An Engineering Model for Healthcare Devices to Control, Detect, and Diagnose Medical Errors

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Abstract

Accurate diagnosis of diseases and their level of intensity is a key aspect of health. A minor error in medical diagnosis, besides diverting the course of treatment and increasing the duration of therapy, raises the cost of services, leads to psychological trauma, and most importantly jeopardizes patient safety. The shorter the time of diagnosis, the easier it is to prevent, fight, treat and control the disease at lower intensity levels. Thus, it is essential to provide a model to deal with the possible errors of diagnosis in healthcare system. The present article introduces an engineering method for detecting and diagnosing faults in patient treatment. In the first phase, the factors affecting the emergence of the disease are predicted using Perceptron neural network. In the second stage residual values are produced; and in the third stage, in case there is a fault, the sources and causes of the fault are examined with the help of statistical quality control charts. Validation of the proposed model is evaluated by providing a numerical example.

Keywords
engineering, health, medical error detection and diagnosis, statistical quality control charts, neural

1. Introduction

Patient safety is one of the basic concepts in the healthcare systems. This issue requires maintaining and increasing system reliability in terms of industrial elements. One way to increase system reliability in the industry is removing and preventing faults to reduce the number and intensity of faults. A means of accomplishing this important task is identifying the sources and causes of faults. In recent years, with advances in technology and complexity of control systems, improving the reliability of these systems has been one of the most important issues for researchers. Nowadays, it is important to design controllers to detect system faults and their resources. Statistical quality control charts are widely used in industry to control the quality of products. These charts are used to explore the process fluctuations, identify the source of changes and efficiency improvement and to maintain the desired quality level. If there is a correlation between the data, among the statistical quality control charts the residual chart will be chosen to reduce false alarms. The residual is defined as the difference between the observed amount of quality characteristics and its estimated value by a model. [1].

Nowadays, with presence of medical errors and application of industrial devices in healthcare systems, it is possible to improve the healthcare system reliability by increasing patient safety. One of the frequent medical errors is failure in diagnosis, which in some cases has severe consequences and plays a prominent role in patient safety [2-4]. According to IOM, patient safety is defined as “preventing damage to the patient” and one of the points it emphasizes is preventing faults. [5, 6] Researches conducted in 2016 in America have revealed that errors in medical diagnosis of heart disease are between the third to the eighth causes of death in America. More than 225

thousand deaths annually occur due to medical errors, which have inflicted physical injury on about a million people [7]. Due to the fact that medical knowledge relies on a wide range of disciplines and patient safety is an important strategy in the field of healthcare, both engineers and physicians are trying to find ways to solve the problems in this area. [8] The present study aims to extend the existing models of industrial systems to healthcare system in terms of diagnosing medical errors using statistical quality control engineering tools in order to increase patient safety and reduce the complexity and time of diagnosis.

2. Literature Review

Among the data-driven methods [9, 10], the most popular methods for fault detection and diagnosis include principal component analysis method, neural networks [11], Bayesian networks [12, 13], statistical quality control charts [14, 15], and partial least squares [16], respectively. These methods reduce the amount of calculations and have an important usage in dynamic processes. One of the applications of Principle Component Analysis (PCA) can be seen in fault detection and diagnosis in researches conducted by Wang and Cui [17]. They have provided an online method for fault detection and diagnosis in centrifugal chillers. In this method they have used the correlation among the sensors and divided them into two groups using two models based on PCA. The suggested method has been based on two stages: training PCA model and online use of PCA. The results showed that PCA is a good method to generate useful residuals for detecting and diagnosing faults. Chen and Lan suggested a developed PCA for detection and diagnosis of heat pump faults. They used PCA to extract correlated variables in heat pumps and reduce data dimension. Data matrix [19, 20] in PCA is used to determine threshold value, and square prediction fault (SPE) index is applied to detect faults. If the index exceeds the determined thresholds it will cause faults. The results showed that the proposed method successfully discovers the condenser fouling fault. Raihan Malik and Imtiaz [21] have provided a hybrid approach based on principal component analysis and Bayesian belief networks (BBN) in order to detect faults. To discover the fault, they have used the PCA method to calculate the residual values and the threshold value (BBN) to identify and explain the fault source. To validate the proposed method, they have offered an example of the fault detection in the solid crystal dissolution reservoir.

Another data-driven technique is the fuzzy inference methods that can be seen in observation Farzad Firouzi Jahantigh et al [22]. Simani et al [23] have presented a model in three stages to identify the fault in nine wind turbines with the premise of uncertainty of wind speed. In the first stage and using Failure Mode Effect Analysis (FME) method, the variables involved in three types of faults in wind turbines were identified. In the second phase, Takagi-Sugeno-kang method is used to predict and produce residuals. In the third stage, for sensitization of the process to input variables and fault detection, they used four fuzzy methods to produce residual values. For fault detection and diagnosis, the threshold value is determined using residuals and Monte Carlo method.

Among the most widely used model-based methods for fault detection and diagnosis is regression method. Cui and Wang [24] have presented a two-stage online model for fault detection and diagnosis in centrifugal chillers. In the first stage, to identify five types of chiller fault, six performance indicators are predicted using the polynomial regression method and the residual values are produced. In the second stage, with the help of residual values and based on a quantitative approach, adaptive threshold values are determined for the six performance indicators. Then, according to the table of rules the process of fault detection and diagnosis is carried out. In the research, besides the uncertainty of the predicted values of indicators, the threshold values of indicators are considered uncertain as well. Wang and Chen [25] have provided a two-stage method to detect multiple faults in the air conditioning system. . In the first phase, the residual values are provided by Auto Regressive Moving Average (ARMA) model. R_EWMA graph is eployed to detect faults. In the second stage, rules-based detection methods are utilized to detect sources of fault. The advantage of the proposed model is the ability to detect multiple faults simultaneously. Wang et al [26] have found an online fault detection and diagnosis model for the air conditioning system in buildings. In the first stage they used the enhanced EWMA prediction method with a genetic algorithm. In the second stage, with the help of the residuals and based on a quantitative approach, the adaptive threshold values are determined. In the third stage, based on the fault rules, three fault categories are provided to discover and detect faults. The results indicated that the proposed method, despite failure in detecting small and gradual changes, has a good performance in term of detecting sudden and big changes. Xiao et al [27] have introduced a model-based approach based on the creation of four modules in order to increase the sensitivity of detection of seven types of faults in centrifugal chillers. The first module is used to create a predictive model for indicators which affect faults using regression method. The second module includes an adaptive threshold estimator with the help of the residual values. The third module is used by means of monitoring data and predicted values in the second module to produce the residual values which is compared with threshold values to detect faults. The fourth module is used to help identify the source and the cause

of fault based on the table of rules. The results show that, compared to other methods, the proposed method is more efficient with less calculation and higher sensitivity in detecting faults.

In 1931, the first data-driven monitoring method, called control chart, was introduced by Shewhart [28]. This graphical method was applied based on a statistical hypothesis testing to control and monitor the process quality variables [15]. The control chart introduced by Shewhart has one fundamental flaw, that is, it only considers the latest data driven from the process. Therefore, it is insensitive in terms of detecting small changes. [29] In 1954, Page introduced the Cumulative Sum Control Charts (CUSUM) and [30] in 1959, Roberts proposed Exponentially Weighted Moving Average (EWMA) control chart for the first time. The diagrams, by taking into account the previous process data, can be applied to detect small changes in processes. Zhao et al [31] used a two-stage model to detect six types of faults in centrifugal chillers in the buildings' air conditioning system. In the first phase, the support vector regression method was applied to predict effective indicators that create fault in centrifugal chillers. By comparing the predicted values with the actual values the residual values are produced. In the second phase, the residual-based Exponentially Weighted Moving Average control chart is used to improve the detection and diagnosis of faults. They compared their proposed model with a combination of multivariate linear regression model and t-statistics. After finding the fault, the process for identifying the causes and sources of faults will start with respect to table of rules. The proposed model is a significant improvement in the detection and removal of faults, especially faults with low intensity.

Tran et al [32] have introduced a two-stage online model for detecting seven types of faults in centrifugal chillers in the buildings' air conditioning system. In the first stage a nonlinear radial basis function (RBF) is used for prediction. In the second stage, the control charts (R_EWMA) is employed to improve the fault detection and diagnosis; and in the third stage the table of rules is used for identifying the sources of fault. They compared their proposed model with the one introduced by Zhao et al [31]. The results show that RBF-EWMA model has achieved significant improvements in accuracy and reliability in terms of fault detection and diagnosis in centrifugal chillers.
Chen et al [33] introduced a two-stage model to detect six types of faults in centrifugal chillers in the buildings' air conditioning system. In the first stage, they used the method of improved nonlinear least squares support vector regression (LSSVR) and differential evolution algorithm (DE) to increase the accuracy in terms of prediction of indicators which are effective in production of faults and residuals. In the second phase the (R_EWMA) control chart is used to improve the fault detection and diagnosis. After finding the fault, with respect to the table of rules, the sources of faults can be identified. They compared their proposed model with the model introduced by Tran et al [32]. The results show that the proposed model improves reliability in detecting faults, especially faults at low intensity levels. Table 1 shows a summary of the literature review.

Table 1. A summary of the researches on the methods of fault detection and diagnosis

Article Title	Year of publication	The method used in the prediction section	Fault detection and diagnose improvement method	Fault decision rules
A statistical fault detection and diagnosis method for centrifugal chillers based on exponentially-weighted moving average control charts and support vector regression	2013	SVR	Control Chart R_EWMA) (	Table of rules
A robust online fault detection and diagnosis strategy of centrifugal chiller systems for building energy efficiency	2015	RBF	Control Chart R_EWMA) (	Table of rules

An enhanced chiller FDD strategy based on the combination of the LSSVR-DE model and EWMA control charts	2016	DE-LSSVR	Control Chart R_EWMA) (	Table of rules
A robust fault detection and diagnosis strategy for multiple faults of VAV air handling units	2016	ARMA	Control Chart R_EWMA) (	The use of 2 rule tables
A fault detection and diagnosis strategy with enhanced sensitivity for centrifugal chillers	2011	MLR	Adaptive Threshold estimation with the help of residuals	Table of rules
Sensor-fault detection, diagnosis and estimation for centrifugal chiller systems using principal-component analysis method	2005	PCA	Q-statistics estimation with the help of residual values	Q-contributio n
A model-based online fault detection and diagnosis strategy for centrifugal chiller systems	2005	Polynomial regression	Adaptive Threshold estimation with the help of residuals	Table of rules
Online model-based fault detection an diagnosis strategy for VAV air handling units	2012	EWMA-GA Statistics	Adaptive Threshold estimation with the help of residuals	Flowchart of rules
A fault detection technique for air-source heat pump water chiller/heaters	2009	PCA	Determining the confidence interval for SPE	_
A Hybrid Method for Process Fault Detection and Diagnosis	2013	PCA	Q-statistics estimation with the help of residual values	BBN

Residual Generator Fuzzy Identification for Wind Farm Fault Diagnosis	2014	TSK	Determining the threshold value using residual values and Monte Carlo method	Dedicated Observer Scheme

3. Research methodology

As shown in Figure 1, the proposed model for detection and diagnosis of healthcare errors is made up of two parts, online and offline. In offline part the uncertainty of input data of system is considered through training and applying a prediction model. In this section, the neural networks are used as an instance of predictive model. In the online part, after primary data processing and comparing the predicted value of indicators with their true values, the residuals are produced and applied as input to residual-based EWMA charts. If there is a fault, it can be detected with the help of control charts. Besides, it is possible to investigate the causes of the fault.

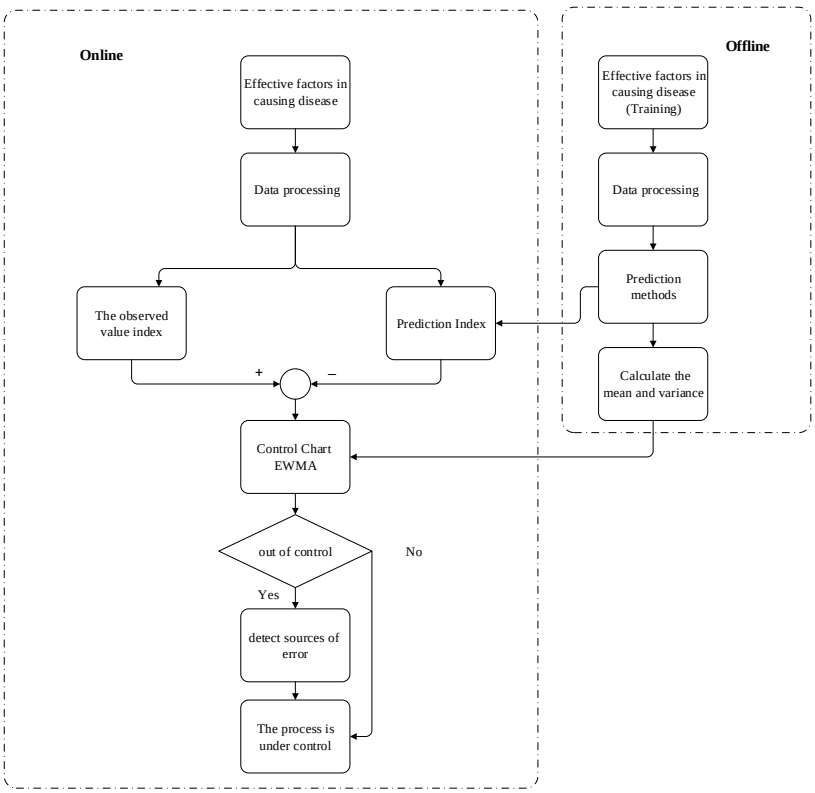

Figure 1. The proposed conceptual model

1.3. Prediction of indicators and offline model training

Multilayer Perceptron Neural Network is one of the most powerful neural network models established based on back propagation algorithm. One of its usages is in predictive models. In the back propagation training algorithm the initial weights are randomly selected. If there is N training samples, and each sample has *n* input and *l* output, the input vector is defined as $X_j = (X_{1j}, \dots, X_{nj})$ and output vector as $B_j = (B_{1j}, \dots, B_{nj})$ with $1 \leq j \leq N$.

Learning process takes place in two steps:

Feed forward: by applying X_j input vector to the input layer, output vector $O_j = (O_{1j}, \dots, O_{nj}$ based on $W = (W_{1l}, \dots, W_{nl})$ current weights is established. O_j is compared with the B_j real output. The E function error is calculated based on the equation (1).

$$E = \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{N}(B_{ij} - O_{ij})^2 \qquad (1)$$

2. Feedback: Error in equation (1) is distributed on the weights with the help of equation (2).

$$\Delta W_{nl} = -\frac{\partial E}{\partial W_{nl}}\eta \qquad (2)$$

Coefficient 0 <η <1 is a parameter that controls the convergence rate of the algorithm. These two steps are repeated until the amount of E is converged with a small pre-determined amount.

3.2. Exponentially Weighted Moving Average Chart of Residuals for Online Error Detection

Exponentially weighted moving average statistics for individual observation of residual values is defined equation (3):

$$EWMA_t = \lambda\bar{Y}_t + (1 - \lambda)EWMA_{t-1} \qquad (3)$$

In this equation, λ has a fixed value between 0 <λ≤1 and is the chart parameter. In general, experience has proved that if λ is selected within $0.05 \le \lambda \le 0.25$ good results will be achieved. Usually, if small changes are very important, λ is low, but the most ideal state is when λ = 0.2, which is the amount considered in the present study. $Z_0 = \mu_0$ and $\bar{Y}_t$ is the average statistics of the *t*th sample with *n* constant volume in each sample, and in the period *t*, $(t = 1, 2, ..)$ which is calculated based on equation (4). To obtain more subsets from the sample groups, the volume of sample groups is considered to be equal to one.

$$\bar{Y}_t = (y_{1t} + y_{2t} + \cdots + y_{nt})/n \qquad (4)$$

$EWMA_t$ statistics is a weighted average of $\bar{Y}_t, \bar{Y}_{t-1}, \dots, \bar{Y}_1$ which is calculated based on equation (5).

$$EWMA_t = \lambda\bar{Y}_t + \lambda(1 - \lambda)\bar{Y}_{t-1} + \lambda(1 - \lambda)^2\bar{Y}_{t-2} + \cdots + \lambda(1 - \lambda)^{i-1}\bar{Y}_1 + +(1 - \lambda)^i\mu_0 \qquad (5)$$

To calculate the high control limits equation (6) and to calculate low control limits equation (7) are used:

$$UCL = \mu_0 + L.\sigma\sqrt{\frac{\lambda}{n(2 - \lambda)}} \qquad (6)$$

$$UCL = \mu_0 - L.\sigma\sqrt{\frac{\lambda}{n(2 - \lambda)}} \qquad (7)$$

l is the width of control limit which equals 2, and σ is the standard deviation and μ_0 the expected residual values.

4. Numerical examples

this section, numerical examples are presented to validate the proposed model. A summary of the statistical description of the data are presented in Table 2.

Table 2. Statistical description

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
output	275	20.37	295.68	316.05	302.1030	4.00236	16.019
input1	275	20.00	308.16	328.16	313.8147	4.97528	24.753
input2	275	.03	-2.99	-2.96	-2.9780	.00599	.000
input3	275	1.20	.00	1.20	.5451	.28117	.079
input4	275	1.63	.25	1.88	.9607	.29429	.087
input5	275	.30	.10	.40	.2131	.07767	.006
input6	275	.30	.70	1.00	.8902	.05614	.003
Valid N (listwise)	275						

It is assumed that I_1 index is effective in causing diseases such as heart disease, and the increase of I_1 creates three levels of intensity for heart disease. Moreover, in the predicting I_1 index a_1, a_2 a_3, a_4, a_5, a_6 parameters are effective. Therefore, according to the proposed model in the first stage, the artificial neural network is used to predict I_1 index. The characteristics of the neural network used in this study are presented in (Table 3).

Table 3. Characteristics of the neural network

Artificial Neural Network	Network Type	Learning algorithm	number of neurons in the first layer	number of neurons in the second layer	inputs	outputs	training data	validation data	testing data
	perceptron	Levenberg-Marquardt	20	1	a_1, a_2 a_3, a_4, a_5, a_6	I_1	70%	15%	15%

The result of the prediction of the model using MATLAB is presented in Figure 2. The amount of regression for neural network is 99% which indicates high prediction accuracy.

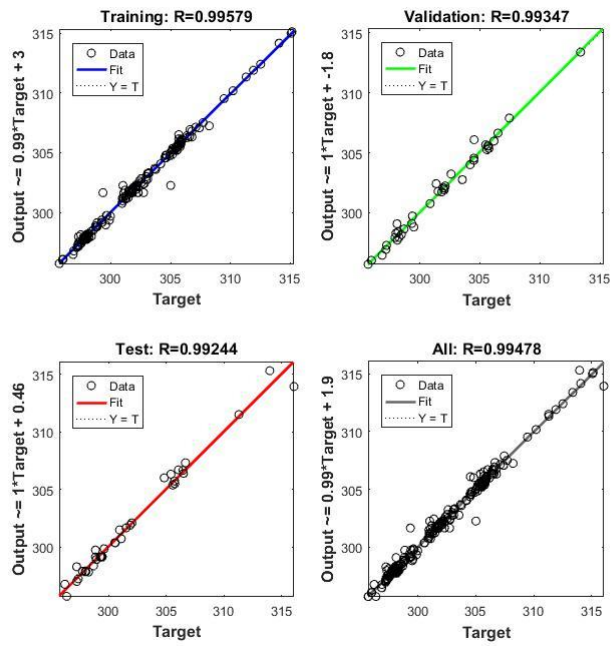

Figure 2. Regression of training, validation and testing data

Using the residual values obtained from all three intensity levels in heart diseases, the R_EWMA control chart is drawn by Minitab software. It is shown in Figure (3). After monitoring the charts and obtaining the ultimate control limits, the chart is prepared for entering new data in order to identify and determine the level of disease severity.

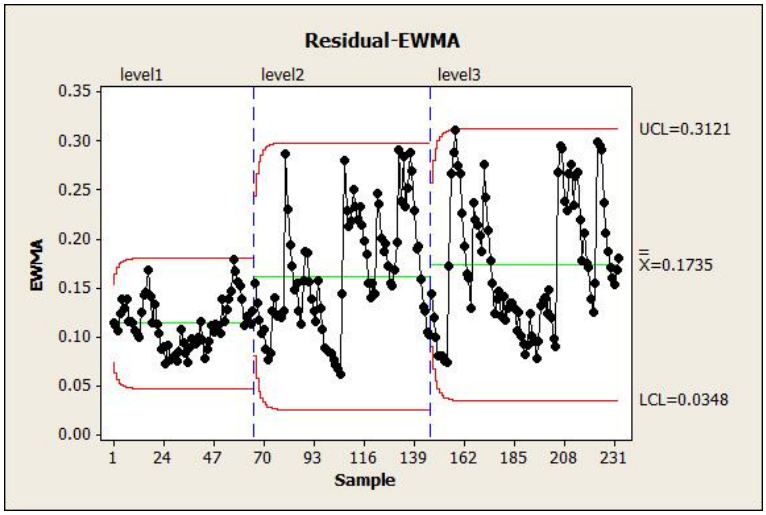

Figure 3. R_EWMA Control Chart

5. Discussion and Results

In order to discover and diagnose medical errors, it is possible to utilize statistical quality control charts. These charts are mostly used in industry. With the help of control charts, three levels of intensity for heart failure can be defined. Furthermore, if any point falls outside the control limits, the course of treatment for patients will be regarded to be out of control and the reasons for the exacerbation of the disease will be examined. It facilitates the diagnosis process and takes the treatment of the disease under control. In addition to psychological comfort and enhancing patient safety, the diagnosis and control of treatment optimizes a large part of the costs of health services for the patients.

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