early warning of process disturbances, process malfunctions or faults. Where early detection of such problems is followed by the location of their source, the efficiency and consistency of production can be significantly improved. Schemes for process monitoring, fault detection and diagnosis can then be used as intelligent supervisory process systems, which can support process operators and engineers in dealing with process deviations and identifying the root cause of these deviations. These schemes are based upon process models built from factory data.

#### On-line Process Measuring

After verifying the test of normality and the test of independence, the control charts of each selected variable are applied as shown in Figure 6. To monitor the new process, it is necessary to measure the four selected key variables and place the point in the corresponding control chart in Figure 6. These values are also used to predict the *NaOCl* as indicated in equation (15).

#### Fault Detection and Diagnosis Based on SPC and EPC

For reasons of simplicity, only a few regulations of EPC were presented in the flow chart of Figure 7. For each control chart of Figure 6, two cases arise, exceeding the upper or lower Control Limits. The production control procedure of a new process should be done in accordance

with the flow chart shown in Figure 7; the process should proceed normally if there is no assignable cause alert; otherwise corrective control action should be taken to remove the assignable cause. Moreover, the production manager can predict the final quality output of *NaOCl* by using equation (15).

### 6.3. Integrated SPC/EPC Phase

This phase will provide the factory process engineer a good toll to regulate or adjust the added salt as instructed by flow chart of Figure 7 in order to maintain feed brine with SPC limits.

Noting that factory process engineers explained for us the fact that maintaining the feed brine concentration in the main tank as close as possible to the target specification values of (295 g/lit) will improve the final products quality and extend membrane cells life, so that we will focus in this phase to comply with this fact by applying an integral control approach.

In order to apply the integral control approach, we will need a process model, with the note that, for purposes of simplicity, we will apply this approach in ferric brine treatment tank only. The process model is based on flow chart of Figure 3, including the input variables: the recycle brine, water, actual brine concentration in tank, and the amount of the salt added to main tank. The output variable is the feed brine concentration.

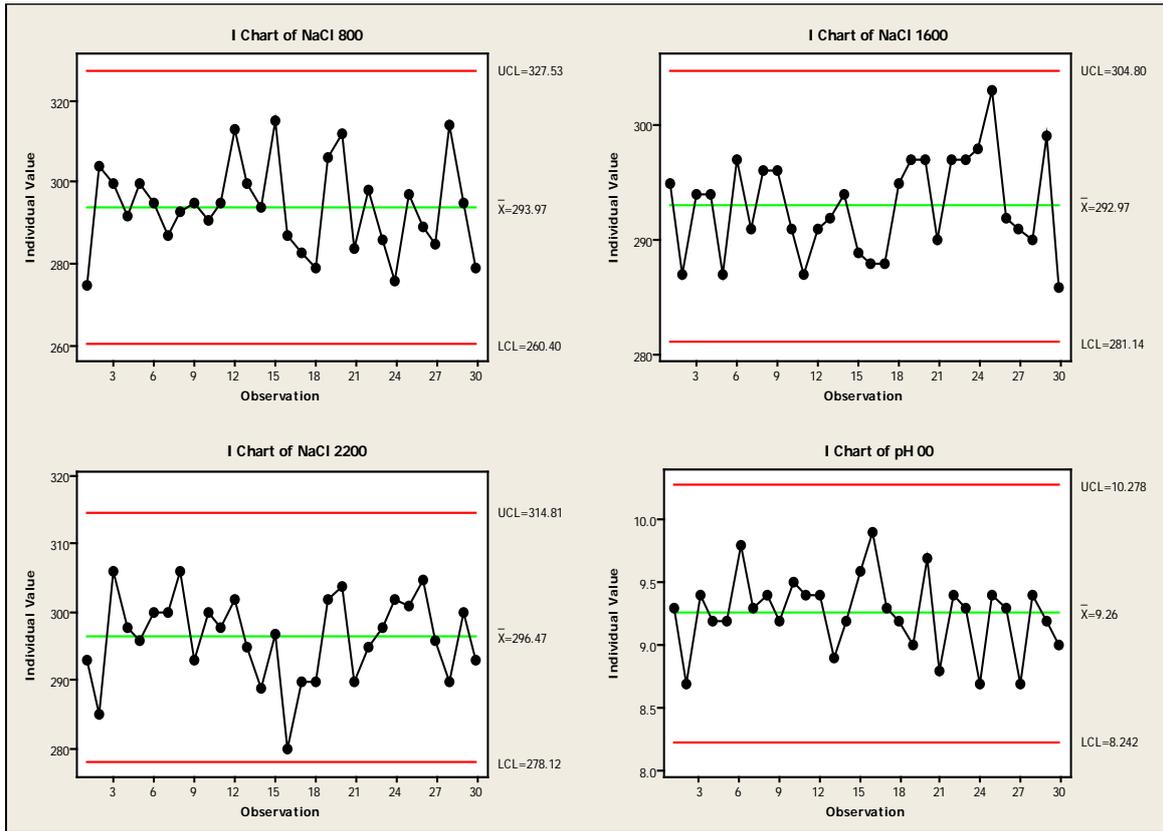


Figure 6. Individual Control Charts for Key Variables

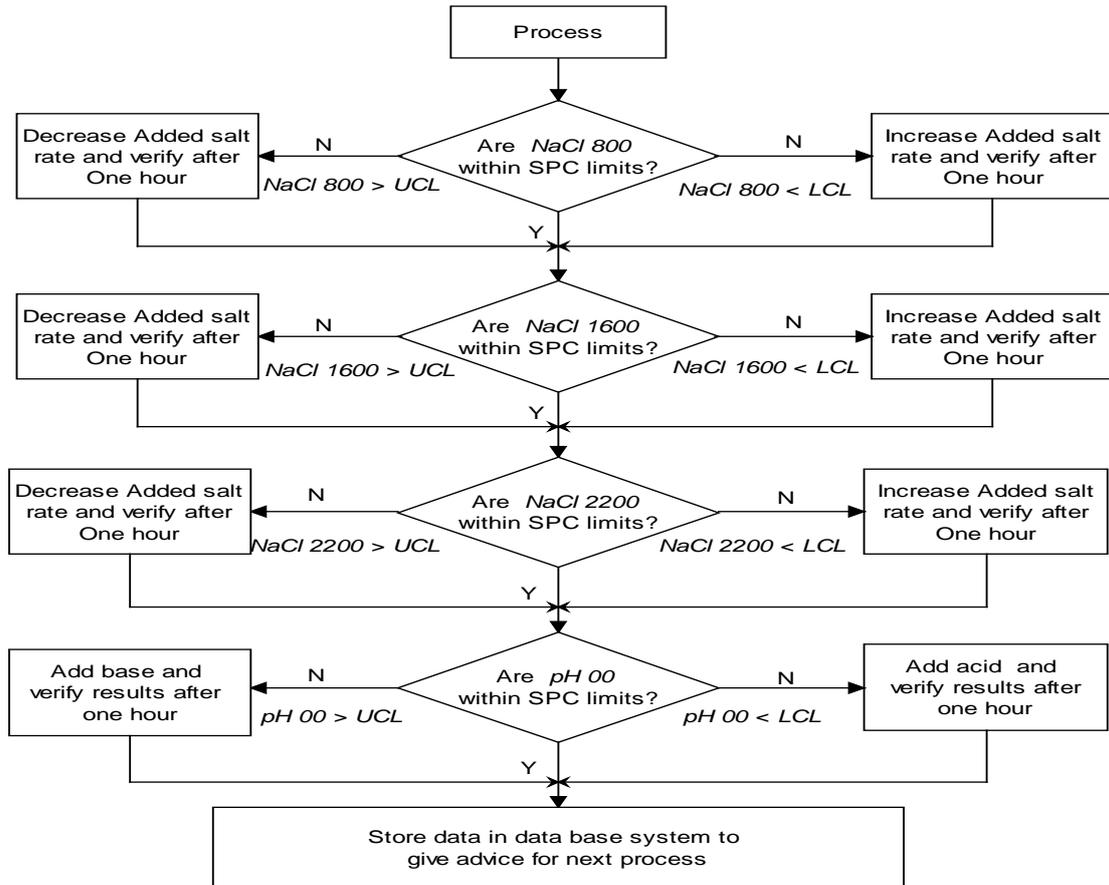


Figure 7. Flow chart for EPC regulations according to SPC charts

We tried to find theoretical equation to compute the value of brine solution concentration in main tank which denoted by  $NaCl_{comp}$  (i.e., considering the recycle brine denoted by  $NaCl_{recy}$  added now denoted by  $NaCl_{added}$  and the actual brine concentration value now in main tank denoted by  $NaCl_{sol}$ ). Equation 16 below is an approximation to calculate  $NaCl_{comp}$  after one hour, all measures in litres ( $1 m^3 = 1000$  litres) and grams.

$$NaCl_{comp} = \frac{(m1 * NaCl_{recy} + NaCl_{added} + m3 * NaCl_{sol})}{(m1 + m2 + m3)} \quad (16)$$

Where  $m1$  is the volume of recycle brine flowing in during one hr,  $m2$  is the volume of water flowing in during one hr and  $m3$  is the main tank capacity.

Equation (16) was derived, because we need to establish a relationship between feed brine in main tank  $y_t$  (output) vs. computed brine  $x$  (input), this relationship is required to apply feedback adjustment control which explained in section (3). The scatter plot & linear regression for  $y_t$  vs.  $x$  is shown in figure 8.

Statisticians explained that R-Sq must be at least 0.70 for the regression line to be considered as meaningful. By using Minitab, the R-Sq value of the regression line was 84.3% as shown below in equation (17).

$$y_t = 40.2 + 0.864x \quad (17)$$

where  $y_t$  represents feed brine solution concentration and  $x$  is computed brine solution from equation 16, hence, the process Gain ( $g$ ) = 0.864. It is desired to maintain feed brine solution  $y_t$  close as possible to the target

specifications value ( $T = 295$  g/lit), this can be done by controlling added salt ( $Kg$ ) through predication of computed salt that required to maintain feed brine within limits. Table 2 column 2 shows 30 observations on the number of unadjusted process data taken every one hour, note that, despite best efforts to bring the process into a state of statistical control, the data tends to wander away from the target.

Individuals and moving range control charts are shown in figure 9, indicating the lack of statistical stability in the process. The actual sample average and standard deviation of feed brine concentration for these 30 observations is (288.8 g/lit) and (13.94) respectively, note that these values obtained by using Minitab.

An EWMA or CUSUM control chart on the output deviation from target would generally detect the assignable cause more quickly than individual moving range chart. We will forecast the disturbances with an EWMA having ( $\lambda = 0.4$ ) as suggested by Hunter (1989), who showed that using this value produce nearly identical weights for current and previous observations as do the Western Electric rules. Figure 10 is a EWMA, and it signals the assignable cause at observation ( $t = 3$ ).

We will use the bounded adjustment chart procedure illustrated in Section 3.3 in which an adjustment will be made only in periods for which the EWMA forecast is outside one of the bounds given by  $\pm L$ . The boundary value  $L$  is usually determined from engineering judgment, taking the costs of being off target and the cost of making the adjustment into account. But we will use equation (14) to set upper and lower boundary limits, the upper limit ( $+L = 302$  g/lit) and lower limit ( $-L = 288$  g/lit). This means that we will only make an adjustment to the process when the EWMA exceeds these two limits.

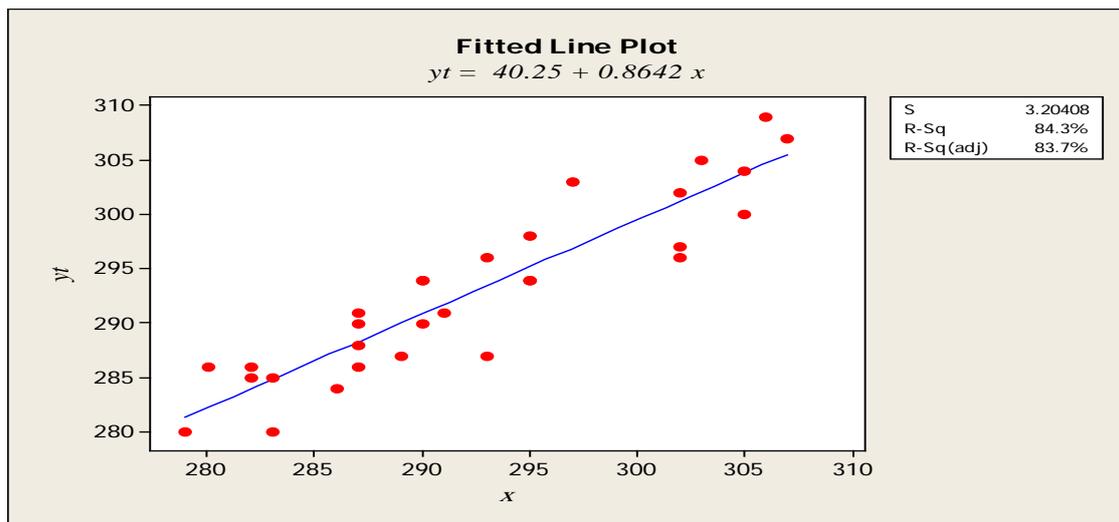


Figure 8. Fitted plot of Feed Brine with Computed Brine

**Table 2.** Process Data for the Boundary Adjustment Chart

Time (hr)	Original Process Output	Adjusted Process Output	EWMA	Adjustment	Cumulative Adjustment or Set point
1	296	296	296	0	0
2	305	305	300	0	0
3	316	316	306	-9.7	-9.7
4	307	297.3	296	0	-9.7
5	301	291.3	294	0	-9.7
6	305	295.3	295	0	-9.7
7	291	281.3	289	0	-9.7
8	295	285.3	288	4.5	-5.2
9	312	306.8	300	0	-5.2
10	280	274.8	290	0	-5.2
11	310	304.8	296	0	-5.2
12	294	288.8	293	0	-5.2
13	299	293.8	293	0	-5.2
14	282	276.8	287	8.4	3.2
15	301	304.2	299	0	3.2
16	286	289.2	295	0	3.2
17	292	295.2	295	0	3.2
18	272	275.2	287	9.2	12.4
19	281	293.4	294	0	12.4
20	287	299.4	296	0	12.4
21	279	291.4	294	0	12.4
22	285	297.4	296	0	12.4
23	277	289.4	293	0	12.4
24	273	285.4	290	0	12.4
25	268	280.4	286	6.8	19.1
26	276	295.1	295	0	19.1
27	270	289.1	293	0	19.1
28	272	291.1	292	0	19.1
29	275	294.1	293	0	19.1
30	278	297.1	295	0	19.1

To evaluate the effect of the suggested controller and the integrated control method, the study chooses to compare some statistical parameters such as adjusted and unadjusted process average, variance, standard deviation, number of adjustments during process and the mean of the squared error or the performance measure (PM), the formula for PM is:

$$PM = \frac{1}{n} \sum_{t=1}^n (y_t - T)^2 \quad (18)$$

where  $n$  is the number of observations in this study ;  $y_t$  is the output of quality characteristics or feed brine solution;  $T$  is the target value, the smaller value of PM is the better.

Based on theoretical background given in this study and data collected from this process, we created a simple program to do required calculations; program outputs are

shown in columns (3-6) of table 2. We will use computed brine as manipulatable variable in this process, and the relationship between the output and this variable as indicated in equation16. The computations for the EWMA are given in table 2 column 4, the EWMA is started off at target, and the first observation in which it exceeds upper limit is at observation ( $t=3$ ). The output deviation from target in observation 3 is (316 g/lit), so the adjustment would be calculated as usual in integral control. That is, we would change the manipulatable variable from its previous setting in observation 3 by (-9.7g/lit). The full effect of this adjustment then would be felt in the next observation, 4. The EWMA would be reset to target value at the end of observation 3 and the forecasting procedure started afresh. The next adjustment occurs in observation 8, where (+4.5 g/lit) of adjustment are made. The last column records the cumulative effect of all adjustments. Note that only five adjustments are made over the 30 observations.

The results of the original unadjusted output variable, the adjusted output, and EWMA forecasts are shown in Figure 11. The variability in the adjusted output around the target has been reduced considerably. The new average is closer to target, variance is smaller, standard deviation is improved by nearly 30% and performance measure is relatively better.

In order to further investigate the integrated SPC/EPC control system based on feedback boundary adjustment model, we conduct more calculations based on different values of  $\lambda$  as shown in table 3, as a conclusion from this table that the best performance for this process occurred when ( $\lambda=0.5$ ) because its provide better process average, variance, standard deviation, number of adjustments and PM.

## 5. Conclusions

Various schemes of integration between SPC and EPC had been proposed in literature, with a view to complement each other's shortcomings. The two classes of methods can be linked and integrated in a unified quality control framework. While intensive work has been focused on developing various efficient and robust EPC controllers, we emphasize the crucial task of monitoring auto correlated processes and EPC systems. In this paper, a scheme of integration was evaluated. The results proved that joint monitoring of EPC regulated processes' outputs, using SPC leads to the earliest detection of assignable causes.

The case study demonstrates the effectiveness of the EPC/SPC integration, since process engineers are now able to use a decision-making tool when the production process is affected by certain disruptions, with obvious consequences on product quality, productivity and competitiveness.

The approach that we proposed does not require continuous adjustments on the process. Therefore, it is suitable for process control when the process is subject to infrequent random shocks. The number of adjustments can be justified by comparing the cost and the benefit of the adjustment. This method requires much less computation effort and is easy to be implemented on the manufacturing floor.

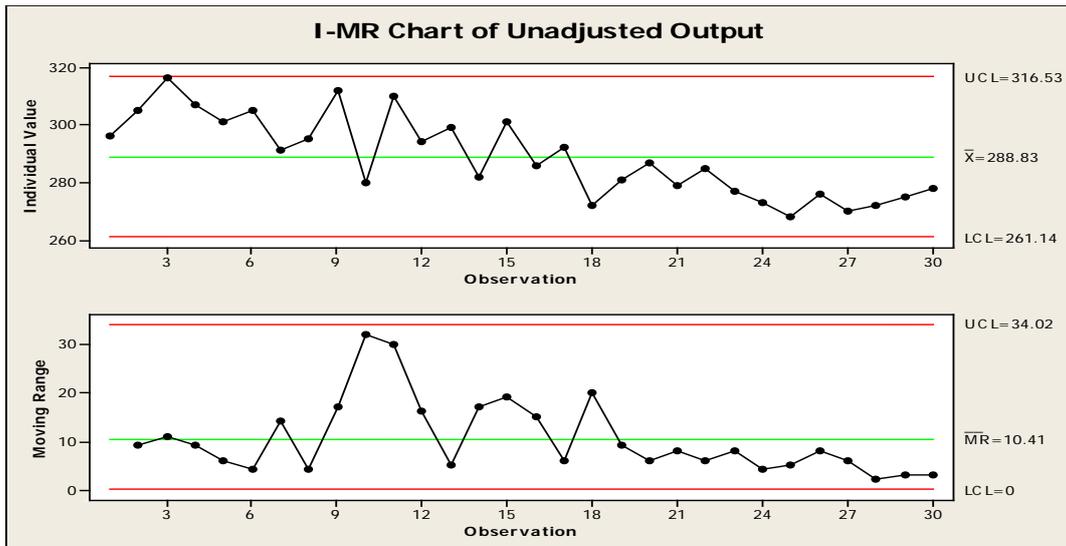


Figure 9. Individual and moving range chart applied to the feed brine

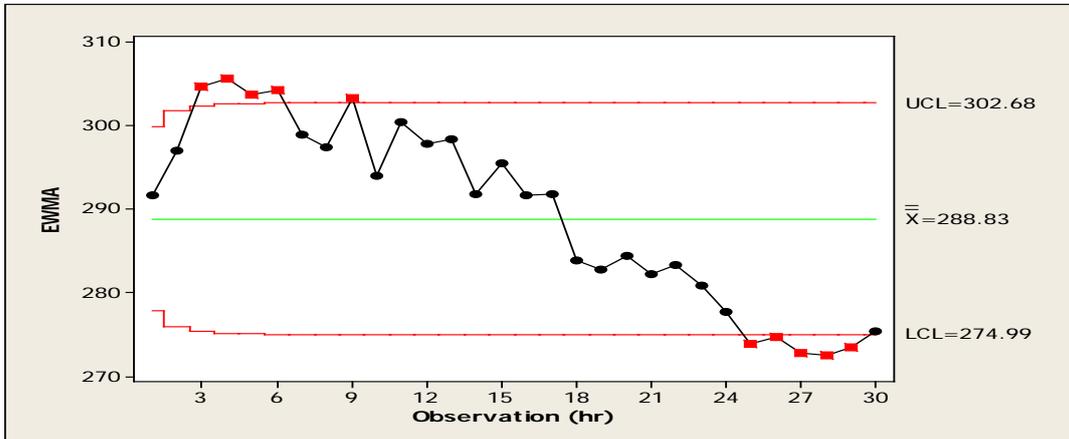


Figure 10. EWMA of Unadjusted output with  $\lambda=0.4$

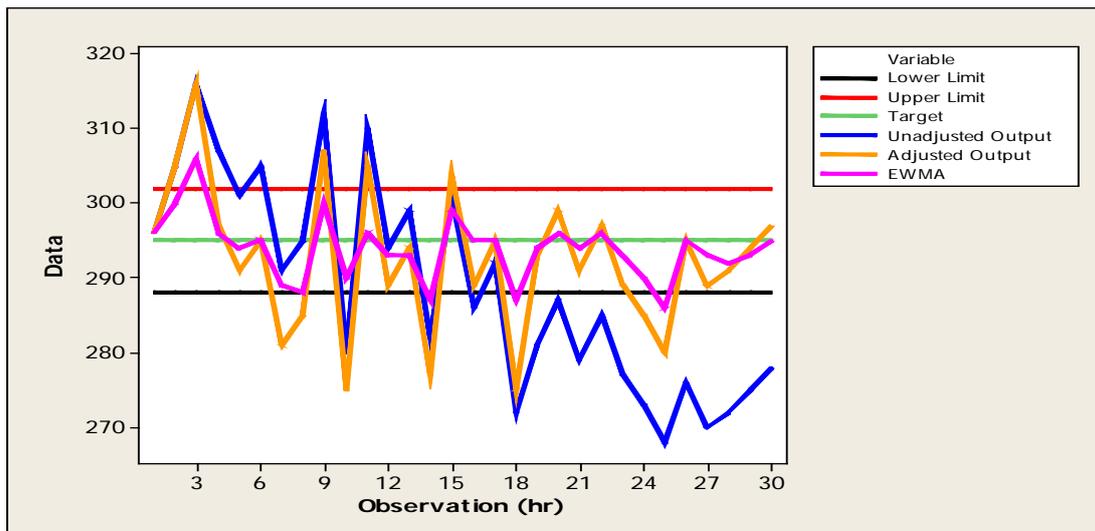


Figure 11: Bounded chart showing the output original unadjusted, adjusted and EWM

**Table 3.** Process Comparison before and after adjustments for different  $\lambda$ 

Process	Target <i>g/lit</i>	Variance	Standard Deviation	No. of Adjustments	Performance Measure
Before Adjustment	288.8	194.3	13.94	-	225.8
After Adjustment, $\lambda=0.1$	289.5	175.85	13.26	2	200.2
After Adjustment, $\lambda=0.2$	290.0	130.9	11.44	4	151.6
After Adjustment, $\lambda=0.3$	290.7	98.4	9.92	5	113.9
After Adjustment, $\lambda=0.4$	292.7	91.05	9.54	5	93.4
After Adjustment, $\lambda=0.5$	293.8	90.1	9.49	4	88.5
After Adjustment, $\lambda=0.6$	295.2	122.34	11.06	7	118.3

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