ISSN: 2251-9246
EISSN: 2345-6221
pp. 105:116

Fault Diagnosis in a Distillation Column Using a Support Vector Machine Based Classifier

Ebrahim Mirakhorli[1], Mehdi Siahi[2]

[1] Faculty of Engineering, Islamic Azad University, Central Tehran Branch, Tehran, Iran
[2] Faculty of Mechanics, Electrical Power and Computer, Science and Research Branch, Islamic Azad University, Tehran, Iran

Abstract

Fault diagnosis has always been an essential aspect of control system design. This is necessary due to the growing demand for increased performance and safety of industrial systems is discussed. Diagnostic classification is not necessarily a problem because we need a mapping from the measurement space to state space system fault will be done. Support vector machine classifier is a new technique based on statistical learning theory and is designed to reduce structural bias. It is famous because of the ability to generalize of Support Vector Machine is significant when compared to conventional classification algorithms offers**.** Support vector machine classification in many applications in various fields of machine learning has been successful and appears to be effective for fault diagnosis in industrial systems. This project is to design a support vector machine fault diagnosis system for a distillation tower as a key component of the process**.** The study included 41 stage distillation condenser and boiler theory is that a combination of two partial products of 99% purity breaks Based on the calculations, modeling and simulation is a tray to tray. Considering the variety of different origins faults in the system under study, a multi-class classification problem can be achieved two techniques commonly used to solve multi-class classification for support vector machine as "one to one" and "one against all" is used. The classifier models designed to detect faults in the systems studied were evaluated as successful results were obtained for all types of faults. The model was designed based on the speed in detecting various faults were compared on the basis of support vector machine model based on a technique called "One on One" have delivered a better performance**.**

Keywords: Fault diagnosis, distillation, support vector machines, a multi-class classification
Article history: Received 08-Feb-2020; Revised 25-Mar-2020; Accepted 22-Jun-2020.

1. Introduction

Faults can always be expected to occur in different forms during the running time of any dynamic system. These faults can occur as any change in the physical conditions of the various components of system, control equipment as well as external conditions. Faults can appear as such as pressure deviation or partial temperature of the system from normal, or physical changes to system components such as leakage, decay, bursting, valve retention, and so on. Even changes in non-measurable system variables, such as the heat transfer coefficient in a heat exchanger, can be a sign of fault. To be more precise, any deviation of characteristic properties or system parameters from acceptable values or standard conditions can be considered as fault [1]. Fault diagnosis in this work means the discovery of the root and the cause of the fault. In fact, the physical cause of the fault, such as failure in a sensor, change in inlet fluid flow, leakage in transmission pipes, and so on must be determined. Research into fault diagnosis and identification, not only to reduce economic costs but more importantly to secure and protect human lives, has received much attention in recent decades. The catastrophe at the 1986 Chernobyl nuclear power plant is a good example of the importance of studying fault in order to achieve modern high security control systems. Full reliance on the human operator to deal with abnormal events is becoming increasingly difficult with complex systems under control in many respects. For a process operator, it is very difficult to detect the occurrence of an fault by timely evaluating the numerous physical variables that are nowadays measured and recorded in modern control systems. Faults are much more difficult to distinguish and identify because of the huge amount of process knowledge they need and the timely diagnosis of faults. It also should be noted the possibility of human faults in decisions, because, as has been reported in previous work, much of industrial accidents that occurred due to human faults [2]. These problems highlight the necessity of machine fault diagnosis and the production of automated decision-making tools to assist the human operator in detecting abnormal behavior in modern control systems. Hence, both academic researchers and industry activists have been keen to work in this field for decades.

2. Fault diagnosis in a dual-distillation tower

A) Introduction

Distillation is one of the most important separation processes used in chemical process units. This is done in the distillation tower and after the distillation operation, the feed is divided into two or more products with different concentrations. In order to achieve optimum quality, distillation tower conditions must be controlled. For this purpose, fault diagnosis is one of the essential requirements. Changes in input fluid characteristics are one of the most important faults that directly affect output quality. These changes must first be identified by the fault diagnosis system to take further steps to address the fault and eliminate its adverse effect on the system output. Typically, the design of a fault diagnosis system is based on data obtained from a simulated model. For the distillation tower, this simulated model is derived from physical equations in the form of tray-to-tray calculations. Using a simulated model for fault diagnosis allows the appropriate amount of data to be retrieved from the system and also to simulate variables that cannot be measured online in a real process. As a result, a more detailed analysis of the performance of the fault diagnosis system and the optimal design can be achieved. If we are to design a fault diagnosis system based on the performance of the actual model, there must first be a process fault, a variety of possible faults, and process performance data. Each of these fault modes has been collected and therefore it would not be possible to design a fault diagnosis system before the system fault occurred. Here, we seek to design and implement a system for the diagnosis and classification of all types of faults in a two-part continuous distillation tower using a support vector machine class. Distillation tower modeling and simulation is then performed. It also discusses how to obtain fault data from the simulated model. In the next steps, it presents the method of designing and implementing a fault diagnosis system using a backup vector machine based on the data obtained. In this section, the support vector machine based on two common techniques one against one and one against all will be used to solve the problem of multi-class fault diagnosis. Finally, the following systems are designed to evaluate and compare the performance of the model online.

B) Distillation modeling and simulation

The two-part distillation tower referred to in [38] has been studied as "column A". The tower has 41 stages of theory including a condenser and a welder that breaks down a two-component compound with a relative volatility of 1.5 to products with 99% purity. The schematic diagram of the distillation tower is shown below.

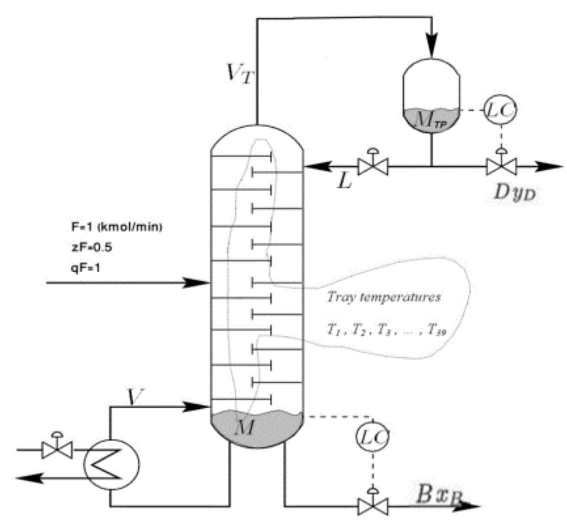

Fig. 1. Schematic diagram of the distillation tower studied

This section presents the distillation modeling equations. In the modeling of the tower, the following assumptions are taken into account:

– Composition of two-component inlet fluid.
– The pressure on the tower is constant.

ISSN: 2251-9246
EISSN: 2345-6221

- Relative volatility is constant.
- Balance is maintained at all stages.
- The distillation is performed in the condenser completely.
- Discard steam.
- Linear fluid dynamics are assumed but the vapor flow effect ("K-2 effect") is considered.

Although these assumptions seem rigorous, the important effects of distillation dynamics that are required for fault diagnosis work are taken into account in the resulting model. Before presenting the model equations, the list of signs and variables of the tower are listed in the table 1. The names of the tower variables are also presented in the table 2.

3. Dynamic Basic Equations of Distillation Tower

- Total mass balance equation in step i:

$$\frac{dM_i}{dt} = L_{i+1} - L_i + V_{i-1} - V_i$$

- Mass balance equation for light component in step i:

$$\frac{d(M_i x_i)}{dt} = L_{i+1}x_{i+1} + V_{i-1}y_{i-1} - L_i x_i - V_i y_i$$

Which results for the molar percentage derivative of the light component in the liquid:

$$\frac{dx_i}{dt} = \frac{\left(\frac{d(M_i x_i)}{dt} - x_i \frac{dM_i}{dt}\right)}{M_i}$$

- Algebraic Equations:

The vapor concentration of y_i is related to the liquid concentration of x_i in the same step by the algebraic liquid-vapor equilibrium equation:

$$y_i = \frac{\alpha x_i}{1 + (\alpha - 1)x_i}$$

Given the steady flow of steam and not taking into account the dynamic effect of steam, we will have the following statement for steam discharge (at all stages except the feed stage):

$$V_i = V_{i-1}$$

And for the feed stage:

$$V_{NF} = V_{NF-1} + (1 - q_F)F$$

Table.1.
List of signs and variables of the tower

Description (unit)	***V***
Step number (1 = boiling point, NF = feed stage and NT = condenser(	i
Relative volatility between light and heavy fluid	α
Time constant for fluid flow dynamics at each step	τ
Constant Effect of Steam Flow on Liquid Flow ("K2-effect("	λ
Liquid flow in phase i (kmol / min)	L_i
Steam flow in phase i (kmol / min)	V_i
Light component concentration in liquid in phase i (mol fraction)	x_i
Light component concentration in vapor in phase i (mole fraction)	y_i
Liquid retention in phase i (kmol)	M_i
High flow distillation product flow rate (kmol / min)	D
High product concentration (mole fraction)	y_D
Low distillation tower flow rate (kmol / min)	B
Low mole fraction product concentration	x_B
Recirculating fluid flow rate (kmol / min)	L=LT
Steam tower flow rate (kmol / min)	V=VB
Input feed rate (kmol / min)	F
Mole fraction of input feed	Z_F
Percentage of steam in the feed	q_F

Table.2.
Tower Variables

Nominal value	***Variables***
41	NT
21	NF
0.063 min	τ
0 min	λ
0.5 kmol/min	D
0.99	y_D
0.5 kmol/min	B
0.01	x_B
2.706 kmol/min	L=LT
3.206 kmol/min	V=VB
1 kmol/min	F
0.5	Z_F
1	q_F

The fluid flow depends on the amount of fluid retention and the steam flow with the following relationship:

$$L_i = L_{0i} + \frac{M_i - M_{0i}}{\tau} + (V_{i-1} - V_{0i-1})\lambda$$

Where L_{0i} and M_{0i} are the nominal values for fluid flow and fluid retention in phase *i*, respectively.

The above equations are for all stages except the highest (condenser), lowest (boiling) and feedstock. We have the following equations for these steps.

For the feed stage (i = NF):

$$\frac{dM_i}{dt} = L_{i+1} - L_i + V_{i-1} - V_i + F$$

$$\frac{d(M_i x_i)}{dt} = L_{i+1}x_{i+1} + V_{i-1}y_{i-1} - L_i x_i - V_i y_i + F z_F$$

For condenser: ($i=NT$, $M_{NT} = M_D$, $L_{NT}=L_T$)

$$\frac{dM_i}{dt} = V_{i-1} - L_i - D$$

$$\frac{d(M_i x_i)}{dt} = V_{i-1}y_{i-1} - L_i x_i - D x_i$$

And for boiling ($i=1$, $M_i = M_B$, $V_i = V_B = V$):

$$\frac{dM_i}{dt} = L_{i+1} - V_i - B$$

$$\frac{d(M_i x_i)}{dt} = L_{i+1}x_{i+1} - V_i y_i - B x_i$$

4. Fault simulation and data generation

The modeled distillation tower consists of a manipulated variable face (L, V, B , D) and four control variables (M_D, M_B, x_B, x_D) that are unstable in the open loop. To stabilize the model, we used two PI controllers to control the water level in the boiler (M_B) and condenser (M_D) by manipulating the low product discharge (B) and high product (D) variables, respectively. For each of the controllers, the values of proportional interest 1 and integral interest are 0.5. The liquid flow (L) and vapor flow (V) variables can then be used to control high and low product concentrations (x_B, x_D). This control structure is called the L-V structure [39]. It is worth noting, however, that since the concentration measurement online is difficult and costly to use in the distillation tower, the inference control system is used to control it. Thus, instead of directly measuring the concentration of high and low products (x_B, x_D), they are measuring the temperatures of high tray (T39) and low tray (T1), respectively, and by using them, the concentration values are estimated. [40]. Since the implementation of the inferential control system is not part of the objectives of this project, the distillation tower is simulated in terms of open loop concentration variables for the design and implementation of the fault diagnosis system. Next, system faults should be simulated. For this purpose, in this work, five types of faults due to changes in input feed variables are considered. These faults are shown in the table 3, which include changes in feed rate (F), change in feed concentration (z_F) and change in feed vapor percentage (q_F).

Table.3.
Changing feed rate(F) in different faults

Fault	Fault root
Fault 1	Increase in input feed rate (F> 1 kmol / min)
Fault 2	Decrease in feed feed rate (F <1 kmol / min
Fault 3	Increase in input feed concentration (ZF <0.5)
Fault 4	Decrease in feed concentration (0.5> ZF)
Fault 5	Fluidization of a portion of the input feed (1> qF)

To simulate each fault, the system is executed when a step change is considered in the corresponding variable and the other variables are kept constant in their name state. System simulation was performed in normal operation mode as well as various fault modes in MATLAB environment. The simulated model was run 6 times corresponding to a normal mode and 5 different fault types. The simulated model runs for 200 minutes for each operating mode because in each fault, after 200 minutes of simulation, the tower variables reach a new steady state after a transient state. To solve the simulated equations, ODESOLVER in MATLAB and ODE45 function with 1 second integration time are used.

Although all the distillation tower variables, including the concentration, retention and temperature of all steps, are derived from the simulated model, but of all the variables, the only variables that are actually measured from a real distillation system are measured as variables. They should be recorded and later included as input to the fault diagnosis algorithm. The variables measured from the tower are the manipulable variables and the control variables as mentioned at the beginning of the section, including liquid level variables in the welder (MB), liquid level in the condenser (MD), high tray temperature (T39), temperature Low tray (T1), high product flow (D), low product flow (B), liquid flow (L) and steam flow (V). Also, since the control system is not considered for concentration control, the manipulable variables L and V are always constant and equal to their nominal values during the simulation, so we exclude them from the set of measured variables. As a result, at each

simulation moment, the measurement vector contains 6 variables as follows:
$X = [M_B, M_D, T_1, T_{39}, D, B]$

Also, some Gaussian noise as a measurement noise was added to all the measured variables to bring the data from the simulated model as close as possible to the actual data. The following figure shows the measurement variables under normal operation mode as well as various faults for 200 minutes of simulation.

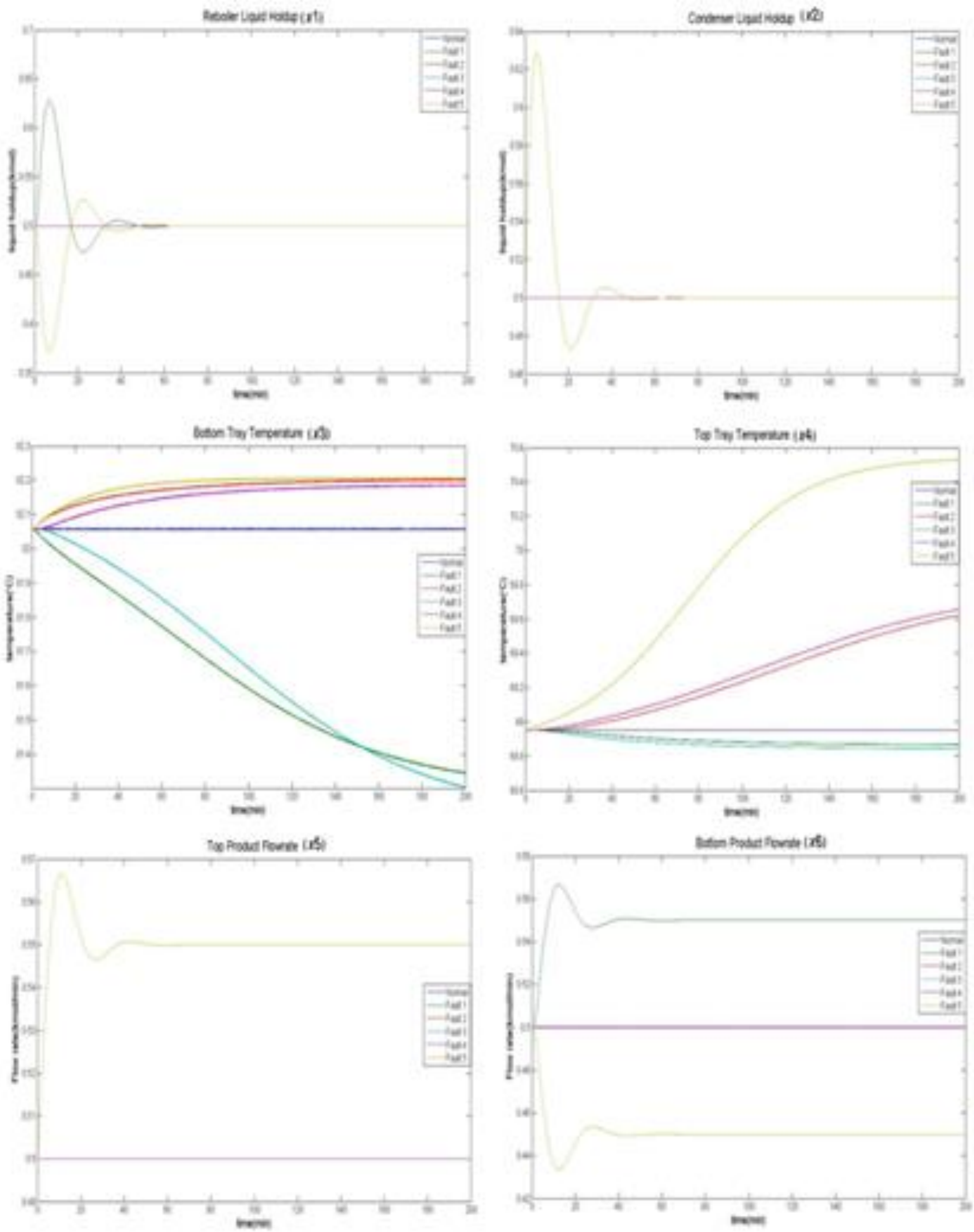

Fig. 2. Distillation function in normal mode and various faults

5. Training the classifier

Next, the classification algorithm should be designed using the data sampled from the simulation model. Typically, each algorithm has parameter classification or parameters that must be appropriately selected during training to achieve optimal performance. For example, for neural networks, the number of hidden layers as well as the number of neurons within these layers should be determined. For the support vector machine, the penalty parameter C must be set before training the algorithm.

Also, if you want to use a nonlinear classifier, which in most cases is necessary to take into account the nonlinearity of the systems, it is necessary to specify a proper kernel function as well as the values of its related parameters. Of the various kernels introduced for this purpose, the Gaussian function is the most common. The Gaussian kernel function is determined by only one parameter (γ) that can approximate the linear kernel functions as well as polynomials by setting this parameter. It also faces fewer numerical problems than the polynomial kernel and sigmoid [44]. Hence in this work we use Gaussian kernel function for nonlinear backup vector machine. Therefore, in order to train the algorithm, parameter pairs (C, γ) must be selected. The selection of the parameters of the model design classification algorithm is called. Model design is a major step in teaching the classification algorithm.

A) Online evaluation of the fault diagnosis system

We have defined all the faults that occur for the system, both abruptly and incipiently for 100 minutes of tower performance, simulated, and at each simulation moment the measured variables of the system are designed to both algorithms. (One against one and one against all) are presented and the output of each algorithm is recorded at the same instant. The output of the fault diagnosis algorithm for each input data at any given moment is, in fact, a discrete value indicating the operating state of the system. For both abrupt and incipient fault, the fault start time was set to zero, so it has been operating from the very beginning of the system simulation in the desired fault state. Also, the fault session time was set to incipient fault and 100 minutes for all faults. The following figures show the results. Note that zero output in these diagrams means the normal state of the system.

As can be seen from the results, both models work one against one and one against all against the diagnosis and diagnosis of all faults in both abrupt and incipient failure, though in some cases at the beginning of time Fault startups, system operating state not correctly detected. Also, for all fault cases, as expected, both models were able to detect abrupt type faults in a shorter time than incipient type faults. Because, as mentioned, the incipient faults in the early simulation times are low intensity and do not cause significant deviation in the system variables. But as time goes on, the fault grows and exerts its effect on the system, so as shown in the graphs, both algorithms designed at the beginning of the fault classify the system as normal. Also, in most cases (faults 1, 2 and 5) after some time the fault in the system has been detected by the algorithm but the type of fault has been misidentified. Finally, the algorithm has been able to correctly identify and report the type of fault at the end times when the fault approaches its session state. It should be noted, however, that this behavior of the algorithms designed to detect incipient faults should not be regarded as weaknesses of the algorithm. Because, as discussed earlier in this section, incipient faults are not easy to identify for each fault diagnosis algorithm because of the type of behavior they have. In sum, if an algorithm can detect an incipient fault before the fault arrives at its session time, it can be stated that the algorithm has been successful in detecting that fault. Therefore, given the diagrams since all the simulated incipient faults in this work are correctly identified before their session time (100 minutes) is correct, the performance of both algorithms designed in this work can be considered acceptable. As can be seen, the performance of one-to-one and one-to-one algorithms are very similar in most cases.

In order to evaluate the performance of these two algorithms more precisely and quantitatively compare them, we define the diagnosis time parameter as the first time that the algorithm has been able to detect a fault in the system. Of course, this diagnosis can be true if the fault label predicted by the algorithm matches the actual label of the fault occurring in the system and is otherwise incorrect. According to this definition, diagnosis times for abrupt and incipient faults are also reported respectively. As can be seen, the performance of the two algorithms one against one and one against all is very close to each other, but in most cases and also based on the calculated average fault, the algorithm has been more successful against one.

Previous work has also compared the performance of the two algorithms based on classification accuracy, with the predominance of algorithm one over the other [36]. It should be noted, however, that, as noted earlier, the ratio of binary classes in algorithm one to one in binary classes in algorithm one is equal to m-1 (m is the number of classes). This ratio is significant for problems with high class numbers, which makes the computation volume one by one much larger than one by all. Thus, although one-to-one algorithms may often provide more classification power than one-to-all, as the results in this work indicate, but for problems with high class numbers, many becoming an educational calculator is not recommended.

6. Conclusion

In this work, fault diagnosis, which means finding the root of the fault occurring in a dynamic system, was investigated using pattern recognition techniques or classification techniques. In Section 2, it is argued that the main idea behind pattern recognition fault-based methods is that the fault of different origins affects the system variables in different ways and excludes them from their normal states. In this case, any operating mode of the system, both normal or fault types can be considered as a template, and data from different system measurements in each of these patterns are introduced to the pattern recognition algorithm. Then the pattern recognition algorithm based on the different working patterns of the training system will then be able to separate the trained patterns and predict the working state of the system for each new input data.

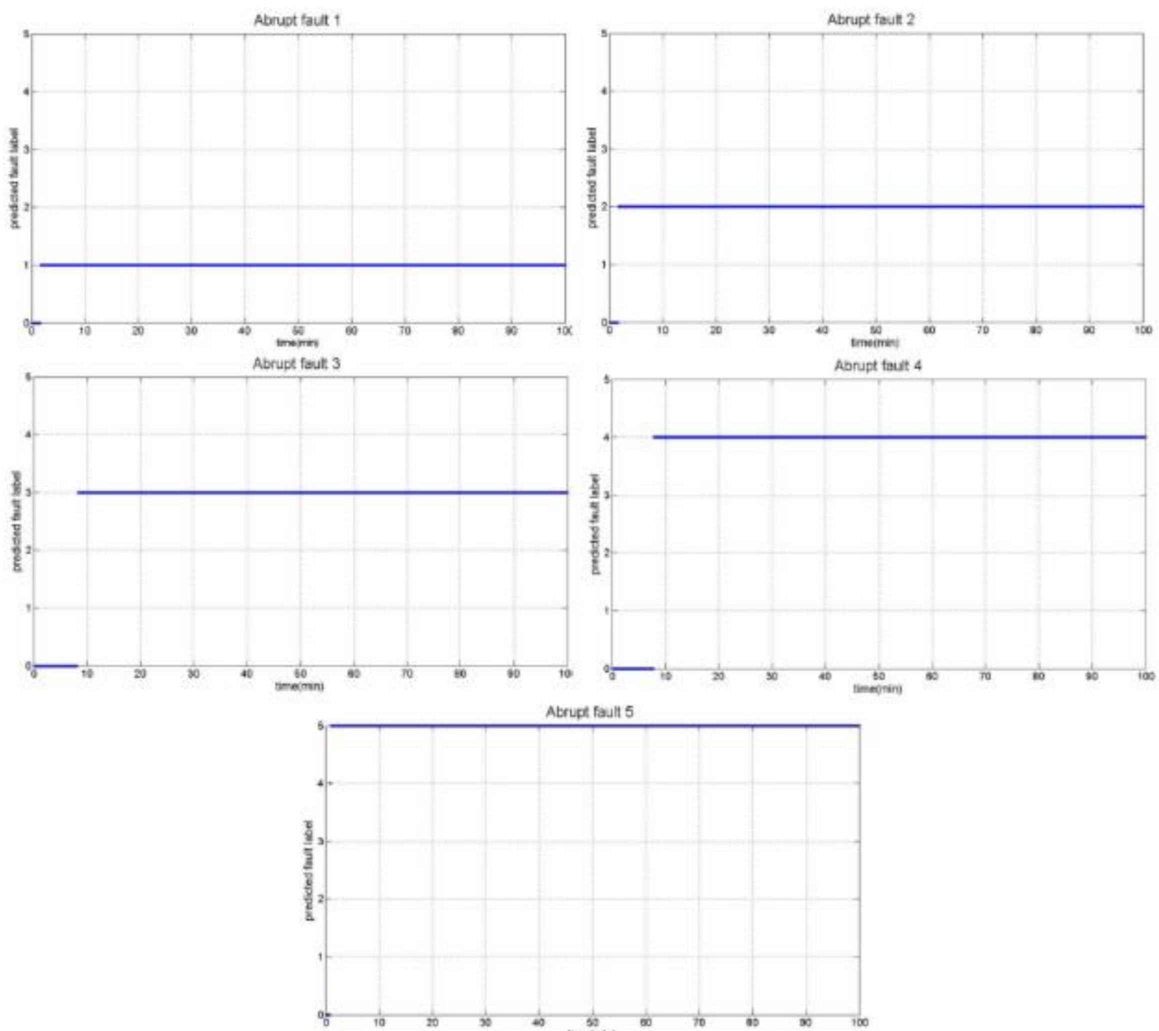

Fig. 3. Model one-to-one output in detecting abrupt faults

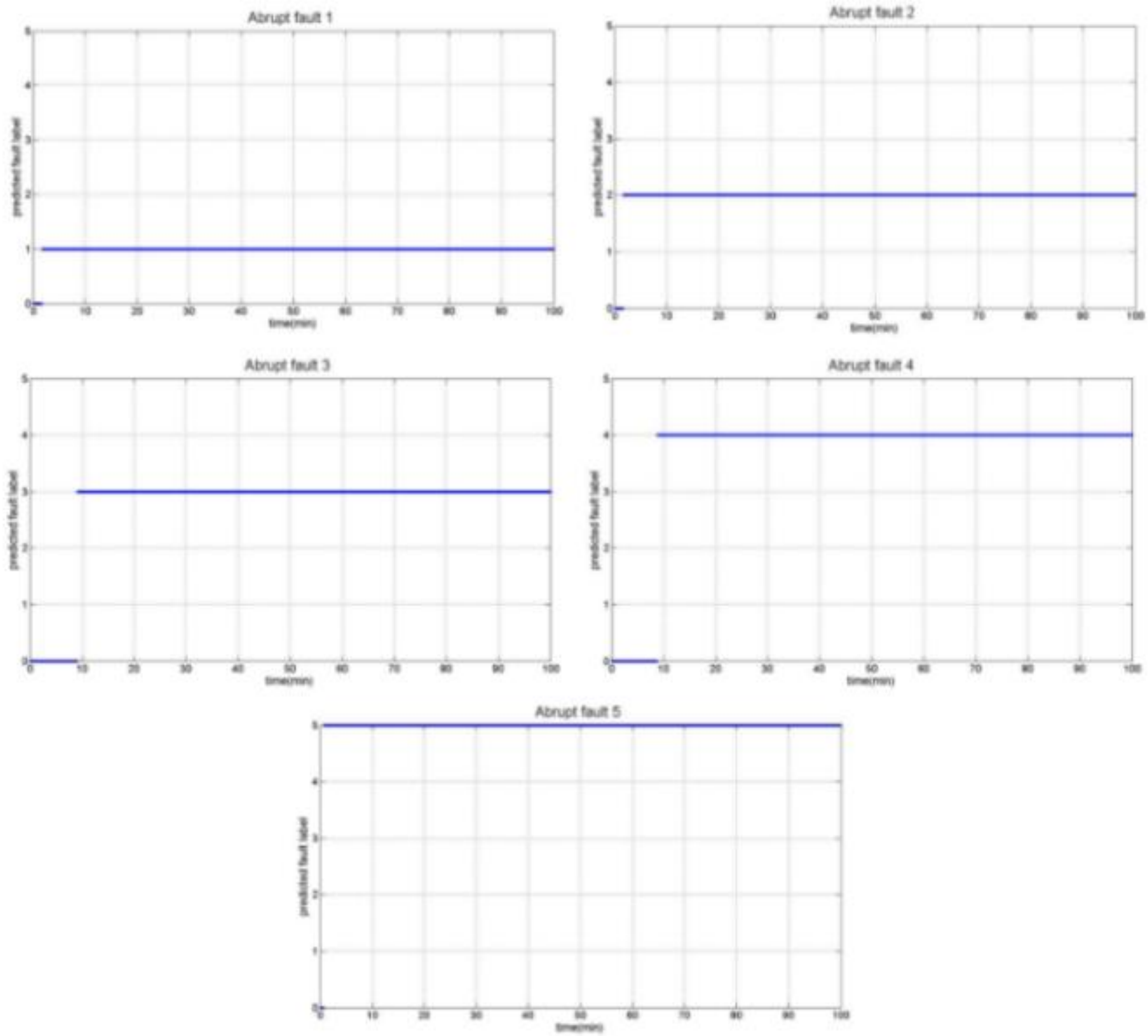

Fig. 4. Model output one against all in detecting abrupt faults

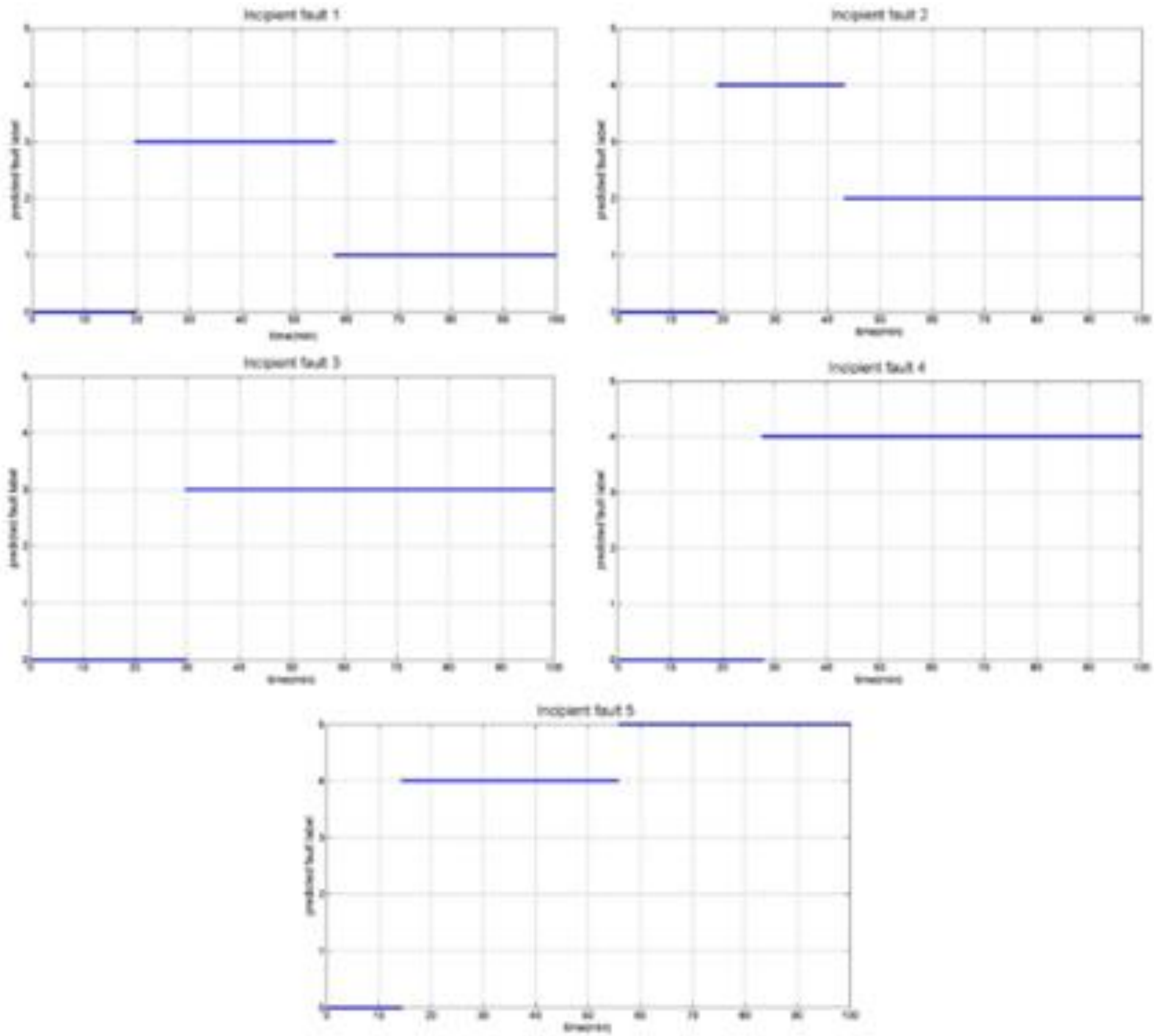

Fig. 5. Model one-by-one output in the diagnosis of incipient faults

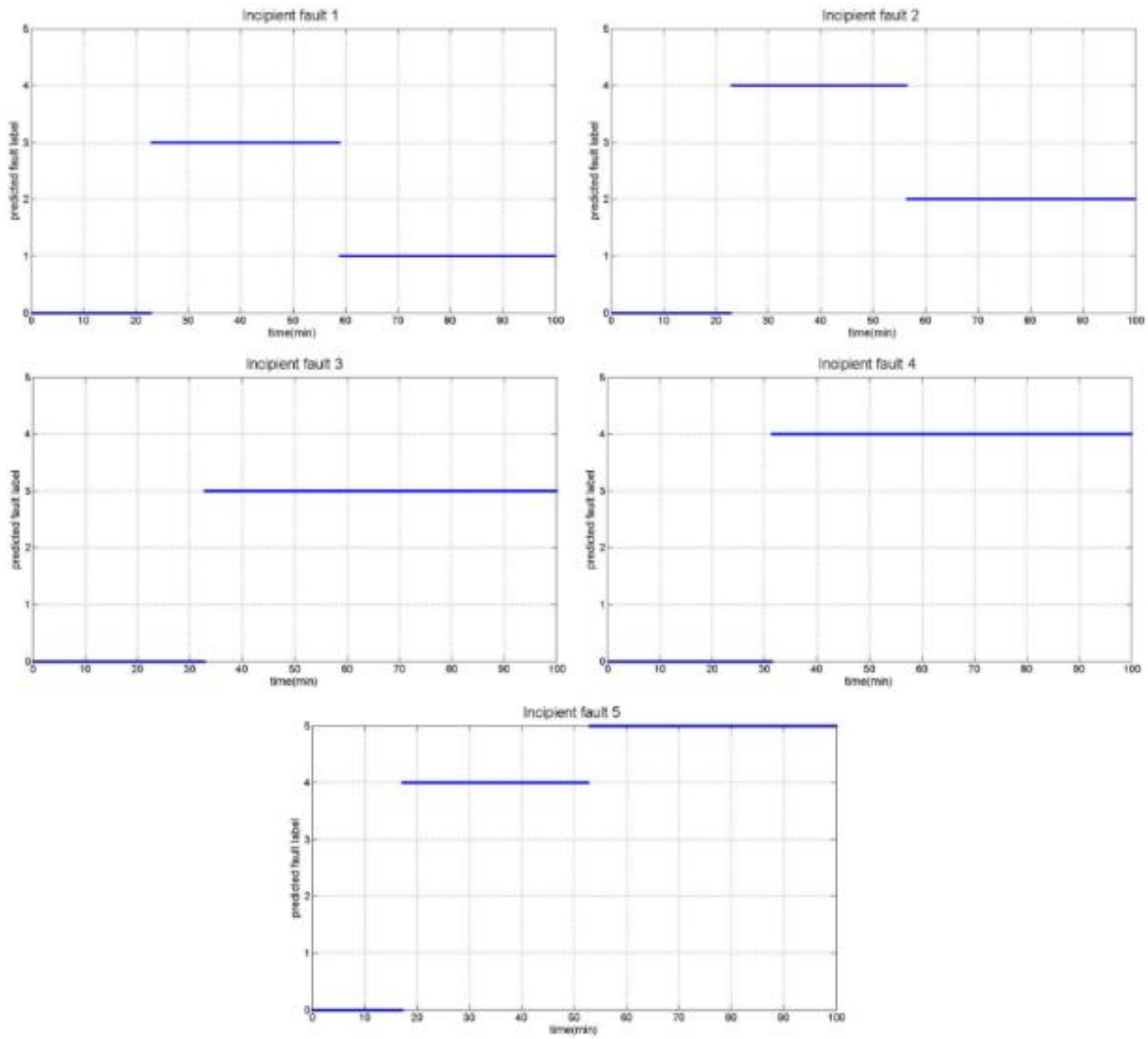

Fig. 6. Model output one against all in the diagnosis of incipient faults

The most important advantage of these methods is that there is no need for quantitative mathematical modeling or qualitative knowledge of the system under study, and the fault diagnosis algorithm is designed only using data collected from system historical performance. Of course, there is a need for all modes of data system operation as well as the quality and quantity of data available has a direct impact on the performance of the designed system. The main disadvantage of these methods is that the designed pattern recognition algorithm is only able to detect the faults based on which it is trained and fails to identify faults where the training data was not available. It was found that among the various methods available for classification, the powerful back-vector algorithm is more popular. It was pointed out that vector machine support is a new machine learning method designed to reduce structural fault. This means that in support vector machine training, unlike previous classification methods, it is not only about reducing the fault for the training data but also about the fault process for the training of the neglected data. For this purpose, a parameter named margin was introduced in relation to the two-class data splitter pages, and it was noted that based on statistical learning theories, the optimal splitter page with the least fault for the ignored data is the page with the most margins. Be it. According to this principle, the objective function in the support vector machine is defined to obtain the most margin. A significant reduction in generalization fault compared to classical classification methods is one of the most important advantages of a support vector machine, especially when it comes to quantitative training data. One of the major disadvantages of a support vector machine is that it is designed to solve two-class problems and cannot be directly used in multi-class problems. In practice, however, we encounter a multi-class problem in many classification applications, including the fault diagnosis discussed in this article. To solve this problem, two techniques were introduced, one against one and one against all, which are based on converting a multi-class problem into several two-class problems and then using a support vector machine to solve these two-class problems.

In this work, a two-component distillation tower was selected as the case study. Dynamic equations of this distillation tower were obtained by tray-to-tray calculations and then these equations were programmed in MATLAB environment. In this way, a simulated model was developed that used the data needed for the fault diagnosis algorithm. For this purpose 5 types of faults of different origin were defined and simulated distillation was performed under each of these faults and different measurements were recorded. Then, using the data obtained, the classification vector algorithm was designed based on the support vector machine as a fault diagnosis system. Since we faced a multi-class classification problem, we used one-to-one and one-to-one techniques and trained two different classification models. The most important issue to consider in class instruction is the correct selection of the training parameters of the models, using a method called cross-evaluation based on the network search process. Finally, the designed models were evaluated in the online distillation performance. In evaluating online classification models, two different types of abrupt and incipient faults were considered, both models being able to correctly detect all faults in the system. However, by introducing a parameter called the diagnosis time, which represents the time between the start of the fault in the system and its diagnosis by the fault diagnosis algorithm, it was found that the model based on the one-to-one technique performed better. However, using one-to-one techniques in fault diagnosis problems with a high number of faults is not recommended due to the high amount of training calculations.

Reference

[1] R. Isermann, Fault-diagnosis systems: an introduction from fault detection to fault tolerance. Springer, 2005.

[2] V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S. N. Kavuri, “A review of process fault detection and diagnosis: Part I: Quantitative model-based methods,” Computers & chemical engineering, vol. 27, no. 3, pp. 293-311, 2003.

[3] V. Venkatasubramanian, R. Rengaswamy, S. N. Kavuri, and K. Yin, “A review of process fault detection and diagnosis: Part III: Process history based methods,” Computers & chemical engineering, vol. 27, no. 3, pp. 327-346, 2003.

[4] C. M. Bishop, Neural networks for pattern recognition. Oxford university press, 1995.

[5] V. Vapnik, The nature of statistical learning theory. springer, 2000.

[6] L. Wang, Support Vector Machines: theory and applications, vol. 177. Springer, 2005.

[7] L. H. Chiang, M. E. Kotanchek, and A. K. Kordon, “Fault diagnosis based on Fisher discriminant analysis and support vector machines,” Computers & chemical engineering, vol. 28, no. 8, pp. 1389-1401, 2004.

[8] J. J. Downs and E. F. Vogel, “A plant-wide industrial process control problem,” Computers & Chemical Engineering, vol. 17, no. 3, pp. 245-255, 1993.

[9] Y. Mao, Z. Xia, Z. Yin, Y. Sun, and Z. Wan, “Fault diagnosis based on fuzzy support vector machine with parameter tuning and feature selection,” Chinese Journal of Chemical Engineering, vol. 15, no. 2, pp. 233-239, 2007.

[10] I. Yélamos, M. Graells, L. Puigjaner, and G. Escudero, “Simultaneous fault diagnosis in chemical plants using a multilabel approach,” AIChE Journal, vol. 53, no. 11, pp. 2871-2884, 2007.

[11] I. Yélamos, G. Escudero, M. Graells, and L. Puigjaner, “Performance assessment of a novel fault diagnosis system based on support vector machines,” Computers & Chemical Engineering, vol. 33, no. 1, pp. 244-255, 2009.

[12] I. Monroy, R. Benitez, G. Escudero, and M. Graells, “A semi-supervised approach to fault diagnosis for chemical processes,” Computers & Chemical Engineering, vol. 34, no. 5, pp. 631-642, 2010.

[13] C. S. Tyagi, “A comparative study of SVM classifiers and artificial neural networks application for rolling element bearing fault diagnosis using wavelet transform preprocessing,” Neuron, vol. 1, p. 1, 2008.

[14] A. Prieto-Moreno, O. Llanes-Santiago, and E. Garcıa-Moreno, “Fault diagnosis in industrial process: A comparison of classification methods.”

[15] M. Guo, L. Xie, S.-qing Wang, and J.-M. Zhang, “Research on an integrated ICA-SVM based framework for fault diagnosis,” in Systems, Man and Cybernetics, 2003. IEEE International Conference on, 2003, vol. 3, pp. 2710-2715.

[16] X. U. Jie and H. U. Shouson, “Nonlinear process monitoring and fault diagnosis based on KPCA and MKL-SVM,” Chinese Journal of Scientific Instrument, vol. 31, no. 11, pp. 2428-2433, 2010.

[17] J. Xu, J. Zhao, B. Ma, and S. Hu, “Fault Diagnosis of Complex Industrial Process Using KICA and Sparse SVM,” Mathematical Problems in Engineering, vol. 2013, 2013.

[18] D. A. Brydon, J. J. Cilliers, and M. J. Willis, “Classifying pilot-plant distillation column faults using neural networks,” Control Engineering Practice, vol. 5, no. 10, pp. 1373-1384, 1997.

[19] R. Sharma, K. Singh, D. Singhal, and R. Ghosh, “Neural network applications for detecting process faults in packed towers,” Chemical Engineering and Processing: Process Intensification, vol. 43, no. 7, pp. 841-847, Jul. 2004.

[20] R. M. Behbahani, H. Jazayeri-Rad, and S. Hajmirzaee, “Fault detection and diagnosis in a sour gas absorption column using neural networks,” Chemical engineering & technology, vol. 32, no. 5, pp. 840-845, May 2009.

[21] L. H. Chiang, R. D. Braatz, and E. L. Russell, Fault detection and diagnosis in industrial systems. Springer, 2001.

[22] R. Isermann, “Model-based fault-detection and diagnosis–status and applications,” Annual Reviews in control, vol. 29, no. 1, pp. 71-85, 2005.

[23] V. Venkatasubramanian, R. Rengaswamy, and S. N. Kavuri, “A review of process fault detection and diagnosis: Part II: Qualitative models and search strategies,” Computers & Chemical Engineering, vol. 27, no. 3, pp. 313-326, 2003.

[24] Q. P. He and J. Wang, “Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes,” Semiconductor Manufacturing, IEEE Transactions on, vol. 20, no. 4, pp. 345-354, 2007.

[25] S. Verron, T. Tiplica, and A. Kobi, “Fault diagnosis of industrial systems by conditional Gaussian network including a distance rejection criterion,” Engineering Applications of Artificial Intelligence, vol. 23, no. 7, pp. 1229-1235, 2010.

[26] L. H. Chiang and R. J. Pell, “Genetic algorithms combined with discriminant analysis for key variable identification,” Journal of Process Control, vol. 14, no. 2, pp. 143-155, 2004.

[27] T. Sorsa and H. N. Koivo, “Application of artificial neural networks in process fault diagnosis,” Automatica, vol. 29, no. 4, pp. 843-849, 1993.

[28] H. N. Koivo, “Artificial neural networks in fault diagnosis and control,” Control Engineering Practice, vol. 2, no. 1, pp. 89-101, 1994.

[29] Y. Maki and K. A. Loparo, “A neural-network approach to fault detection and diagnosis in industrial processes,” Control Systems Technology, IEEE Transactions on, vol. 5, no. 6, pp. 529-541, 1997.

[30] B. E. Boser, I. M. Guyon, and V. N. Vapnik, “A training algorithm for optimal margin classifiers,” in Proceedings of the fifth annual workshop on Computational learning theory, 1992, pp. 144-152.

[31] مهدی صالح پور. "بازنویسی ارقام دستنویس فارسی مقاوم در برابر چرخش فازی مبتنی بر خوشه بند SVMو تغییر مقیاس توسط طبقه بندی کننده "k-means. نخستین کنفرانس پردازش خط و زبان فارسی، ۱۳۹۱.

[32] محمد شهرام معین، ابراهیم بهینه. "بررسی برای SVM روش سازی روزگار. تصویر از استفاده با هویت چهره".

[33] محمدمهدی همایون پور، محمدحسین سنی گوینده به خسروی. "تعیین محدوده سنی گوینده به کمک صدا با استفاده از ماشین بردار پشتیبان".

[34] فاطمه السادات طباطبایی عینکی، بهروز مینایی بیدگلی، فریبا مینایی بیدگلی. "ترکیب Feature Selection و SVM جهت تشخیص سرطان سینه". پنجمین کنفرانس داده کاوی ایران، ۱۳۹۰.

[35] S. R. Gunn, “Support vector machines for classification and regression,” ISIS technical report, vol. 14, 1998.

[36] C. W. Hsu and C. J. Lin, “A comparison of methods for multiclass support vector machines,” Neural Networks, IEEE Transactions on, vol. 13, no. 2, pp. 415-425, 2002.

[37] S. Mahadevan and S. L. Shah, “Fault detection and diagnosis in process data using one-class support vector machines,” Journal of Process Control, vol. 19, no. 10, pp. 1627-1639, Dec. 2009.

[38] S. Skogestad and M. Morari, “Understanding the dynamic behavior of distillation columns,” Industrial & engineering chemistry research, vol. 27, no. 10, pp. 1848-1862, 1988.

[39] S. Skogestad, “Dynamics and control of distillation columns: A tutorial introduction,” Chemical Engineering Research and Design, vol. 75, no. 6, pp. 539-562, 1997.

[40] جواد ایوک پور، تیمور منصور لکورج، فرشته نعیم پور. "کنترل استنتاجی برج تقطیر". نهمین کنگره ملی مهندسی شیمی ایران، ۱۳۸۳.

[41] I. Yélamos, G. Escudero, M. Graells, and L. Puigjaner, “Performance assessment of a novel fault diagnosis system based on support vector machines,” Computers & Chemical Engineering, vol. 33, no. 1, pp. 244-255, Jan. 2009.

[42] J. Fan and J. Lv, “A selective overview of variable selection in high dimensional feature space,” Statistica Sinica, vol. 20, no. 1, p. 101, 2010.

[43] C. C. Chang and C. J. Lin, “LIBSVM: a library for support vector machines,” ACM Transactions on Intelligent Systems and Technology (TIST), vol. 2, no. 3, 2011.

[44] C. W. Hsu, C. C. Chang, and C. J. Lin, “A practical guide to support vector classification,” 2010.

[45] T. G. Dietterich, “Ensemble methods in machine learning,” in Multiple classifier systems, Springer, 2000, pp. 1-15.

[46] J. Zhang, “Improved on-line process fault diagnosis through information fusion in multiple neural networks,” Computers & chemical engineering, vol. 30, no. 3, pp. 558-571, Jan. 2006.