Chapter 87
The Application of Statistical Quality Control Methods in Predictive Maintenance 4.0: An Unconventional Use of Statistical Process Control (SPC) Charts in Health Monitoring and Predictive Analytics

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Abstract Statistical Process Control (SPC) is a technique of gauging and monitoring quality by closely observing a given manufacturing process. Appropriate quality data is collected in the form of product measurements or readings from various machines. This data is used in evaluating, monitoring and controlling the variability of the considered manufacturing process. This paper proposes the expansion of SPC methods to predictive maintenance. Applications of SPC techniques in various fields outside of basic production systems have been increasing in popularity. This paper investigates the practicality and viability of using Control Charts in predictive maintenance and health monitoring. Moreover, this study discusses numerous enabling technologies, such as Industrial Internet of Things (IIOT), that help to advance real-time monitoring of industrial processes. This study also expands on the use of Naïve-Bayes and other Machine Learning methods to identify strong (naïve) dependencies between specific faults and special patterns in monitored measurements. Despite its idealistic independence assumption, the naïve Bayes classifier is effective in practice since its classification decision may often be correct even if its probability estimates are inaccurate. Optimal conditions of naïve Bayes will be also identified, and a deeper understanding of data characteristics that affect the performance of naïve Bayes is analyzed.

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87.1 Introduction

Control charts are used to detect special cause variation but other tools such as Pareto diagrams or fish-bone diagrams are sometimes needed to address root causes. If the data is normally distributed, standard Shewhart control charts are used. If the data is non-normally distributed with correlation, conventional control charts give too many false alarms. Selecting an appropriate control chart depends on the characteristic and attributes of data and economic factors such as sampling, testing, investigation costs [4].

The modelling of the explicit relationship between maintenance and quality of the final product has not been adequately addressed. Ben-Daya and Duffuaa's study on maintenance and quality highlights the missing link between the two and proposes a broad framework for modelling the maintenance-quality relationship. A common feature of the existing models to determine economic production quantity (EPQ) and maintenance schedules jointly does not account for the optimization of maintenance amount. The new dimension brought to the modelling of this problem includes the maintenance effort as a decision variable to be optimized. In many PM models, system is assumed to be in new quality after maintenance, but a more realistic approach is when the failure of a system changes by assuming the system quality is between before failure and after maintenance states. However, there is no attempt in these models to optimize the PM effort to change the failure pattern in order to achieve given quality goals. One of the two proposed approaches is based on the idea that maintenance affects the failure pattern of the equipment and that it should be modelled using the concept of imperfect maintenance. The second approach is based on Taguchi's approach to quality [1].

MacCarthy and Wasusri's paper expands on the lack of connection between the failure detection patterns and maintenance processes identified in Ben-Daya's paper. It reviews and highlights the critical issues of the non-standard applications of SPC charts in articles from 1989 to 2000, classified in five categories: monitoring of non-manufacturing processes using Shewhart charts, monitoring of non-manufacturing processes using more advanced charts, deriving appropriate plans and schedules, evaluating customer satisfaction, and developing forecasting models. The articles reviewed are broken down in layered categories as below:

- Application Domain:
  - Engineering, industrial, and environmental applications
  - Healthcare applications
  - General service sector application
  - Statistical application
- Data Sources Used
- Types of Control Chart Technique Employed

It is shown that application boundaries of SPC charts reach beyond manufacturing. In non-manufacturing applications, the nature and scope of the process and relevant quality characteristics must be clearly defined, as well as the concepts and interpretation of statistical control states. If the assumptions underlying the Shewhart Theory are violated, more advanced control charts are needed. A step-by-step, holistic guide for selecting the best type of control chart for the objective is given. It is necessary to experiment with many types of control charts because of various data characteristics [4].

Jennings and Drake further examine the non-manufacturing use of control charts and propose the development of an original method of normalizing the interdependent measurement parameters in machine tool monitoring. Since some machine tool sub-systems operate continuously, intermittently, and at various torques and speeds, the measured data during steady-state and transient tests must be normalized during pre-processing before the construction of control charts. This value will often be in error due to the error between the mean value of the group and the true value. Three-variable chart is created in a very similar fashion to the two-variable chart by using the residual values calculated from the deviation from means. The authors present these three examples of measurement normalization as a verification of their performance parameter inter-dependence compensation method [3].

The assumption of a steady state process presents an issue for the implementation of control charts in dynamic and unstable non-manufacturing applications such as predictive maintenance. Since the conventional Shewhart average level chart is not applicable when the variation is not purely random, adaptive moving charts are studied. Wang and Zhang's objective in their study is to use adaptive SPC methods based on an autoregressive model to create an adaptive control chart that does not readily assume constant steady state and normal distribution of variables. Two-stage failure criteria are used as the basis for the SPC charts. This article attempts to analyze processes where no previous knowledge is present and the process is non-stationary and most likely non-Gaussian. The autoregression model used is basically a one-step ahead prediction based on the output values before being regressed on to the function itself. The coefficients and the error term of a linear, parametric autoregression model can be determined to levels of accuracy using published algorithms, such as the forwards least-squares algorithm. The adaptive moving average is also considered for the same vibrations data where it is found to be more conservative than the adaptive moving range method. The adaptive Shewhart average level chart is used simultaneously for all the variables and is found to be ideal because it does not need a subjective threshold level; however, it is very insensitive to small changes in measurements [2].

Yin and Makis take a Bayesian approach due to the inconclusiveness of the steady state information about process control in their 2009 publication. In this paper, design of a multivariate Bayesian control chart for condition-based maintenance (CBM) applications is considered using the control limit policy structure and including an observable failure state. In addition to the Bayesian chart to optimize the probability of true alarms and to find the best sample size, sampling rate, and control limits, optimization models for economic and economic-statistical design of the Bayesian chart are developed to determine the optimal control chart parameters to minimize the expected average maintenance cost. The proposed multivariate Bayesian control chart performs better and compromises its economic performance much less than the traditional chi-square chart when probability of failure prevention increases [8].

Applications of SPC techniques in various fields outside of basic production systems have been increasing in popularity. This paper investigates the practicality and viability of using Control Charts in predictive maintenance and health monitoring. This study also expands on the use of Naïve-Bayes and other Machine Learning methods to identify strong (naïve) dependencies between specific faults and special patterns in monitored measurements.

87.2 The Application of Statistical Process Control (SPC) Charts in Health Monitoring and Predictive Maintenance

In the process of determining which SPC method is more fit to our application, many aspects of the model development were assessed. Shewhart control charts (mainly $\overline{x}$ and R chart or $\overline{x}$ and s chart) are particularly useful in the first phase of an SPC application: the process is to be expected to be out of control and undergoing assignable causes that are reflected in big changes in the observed parameters. However, a main drawback of the Shewhart control chart is its use only of process data contained in the last sample observation and its unawareness of any indication given by the full sequence of collected data. This feature renders Shewhart control chart unresponsive to slight process shifts (around 1.5 * s or less). In cases where the process inclines to function in control, consistent estimates of process parameters (for instance, mean and standard deviation) are obtainable, but assignable causes do not normally result in great process upsets or disturbances. This issue can be addressed by introducing other criteria, such as warning limits and other sensitizing rules, which can be applied to Shewhart control charts to improve their performance against small shifts. Nonetheless, using such measures reduces the practicality and simplicity of understanding a Shewhart control chart, and intensely decreases the average run length (ARL) of the chart when the process is actually in control.

An effective unconventional approach to the Shewhart Theory that may be used when small process shifts are of interest is the cumulative sum (CUSUM) control chart. In this section, we focus on the cumulative sum chart for the process mean. First, if the process is in control at a target value $\mu0$ (determined by training data from in-control process), the cumulative sum defined is a random walk with mean zero (check Figs. 87.2, 87.4, and 87.6). On the other hand, if the mean shifts upward ($\mu1 > \mu0$), an ascendant shift will develop in the cumulative sum. On the contrary, if the mean swings downward ($\mu1 < \mu0$), then a descending shift will progress. Consequently, if a trend develops upward or downward, we should consider this as evidence that the process mean has shifted and a search for some assignable cause should be performed.

87.2.1 Application 1: High Pressure Pump and Water Desalination

Cavitation Detection. The testing kit parts are installed and mounted on a moveable steel frame. The motor is fixed by bolts on the steel frame. Pump is connected with Tank by 1 in. PVC pipe, with a manual valve installed between them to control the flow entering the pump. A pressure gauge is installed on the discharge pipe of the pump and the discharge line passes through a magnetic Flow meter, then a manual valve to control the system head, and finally connected with the tank again (Fig. 87.1).

Vibration sensors (Accelerometer) are fitted on the pump casing and motor sensing the pump casing vibration and shaft bearing movement. The three accelerometers are connected by Low Noise Coaxial Cables to the NI 9232 series card. Two pressure transducers at the pump inlet and outlet pipes are connected to the NI 9207 card. The two NI cards are fitted on the Compact DAQ Chassis (cDAQ-9174) slots. DAQ Chassis is connected by USB cable to the computer.

In Fig. 87.2, the graphs are divided into 2 sections. The non-grayed section represents the training of the data (not reflected in upcoming graphs). The model was trained using normal condition data. The CUSUM calculations used to develop the graphs in Fig. 87.2 show the system is in control (all points are grey and in control between H+ and H−). Once cavitation is detected, the graph shows that the system goes out of control, showing that cavitation likely happed around the 34–35th second.

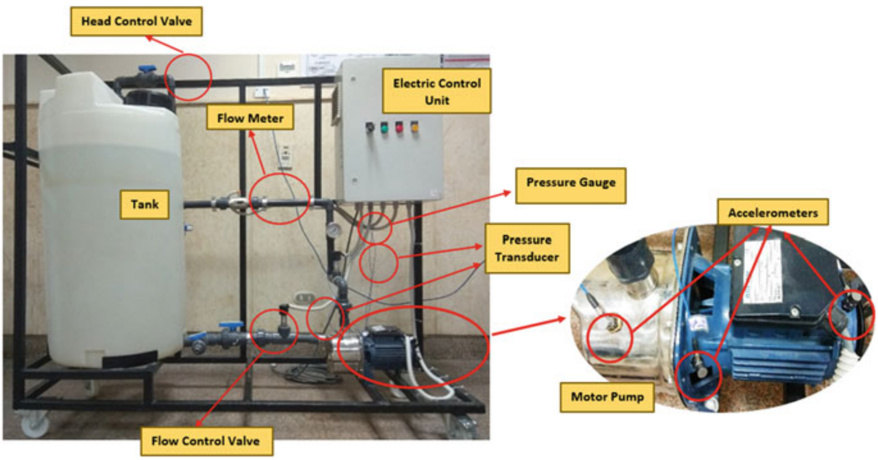

Fig. 87.1 Centrifugal pump demo used for cavitation detection

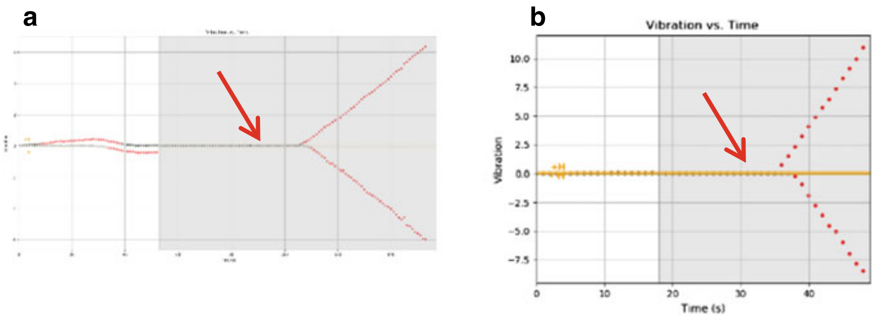

Fig. 87.2 Cavitation detection. **a** Motor DE, **b** casing

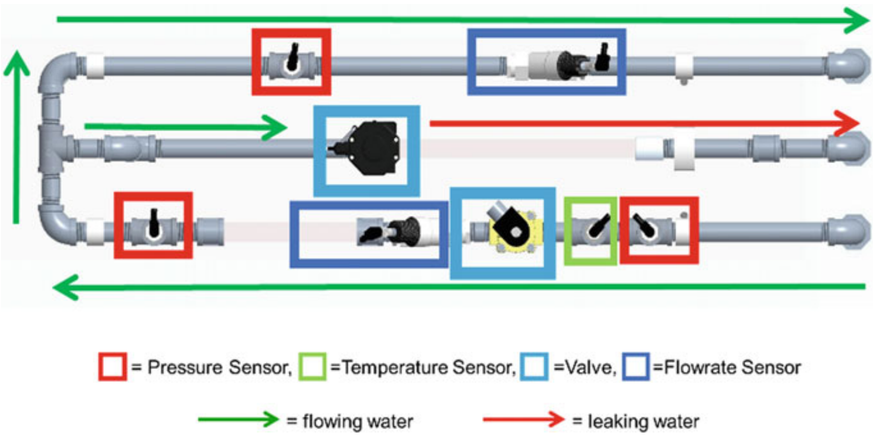

Fig. 87.3 Demo setup used for leak detection

Leak Detection. The digital transformation in the chemical and petrochemical industries has progressed at a rather slow pace due to reliance on more traditional methods. The process control demonstration is used to show how sensors can be used and how digital transformation can help optimize the usefulness of the system. Currently the process control demonstration simulates a leak by opening an EPS valve, and the sensor readings will then change based on the severity of the leak (Fig. 87.3).

Two pressure sensors, one flow sensor and one temperature sensor, are located on the first row of piping in the system. The EPS valve is located in the middle section. The other pressure and flowrate sensors are located on the last row of piping. The demonstration has water pumped in one way and flowing out the other two. The solenoid valve is used initially to allow water into the system. The water then flows to the EPS valve that can be opened to a specific position to induce a leak.

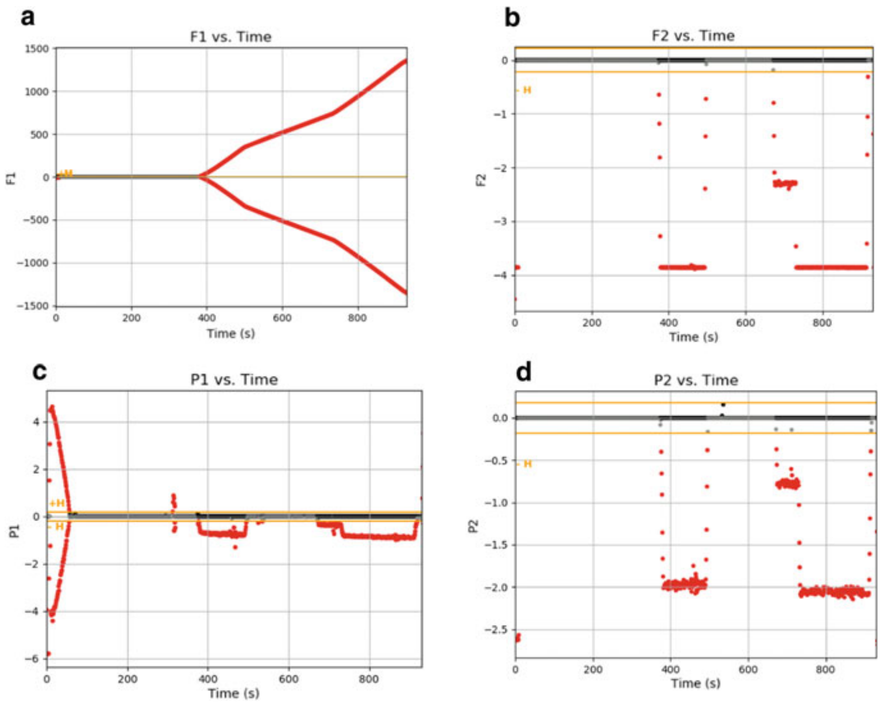

Fig. 87.4 Leak detection simulation: **a** F1 (malfunctioning), **b** F2, **c** P1, **d** P2

In the case of leak detection (Fig. 87.4), a longer scenario was simulated where a leak was induced twice: the first induced leak was a full leak, as for the second one, it was a 2-stage induced leak. Observing the CUSUM graphs monitoring several parameters of the system, we see that we have 3 separate phases of out-of-control: (a) the first out-of-control phase (0–40 s): this where the pump is reaching its steady-state after launching the system, (b) the second OOC phase (380–500 s): the CUSUM method was able to detect the leak and its fix, (c) the third OOC phase (640 s-end): this phase shows how the program was to detect different levels of the leak. Furthermore, the behavior of the CUSUM on the data collected from the flow sensor F1 compared to the other data behavior, shows that the sensor is malfunctioning and needs calibration.

87.2.2 Application 2: Apache Gearbox

The intermediate gearbox is a critical component of the aircraft that requires frequent maintenance actions. Sensors are used to monitor the health of the component, and data is collected and models built to detect faults and develop trends based on the health and usage. Predictive modeling is used to assess the health of the component to diagnose if a fault is occurring (Fig. 87.5).

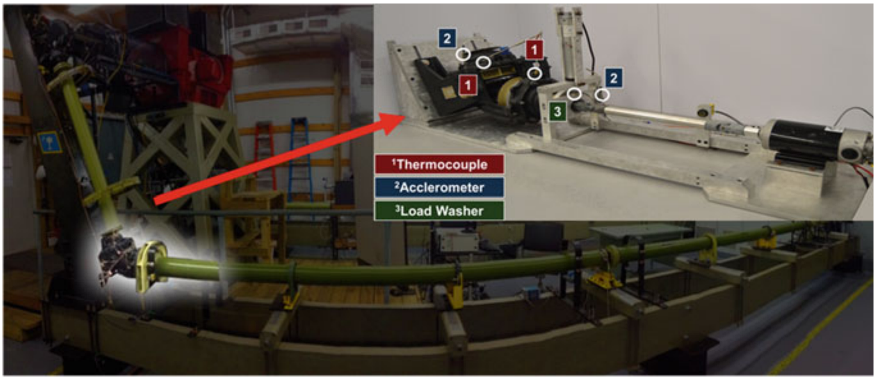

Fig. 87.5 Gearbox demo used for fault detection

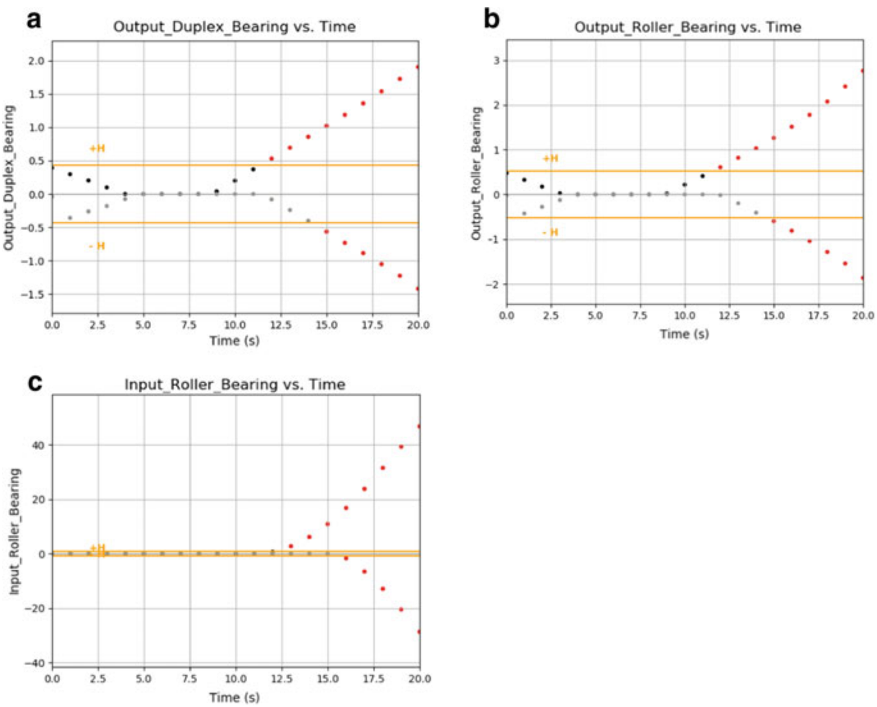

Fig. 87.6 Gearbox fault detection. **a** Output duplex bearing. **b** Output roller bearing. **c** Input roller bearing

Data for the gearbox demo was also used to validate the CUSUM model developed for fault detection. Figure 87.6 shows how the fault induced was detected leading an out of control chart.

87.3 Machine Learning Approach for Condition/Fault Dependency

In our future work, Machine Learning approaches will be pursued in condition-based fault detection problems given their capability to handle data-intensive processes, signal cognitive complexities, and extrapolation/prediction analysis. Moreover, Machine Intelligence will also become our interest to assist manual decision-making for condition-based predictive maintenance.

87.3.1 Fault Type Predictions with Naïve-Bayes

In our application, the process data are usually high-dimensional with multi-categorical variables, as the processes are being monitored with multiple sensor signals. In such cases, one classic fault classifier to correlate categorical features with a labeled fault will be Naïve-Bayes classifier. The prediction formula is:

$$P_{(F|S_1,S_2,S_3\ldots)} = \frac{P_{(S_1,S_2,S_3\ldots)}P_{(S_1,S_2,S_3\ldots|F)}}{P_{(F)}} \tag{1}$$

In Eq. (1), Posterior $P_{(F|S_1,S_2,S_3\ldots)}$ represents the possibility of the system having fault F when signal sequence $(S_1, S_2, S_3\ldots)$ is being observed, which could be temperature fault F_t, pressure fault F_p, vibration fault F_v, or leaking fault F_l. More specifically, the faults at different components can be singled out and predicted. Prior to $P_{(S_1,S_2,S_3\ldots)}$, Likelihood $P_{(S_1,S_2,S_3\ldots|F)}$ and Evidence $P_{(F)}$ can be calculated based on the fault occurrence possibilities from experimental results (Table 87.1). Note that the Bayes rule can only handle categorical data, which requires sensor signals to be categorized using above SPC Charts to decide whether each signal is located within a safe range at the current monitor time.

Table 87.1 Fault occurrences and signal indicators form experimental data

Time stamp	Sensor signals in safe range	Temperature fault	Vibration fault	Leaking fault
T_1	$S_1 = True, S_2 = True, S_3 = True\ldots$			
T_2	$S_1 = False, S_2 = True, S_3 = True\ldots$	Detected		
T_3	$S_1 = True, S_2 = True, S_3 = False\ldots$			Detected
…	…	…	…	…
T_n	$S_1 = False, S_2 = True, S_3 = False\ldots$	Detected		Detected

The superiority of Naïve-Bayes lies in that it can robustly handle missing values irrelevant feature signals. It is also a relatively fast algorithm dealing with big datasets, which is particularly important for online decision-making process.

87.3.2 *Online Decision-Making*

Machine Intelligence has also been investigated under the scope of online autonomous systems. The outlined system that is able to make predictions based on signal data and make remedy actions accordingly will be suited in the context of Predictive Maintenance.

A digital transformation philosophy named Virtual Commissioning [7] has been investigated and implemented towards an intelligent robotic actuation system that adopted Machine Learning Techniques such as Reinforcement Learning and Deep Neural Network in dynamic operation scheduling problems (Fig. 87.7). Deep Reinforcement Learning algorithm trained on both virtual and physical platforms will serve as the baseline for the autonomous actions taken upon condition-based fault detections.

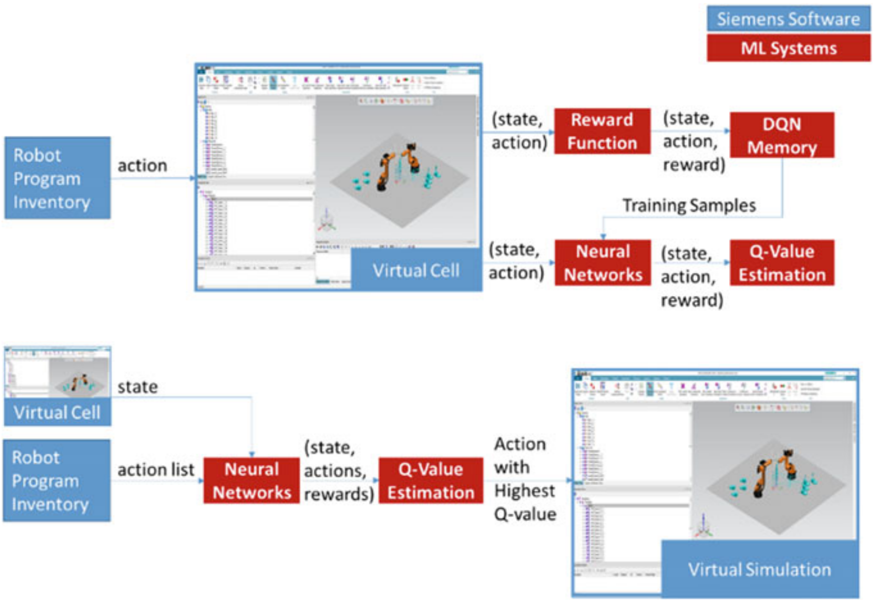

Fig. 87.7 Deep reinforcement learning based operation scheduler training (Top) and testing (Bottom) procedures

87.4 Conclusion

We have observed in this paper how the CUSUM control chart was effective in sensing shifts in processes when faults were induced. In order to enhance detectability (especially for large alterations in the system), our team is currently implementing other sensitizing rules. These rules help in the understanding of patterns in the process and in the prediction and detection of faults/out-of-control phases [5]. In short, this paper describes the rationale behind the fault detection algorithm used in the development of a predictive maintenance dashboard for water desalination industry [6]. This final platform will help monitor data collected from desalination plants across Egypt in order to maximize plant availability and smart monitoring of features incorporated in these plants to ensure reliable operation at optimal efficiency, and minimize maintenance burdens for the water desalination industry.

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