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A fault detection, diagnosis, and reconfiguration method via support vector machines

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Abstract: This paper presents a fault detection, diagnosis, and reconfiguration method based on support vector machines. This method is appropriate for certain or predetermined faults and involves a fault detection and diagnosis unit and an online controller selection type reconfiguration mechanism. In this method, when a fault is detected and diagnosed by the fault detection and diagnosis unit, a suitable controller, which has been determined via an optimization algorithm in an off-line fashion, is activated to maintain proper closed-loop performance of the system in an on-line manner. In the detection, diagnosis, and reconfiguration stages of the method, support vector classification and regression machines are used and the performance is tested on a simulation model of a two-tank level control system for various fault scenarios.

Key words: Fault-tolerant control, fault detection and diagnosis, support vector machines, PID controllers, two-tank liquid level system

1. Introduction

Fault-tolerant control (FTC) systems have become highly significant, since there has been a rising necessity for dependability, safeness, preservability, and stability in technological systems in last 3 decades. FTC systems have been revealed to defeat some of the weaknesses in the traditional feedback control scheme, such as unstableness and unrewarding success in faulty events. The results of a small fault in the system can be devastating in complicated structures such as nuclear power stations, aircrafts, or chemical equipment [1]. For this reason, it is imperative to build control systems that are capable of tolerating possible faults in such systems. A control system that has this kind of fault tolerance skill is called a FTC system [2]. Fault detection and diagnosis (FDD) is a significant part of the FTC structure. At first, the existence of the fault must be obtained; this is detection. The obtained fault must then be classified correctly; this is diagnosis. Finally, for a decision to be made on the reconfiguration operation, a suitable configuration rule and associated information can be dispatched to a supervision mechanism [3]. In this respect, the detection and the diagnosis of process faults or abnormal situations are essential for any process to operate efficiently. Any equipment within the system may cause faults, such as measurement sensors and/or control actuators. Many FDD techniques have been developed over the last 4 decades [4–10].

Generally speaking, FTC systems are grouped as passive and active types [11–13]. In active FTC systems, the reconfiguration mechanism can be classified as on-line controller selection and on-line controller calculation techniques [14]. In the on-line controller selection approach, the controllers associated with cer-

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tain/predetermined faulty conditions are computed in an off-line manner in the design stage and they are selected in an on-line manner based on real-time data from the FDD algorithm [15]. In the on-line controller calculation approach, the controller parameters are calculated in an on-line manner right after the occurrence of the fault [14,16].

An active FTC technique having an on-line controller selection type reconfiguration mechanism is presented in this study. This method also includes a FDD technique that is appropriate when certain/predetermined faults are considered. In this method, when a fault is diagnosed by the FDD unit, a suitable controller, which has been designed to be optimal according to certain/predetermined faults in an off-line fashion, is selected and activated in an on-line manner to preserve the closed-loop success of the system. The detection and diagnosis parts of the method can be used independently. If it is wanted to find only the existence of the fault, then the regression part of the method can solely be used while the multiclass classification part of the method can be exploited to diagnose any fault that was previously presumed.

Classification and regression mechanisms of support vector machines (SVMs) are described in Section 2, and the method is presented in Section 3. Simulations related to the method are carried out on a two-tank liquid level system and their results are given and discussed in Section 4. Final conclusions and discussions are presented in Section 5.

2. Support vector machines

SVMs have become some of the most famous intelligent learning machines and are a very good option for neural networks. SVMs were introduced by Vapnik [17]. SVMs are used for data analysis, pattern recognition, nonlinear modeling, classification, and regression analysis [18–20]. The SVM is a popular and well-known method used for solving many problems in various areas such as control, communication, and signal processing [21].

2.1. Support vector classification (SVC)

A binary classification method, SVC requires a training set (D) with n-dimensional data vectors ($\mathbf{x} \in R^n$) and their labels $y \in \{-1,\ +1\}$.

$$\begin{array}{l} D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2)...(\mathbf{x}_l, y_l)\}\ , \\ \mathbf{x} \in R^n,\ y \in \{-1, +1\} \end{array} \tag{1}$$

Here, l is the number of training data. The goal is to obtain a linear hyperplane as a separator. This hyperplane must classify the data vectors and the unseen data equally well, as in Eq. (2).

$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = 0 \tag{2}$$

Here, $\mathbf{w} \in R^n$ determines the orientation of the discriminating hyperplane, and $b \in R$ is a bias. For the linearly separable case, a separating hyperplane can be defined for the two classes as follows.

$$\begin{array}{ll} \mathbf{w}^T\mathbf{x}_i + b \geq 1 & \text{if} \quad y_i = 1 \\ \mathbf{w}^T\mathbf{x}_i + b \leq -1 & \text{if} \quad y_i = -1 \end{array} \tag{3}$$

The above two equations can be combined as follows.

$$y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1$$

$$\text{or } sign((\mathbf{w}.\mathbf{x}_i)) + b = y_i \quad i = 1, 2, ..., l \tag{4}$$

Slack variables $\xi_i > 0$ are used to decrease the results of misclassification. The equation above can then be written as follows.

$$y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 - \xi_i \tag{5}$$

The "optimal" hyperplane is located where the margin between two classes of interest is maximized. The problem is to obtain a hyperplane maximizing the interval between the positive and negative data and minimizing the error. This constrained optimization problem can be given as follows.

$$\begin{array}{l} \text{Minimize : } \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{l}\xi_i \\ \text{subject to: } y_i(\mathbf{w}^T\mathbf{x}_i + b) \geq 1 - \xi_i\,, \quad \xi_i \geq 0 \end{array} \tag{6}$$

The constant $C > 0$ is a tradeoff parameter defined by the user. In order to solve this optimization problem, the Lagrangian function is constructed and solved. Some of the Lagrangian multipliers determined will be zero, and the nonzero multipliers are called support vectors. Optimal hyperplane parameters $(\mathbf{w}, b)$ can be determined as:

$$\mathbf{w} = \sum_{j=1}^{s}\alpha_j y_j \mathbf{x}_j \text{ and } b = -\frac{1}{2}\mathbf{w}\left[\mathbf{x}_{+1} + \mathbf{x}_{-1}\right], \tag{7}$$

where α is the Lagrangian multiplier, s is the number of support vector, and $\mathbf{x}_{+1}$ and $\mathbf{x}_{-1}$ are support vectors of two classes. For new test data included in **z**, SVC can be assembled as

$$f(\mathbf{z}) = sign(\mathbf{w}^T\mathbf{z} + b) = sign\left(\sum_{j=1}^{s}\alpha_j y_j(\mathbf{x}_j^T\mathbf{z}) + b\right), \tag{8}$$

where sign(**.**) is the signum function that gives +1 (one class) or –1 (second class).

If the linear hyperplane cannot separate the classes, the input data are mapped onto a higher-dimensional feature space with nonlinear mapping. By means of this mapping, linear classification in the new higher-dimensional feature space stands for nonlinear classification in the original input space [17]. Kernel functions have been introduced to decrease all of these inner product difficulties in the feature space [18]. Replacing the kernel function satisfying the Mercer condition instead of the inner product, the decision function becomes:

$$f(\mathbf{z}) = sign\left(\sum_{j=1}^{s}\alpha_j y_j K(x_j x) + b\right) \quad . \tag{9}$$

Two of the most commonly used kernel functions are:

Polynomial kernel function: $K(\mathbf{x}, \mathbf{x}') = (\langle\mathbf{x}, \mathbf{x}'\rangle + 1)^p$,

Radial basis function: $K(\mathbf{x}, \mathbf{x}') = \exp\left(-\left\|\mathbf{x} - \mathbf{x}'\right\|^2 \Big/ 2\sigma^2\right)$.

2.2. Support vector regression (SVR)

The SVM is largely used for regression problems successfully [21]. Let us consider the data set of the problem:

$$D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2)...(\mathbf{x}_a, y_a)\}\ , \quad \mathbf{x} \in R^n, \quad y \in R \quad , \tag{10}$$

where y is the output and $\mathbf{x}$ is the input of the regression problem. The input-output relation is shown as a regression function to be estimated:

$$f(\mathbf{x}, \mathbf{w}) = \mathbf{w}^T\mathbf{x} + b \quad . \tag{11}$$

In SVR, as distinct from SVC, the approach error is used. There are several loss functions. The ε-tolerance loss function is one of the most popular ones.

$$Y_{\varepsilon} = \begin{cases} 0 \quad if \quad |y - f(\mathbf{x}, \mathbf{w})| < \varepsilon \\ |y - f(\mathbf{x}, \mathbf{w})| - \varepsilon \quad \text{other} \end{cases} \tag{12}$$

In SVR there is a tube or a band with radius ε. This tube is identified around the regression function f(**x**,w). ε can be thought of as a limit of the errors. If the value of the function is inside the tube, it means that there is no loss. The constrained optimization problem is stated and solved by setting the Lagrangian, similar to SVC. The optimum regression hyperplane can then be written as follows:

$$f(\mathbf{x}, \mathbf{w}) = \mathbf{w}^T \mathbf{x} + b = \sum_{\mathrm{S}} (\alpha_i^* - \alpha_i) < \mathbf{x}_i \mathbf{x} > +b \quad , \tag{13}$$

where α and α^* are Lagrange multipliers. By use of the kernel function, the optimum regression function becomes:

$$f(\mathbf{x}, \mathbf{w}) = \sum_{i=1}^{\mathrm{S}} (\alpha_i^* - \alpha_i) K(\mathbf{x}_i \mathbf{x}) + b \quad . \tag{14}$$

3. Proposed method: FTC for certain/predetermined faulty cases

In this section, an active FTC technique for nonlinear systems based on SVM is presented and Figure 1 illustrates the main blocks of this FTC system. In this method, SVR is used in the fault detection process and SVC is used in the diagnosis process. A support vector multiclassification method, one-against-all, is used to classify the occurring fault within a group of expected and predefined faults in the system. When a fault is detected, a suitable controller is selected and activated to maintain the proper closed-loop performance of the system. PID type controllers are used in reconfiguration of the subsystem and their parameters are obtained using a basic genetic algorithm (GA) in an off-line manner.

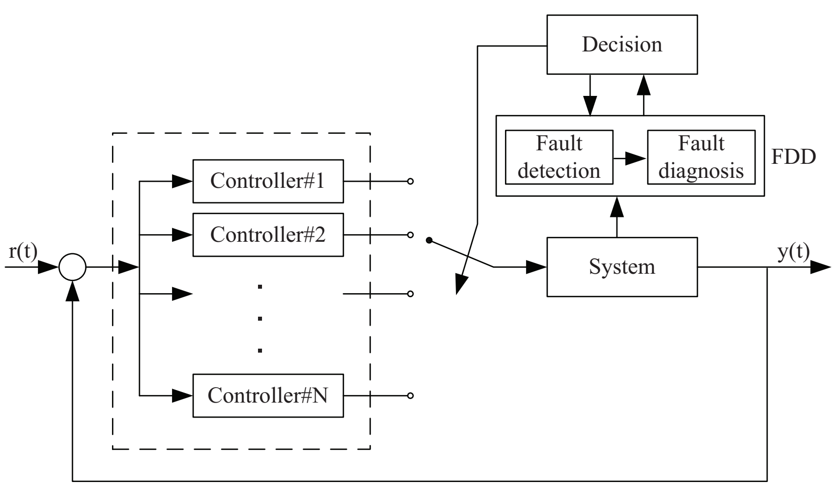

Figure 1. Proposed active fault tolerant control structure.

3.1. FDD via SVM

In this method, the two subtasks of FDD, namely detection and diagnosis, are performed sequentially as given in Figure 2. First, fault detection is performed, comparing the predicted behavior of a system based on SVR models against the actual observation. The normal operation region of the system is obtained using nonfaulty case data. Two SVR machines predict the boundaries of this region. In the training phase, nonfaulty case inputs of the system are used as the input of the SVR machines. Output data on the boundaries are used as the output of the SVR machines. In the testing (operating) phase, inputs of SVR are only system inputs. SVR machines estimate lower and upper boundaries that should be in nonfaulty case. If measurements fall outside the region of normal operation, it means that a fault is detected in the process.

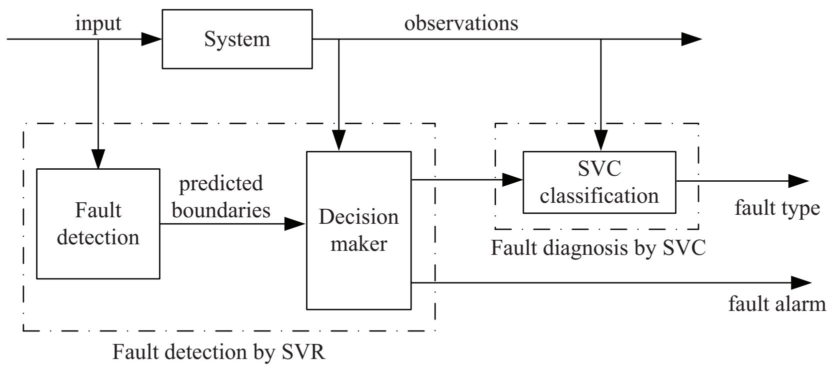

Figure 2. Proposed fault detection and diagnosis structure.

The class of occurring faults needs to be determined correctly. For this purpose, a powerful classification algorithm, SVC, has been used. SVC trained by faulty and nonfaulty input-output data can determine the type of fault.

3.1.1. Fault detection by SVR

Fault detection is the first step of all FDD procedures. In this study, the confidence band idea plays a key role in this step. This band will represent the normal (nonfaulty) operating conditions and it is constituted by the nonfaulty operating input/output measurements of the closed-loop system. For this purpose, a pseudorandom sequence can be applied to the system to cover up the whole range of normal operating modes or conditions of the plant. The upper and lower boundaries of the confidence band $\underline{y}_f(u_f,t)$ and $\overline{y}_f(u_f,t)$ are then individually modeled by two SVRs as presented in Figure 3. In order to derive models for boundaries, the SVRs are designed using NARMAX modeling and SVM. In order to find upper and lower limits of the outputs, a computer program code is written. This code includes an algorithm with a large/small point search and curve fitting.

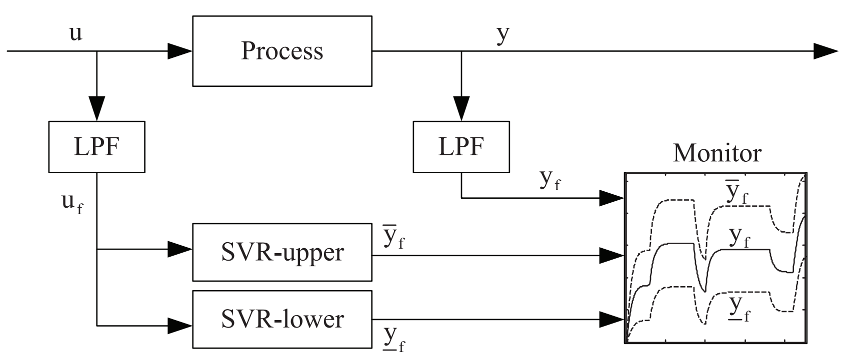

Figure 3. Fault detection with the structure of defining the bounds via SVRs.

When a mathematical system model is not known, the NARMAX model of the system can be expressed as a function of g numbers of previous output samples and m numbers of previous input samples:

$$y(k+1) = f(y(k), ..., y(k-g+1), u(k-d), ..., u(k-d-m+1), \eta(k), ..., \eta(k-o)) = f(\mathbf{x}(k)), \quad (15)$$

where y is the system output; u is the control input; $\eta(k)$ is uncertainties representing noise and unmodeled dynamics; g, m, and o represent the maximum delays of output, input, and noise, respectively; and d stands for the delay step measured between samples. The input vector to the SVM can then be defined as:

$$\mathbf{x}(k) = [y(k), ..., y(k-g+1), u(k-d), ..., u(k-d-m+1),\ \eta(k), ..., \eta(k-o)]^T, \quad (16)$$

where $\mathbf{x} \in R^{g+m+o}$, $k = d+1, \ldots, d+N$. The output is $\hat{y}(k+1)$, the estimated value of the output $y(k+1)$ at the moment of $k+1$. Consequently, the model of the nonlinear system defined by Eq. (15) is

$$\hat{y}(k+1) = \sum_{i=1}^{S} (\alpha_i^* - \alpha_i) K(\mathbf{x}_i \mathbf{x}(k)) + b. \quad (17)$$

Here we have used a special version of SVR given in Eq. (15) and Eq. (16), where the input and output vectors are $\mathbf{x}(k) = [u_f(k)]$ and $y(k) = [y_f(k+1)]$, respectively, so there does not exist any memory in the system. The main idea is that if a filtered output value stays within the interval $[\underline{y}_f(u_f, t), \overline{y}_f(u_f, t)]$, then there is no fault.

Filtering both the input and output signals before the modeling operation for the boundaries further reduces the sensitivity to false alarms. For this purpose, a low-pass filter Q(s) is used. The SVRs are trained with normal operating input and output values of the system. After this off-line training period, in the normal operation phase of the system, when the filtered output exceeds the boundaries generated by the SVRs, it will be assumed that a fault has occurred and an alarm will ring.

3.1.2. Fault diagnosis by SVC

SVMs can be an alternative to data-based FDD methods due to their generalization capabilities and high performance in classification. The SVM has a binary classification structure. When the number of possible faults to be detected by the FDD method is more than one, it is not enough to classify the cases as faulty and nonfaulty. A single binary SVM is not capable to classify all these faults. Some modified SVM algorithms can be used for multiple classifications. One of the common SVM-based methods for multiple classification is "one-against-all" [22]

In this algorithm, "n – 1" number of SVCs are constituted, where n is the number of classes to be classified as illustrated in Figure 4. Data belonging to each class are first collected. The first SVC is trained to distinguish one of the n classes from the rest of the n – 1 classes. This class is labeled with (+1) and it is assigned to the first class of the first SVC. The rest of the classes are labeled with (–1) and they are assigned to the second class of the first SVC. Next, one of the groups in the second class of the first SVC is picked and it is trained against the rest of the groups using the second SVC. After completing the training phase, the algorithm can be run for test data. When the class of test data is determined, execution of the algorithm is stopped even if all SVCs have not been operated. Thus, when a fault is obtained by SVR, a multi-SVC mechanism determines and declares its type.

3.2. Control system reconfiguration via SVM

The reconfiguration stage of a fault-tolerant control mechanism works right after detecting a fault and its type or location. When a fault is detected in the system, a mechanism activates a controller in order to tolerate the occurring fault and get the system to its regular state. This is a brief explanation of the reconfiguration. In this work, an intelligent structure is formed that activates the previously set up and optimally designed PID controller for a certain type of fault. That is, the PID gains are calculated so as to compensate the effects of each particular fault and still attain an acceptable control performance. In this study, a GA is utilized in an off-line manner to determine the gains of the PID controllers and the performance index to be minimized is chosen to be the integral time square error (ITSE). The controllers are then included in the FTC structure as illustrated in Figure 1. The FTC system then selects a proper controller according to the type of detected fault and activates it. It is an important point that there is always the probability of a faulty state occurring after another faulty state. Consequently, it means that there are $n(n-1)$ number of possible states if the sum of the number of faulty and nonfaulty states is n. An example is presented in Figure 5. The classification trainings are separately done for each controller given in this study. In this way, whichever fault comes after another, the decision mechanism will activate the suitable controller in order to tolerate the obtained fault and try to put the system in its regular state.

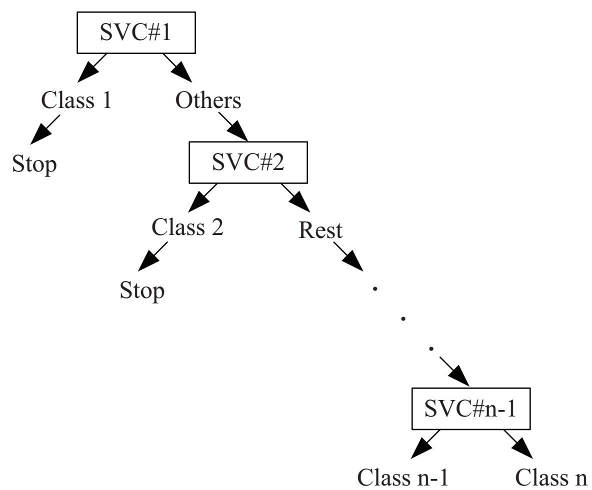

Figure 4. SVM multiple classification method, one-against-all.

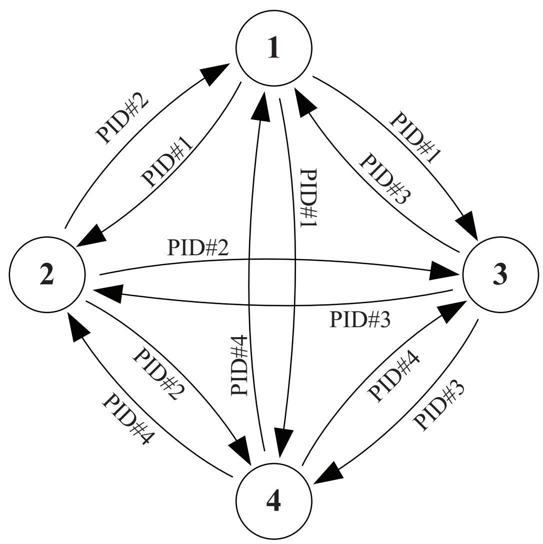

Figure 5. Possible ways for 4 cases (n = 4).

The proposed method is developed to classify the type of any predefined fault when it occurs, and then it tries to tolerate the effects of this fault in the reconfiguration phase. In this method, it is assumed that only one of the predefined faults can occur at any time.

4. Simulations on two-tank liquid level control system

4.1. The model and the parameters of the system

The proposed FTC algorithms will be used in a well-known benchmark problem: the two-tank liquid level system [23,24] that is given in Figure 6. The material balance equations for the two-tank liquid level system are

$$\dot{h}_1(t) = \frac{1}{A_s}\left(-K_{p1}\mathrm{sign}(h_1(t)-h_2(t))\sqrt{2g\,|h_1(t)-h_2(t)|}+q_1(t)\right),$$
$$\dot{h}_2(t) = \frac{1}{A_s}\left(K_{p1}\mathrm{sign}(h_1(t)-h_2(t))\sqrt{2g\,|h_1(t)-h_2(t)|}-K_{p2}\sqrt{2gh_2(t)}\right), \tag{18}$$

where $K_{p1} = a_1\mathrm{S}_{p1}$, $K_{p2} = a_2\mathrm{S}_{p2}$, and $a_1 = a_2 = 1$ for simplicity. The parameters of the benchmark system are given in Table 1.

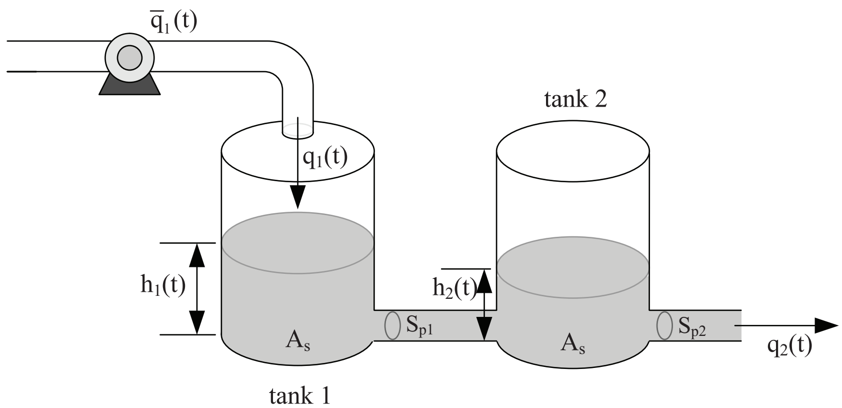

Figure 6. Two-tank liquid level control system.

Table 1. Parameters of the two-tank liquid level control system.

Parameter	Variable/value
Section area of tanks [m^2]	A$_s$ = 0.0154
Cross-sections of connection pipe [m^2]	S$_{p1}$, S$_{p2}$ = 3.6 × 10^{-5}
Gravity acceleration [m/s^2]	g = 9.81
Water levels [m]	h$_1$, h$_2$
Supplying flow rate from pump to tank	q$_1$(t)
Outflow from second tank [m^3/s]	q$_2$(t)
Outflow coefficients	K$_{p1}$, K$_{p2}$

4.2. The results of the method

The method explained in Section 3 can be used when the types of the faults are known. In this example, the following three faults are considered:

(i) Actuator fault in the pump: An actuator fault is modeled by an actuator fault constant $K_f \in [0,1]$ as $\bar{q}_1 = (1-K_f)q_1$. If $K_f = 0$ then there is no actuator fault; otherwise, if $K_f \neq 0$, then it is faulty.

(ii) Leakage flow in tank 1: A circular shape leak with radius r_1 is assumed. The leakage flow rate in tank 1 is given by $q_{f1}(t) = a_1\pi(r_1)^2\sqrt{2gh_1(t)}$.

(iii) Leakage flow in tank 2: Similarly, the leakage flow rate in tank 2 is given by $q_{f2}(t) = a_2\pi(r_2)^2\sqrt{2gh_2(t)}$.

In this example, we consider a nonfaulty case and three different faulty cases as explained above. This means that n is equal to 4 and there are three SVCs in every FDD block designed for each fault as presented in Figure

7. The correct PID gains for all cases are searched by a GA in an off-line manner and they are stored in the FTC structure. In the GA search, the performance index to be minimized has been chosen to be the ITSE in this study. The controllers PID # 1, PID # 2, PID # 3, and PID # 4 belong to four cases: nonfaulty, leakage flow in tank 1, leakage flow in tank 2, and actuator fault in the pump, respectively. Table 2 shows the PID gains for the nonfaulty case. We assume that the system starts in the nonfaulty condition. The closed loop system continues to work with a control signal coming from PID # 1. The FDD structure looks for the faulty conditions by observing a closed-loop response periodically. When a fault is detected, the decision mechanism activates a controller in order to tolerate the fault and tries to force the system into its proper operating conditions. For instance, while the system works in the nonfaulty case (PID # 1 is in charge), we assume that a 'leakage flow in tank 2' fault is detected. In this situation, the decision mechanism should select the PID # 3 controller. At the same time, the third classification mechanism, FDD # 3, is activated. This means that the SVCs of the 'leakage flow in tank 2' case start to work.

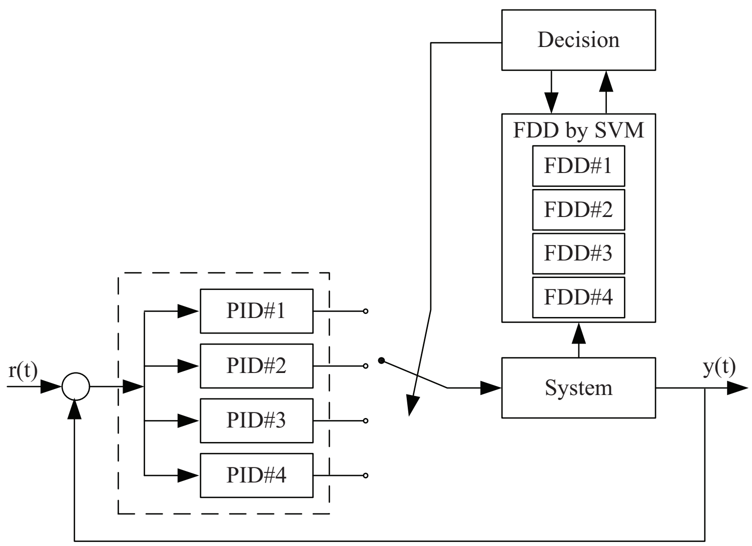

Figure 7. FTC structure of two-tank liquid level control system.

Table 2. PID gains obtained by GA for use in training.

Controller parameters	PID (no fault)	PID (0 cm)	PID (40 cm)	PID (80 cm)
K_p	26.58776	24.8138	26.83225	28.92151
K_i	0.0805	0.90161	1.49756	1.8599
K_d	6.15532	8.14017	0.25	2.16411

First of all, to define a confidence band representing the normal operating condition, the input and output data of the normal condition must be collected. For generality, the 20 input signals in the form of a pseudorandom sequence given in Figure 8 are applied to the process. Each input signal has 1000 points. Hence, totally 20,000 points training input data and their 20,000 response points are taken. The confidence band is obtained with these training data.

The confidence band is given in Figure 9. For modeling the upper boundary, the first SVR (SVR-upper) is set using the data set of the couples (u_f, y_f) and the SVR-lower machine is formed in a similar fashion. In both SVRs, training parameters are chosen in a trial and error fashion as C = 200, ε = 0.0001. Polynomial kernel function is chosen with p value set equal to one. The cut-off frequency w_f is selected according to absolute values of the Fourier transforms of the output signals. The time constant of the low-pass filter $T_f = 1/w_f$ is chosen as 476 s, as illustrated in Figure 10. The three SVCs are trained as explained in Section 3.1.2 for the assumed four (three faulty and one nonfaulty) conditions. Three SVCs are set as follows: the first SVC separates the nonfaulty signals from all the faulty ones. The second one separates the actuator faults from the leakage faults. The last SVC separates the leakage in tank 1 from the leakage in tank 2. These trained SVR machines are built into the closed-loop system. In all SVCs, training parameters are chosen in a trial-and-error fashion as C = 200. The radial basis function kernel is chosen with σ value set equal to 0.1.

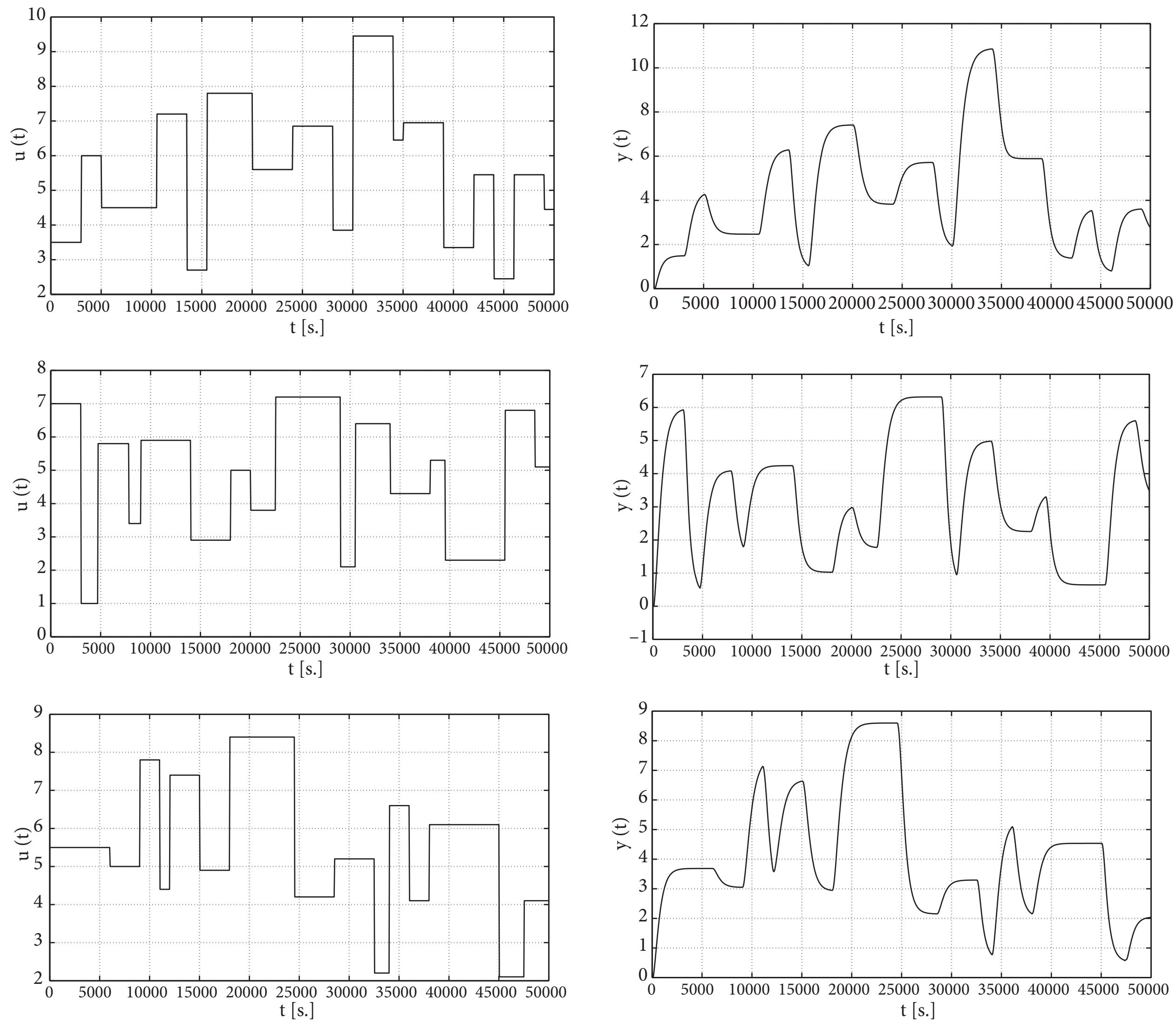

Figure 8. Pseudorandom sequence input signals and corresponding outputs.

The FDD operation of the method can be explained with an example. A leakage of $r_1 = 4$ mm in tank 1 within the period of time t = [5000–10,000], an actuator fault of $K_f = 0.3$ within the period of time t = [15,000–22,000], and a leakage of $r_2 = 5$ mm in tank 2 within the period of time t = [32,000–40,000] are assumed to occur. The input signal, estimated boundaries, and nonfaulty case response are given in Figure 11. The results of this fault detection are given in Figure 12. When a fault occurs, filtered output leaves the confidence band. This provides a fault alarm, as seen in Figure 12. When a fault alarm occurs, then the SVCs start to work, and the nature of the fault is defined in a reasonably short period of time. Moreover, this multiple classification method has a classification satisfying performance.

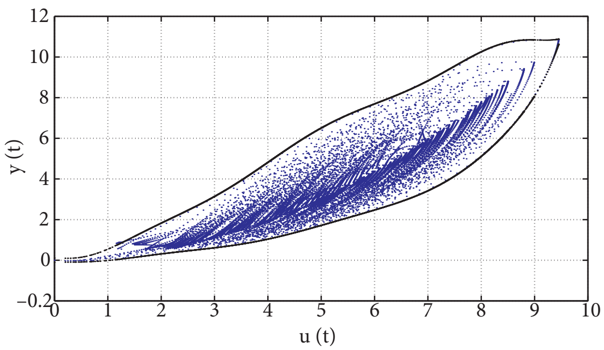

Figure 9. Illustration for the confidence band and its upper-lower bounds.

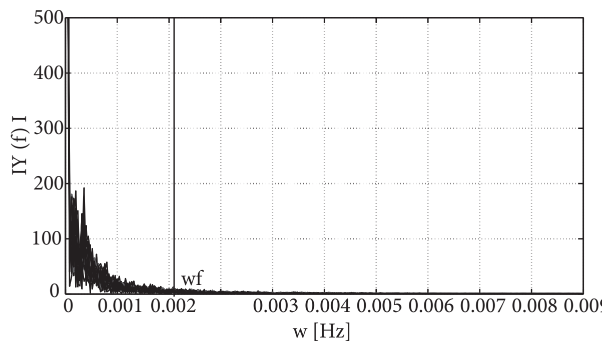

Figure 10. Illustration of the choice of the cut-off frequency.

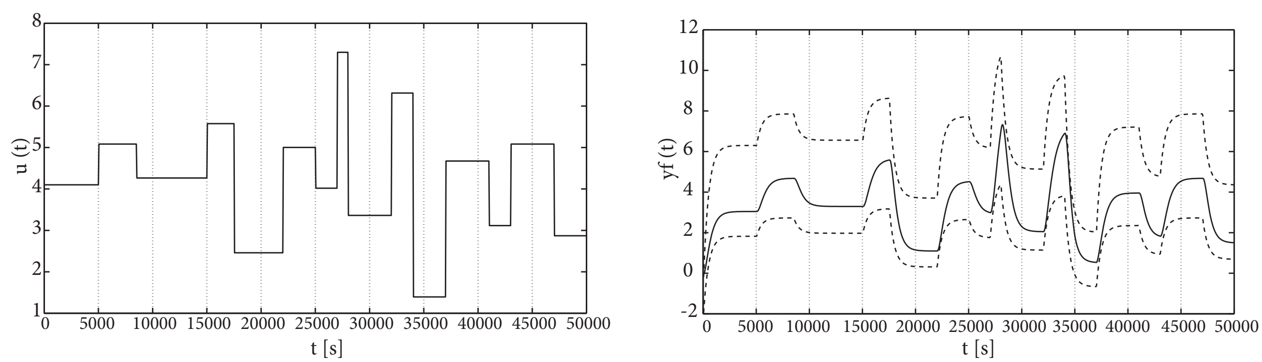

Figure 11. (a) Pseudorandom sequence input, (b) corresponding nonfaulty output (solid line) and predicted boundaries (dashed lines).

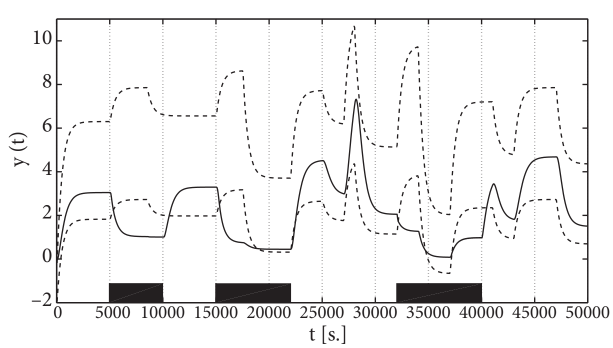

Figure 12. Filtered outputs (solid line), predicted boundaries (dashed lines), and fault alarms (black bands) for a pseudorandom sequence input.

In Figure 12, black bands symbolize the detected faults. As can be seen, when a fault occurs, the system output exceeds one of the boundary lines and a fault alarm rings. This figure is just used as a graphical representation for better explanation of the detection phase of the method. The performance of the FTC method has been tested on the tank system with the following fault scenario: system starts without any fault. A leakage of $r_1 = 4$ mm in tank 1 occurs at t = 3000 s, and then leakage in tank 2 occurs at t = 6000 s. This scenario is illustrated in Figure 13.

Sequential run of the proposed FTC algorithm: When a leakage in tank 1 occurs at t = 3000 s, the FDD # 1 algorithm determines the type of the fault and sends the information to the decision stage. The most suitable controller, PID # 2, is then selected, and thus the effect of the fault is compensated. At the same time, FDD # 2 starts to work. A leakage in tank 2 then happens at t = 6000 s and the FDD # 2 algorithm determines the type of the fault and sends the information to the decision stage. Similarly, the most suitable controller PID # 3 is selected and the effect of the fault is tried to be compensated; FDD # 3 starts to work. This procedure is illustrated in Figure 14.

Figure 14 shows very clearly that if a conventional controller is used for these kinds of faults it would not be possible to come up with a plausible system response. However, the proposed FTC method is capable of tolerating these faults with its reconfigurable controllers.

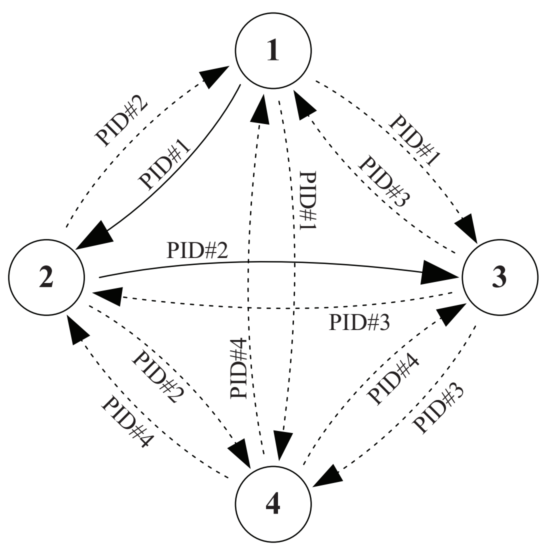

Figure 13. Fault scenario representation.

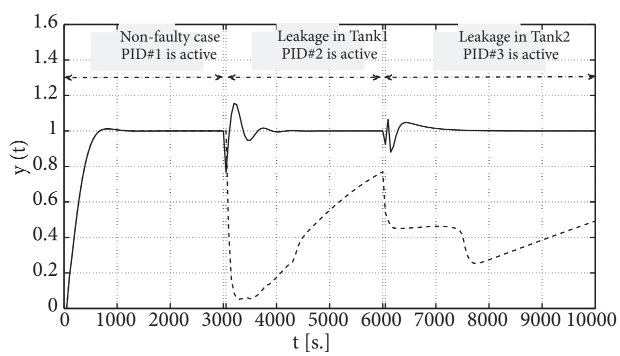

Figure 14. Proposed FTC system response (solid line) and conventional closed-loop system response (dashed line).

5. Conclusions

The SVM is a popular machine learning technique with a very high generalization capacity. Although SVMs are trained by a small data set, they can scan a very wide region. They are fast algorithms and do not need complex processes. In this study, an active SVM-based FTC method is presented. In the method, the SVR machines are used in fault detection and the SVC machines are used in the fault diagnosis phase of the problem; once a fault occurs, the decision mechanism selects a suitable controller so that an acceptable closed-loop performance is maintained. This approach provides a powerful tool for solving the FTC problem for certain faults and has good performance from the perspective of reliability. As a designer, one achieves high performance in terms of speed and memory since the method utilizes only the current input and output of the process. The performance of the proposed FTC technique was illustrated by simulations done over the two-tank liquid level control system. In general, one can conclude that the compensation performance of the FTC technique is very high, even for a large degree of faulty conditions.

References

[1] Blanke MS, Marcel M, Wu EN. Concept and methods in fault tolerant control. In: Proceedings of the American Control Conference; Arlington, VA, USA; 2001. pp. 2606–2620.

[2] Patton RJ. Fault-tolerant control: the 1997 situation. In: 3rd IFAC Symposium SAFEPROCESS'97; Hull, UK; 1997. pp. 1033–1055.

[3] Puig V, Quevedo J. Fault-tolerant PID controllers using a passive robust fault diagnosis approach. Control Eng Pract 2001; 9: 1221–1234.

[4] Isermann R. Model-based fault-detection and diagnosis - status and applications. Annu Rev Control 2005; 29: 71–85.

[5] Isermann R. Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance. Berlin, Germany: Springer, 2006.

[6] Zhong M, Fang H, Ye H. Fault diagnosis of networked control systems. Annu Rev Control 2007; 31: 55–68.

[7] Patton RJ, Frank PM, Clark RN. Issues of Fault Diagnosis for Dynamic Systems. London, UK: Springer, 2000.

[8] Desobry F, Davy M. Support vector-based online detection of abrupt changes. In: IEEE ICASSP; Hong Kong; 2003. pp. 872–875.

[9] Oblak S, Skrjanc I, Blazic S. On applying interval fuzzy model to fault detection and isolation for nonlinear input-output systems with uncertain parameters. In: IEEE Conference on Control Applications; Toronto, Canada; 2005. pp. 465–470.

[10] Tarassenko L, Nairac A, Townsend NW, Buxton I, Cowley P. Novelty detection for the identification of abnormalities. Int J Syst Sci 2000; 31: 1427–1439.

[11] Liang YW, Liaw DC, Lee TC. Reliable control of nonlinear systems. IEEE T Automat Contr 2000; 45: 706–710.

[12] Zhang YM, Jiang J. Issues on integration of fault diagnosis and reconfigurable control in active fault tolerant control systems. In: 6th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes; Beijing, China; 2006. pp. 1437–1448.

[13] Zhang YM, Jiang J. Bibliographical review on reconfigurable fault-tolerant control systems. Annu Rev Control 2008; 32: 229–252.

[14] Mahmoud M, Jiang J, Zhang Y. Active Fault Tolerant Control Systems: Stochastic Analysis and Synthesis. Lecture Notes in Control and Information Science. Berlin, Germany: Springer, 2003.

[15] Saludes S, Fuente MJ. Support vector based novelty detection for fault tolerant control. In: Proceedings of the 44th European Control Conference and CDC; Seville, Spain; 2005. pp. 5820–5825.

[16] Saludes S, Fuente MJ. Fault tolerance in the framework of support vector machines based model predictive control. Eng Appl Artif Intel 2010; 23: 1127–1139.

[17] Vapnik VN. The Nature of Statistical Learning Theory. New York, NY, USA: Springer-Verlag, 1995.

[18] Cristianini N, Shawe-Taylor J. An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge, UK: Cambridge University Press, 2000.

[19] İplikçi S. A support vector machine based control application to the experimental three-tank system. ISA T 2010; 49: 376–386.

[20] Vapnik VN. Statistical Learning Theory. New York, NY, USA: John Wiley and Sons, 1998.

[21] Smola AJ, Schoelkopf B. A Tutorial on Support Vector Regression. NeuroCOLT2 Technical Report NC-TR-98-030, Royal Holloway College. London, UK: University of London, 1998.

[22] Ge M, Zhang G, Du R, Xu Y. Application of support vector machine based fault diagnosis. In: Proceedings of the 15th Triennial IFAC World Congress; Barcelona, Spain; 2002. p. 766.

[23] Oblak S, Skrjanc I, Blazic S. Fault detection for nonlinear systems with uncertain parameters based on the interval fuzzy model. Eng Appl Artif Intel 2007; 20: 503–510.

[24] Zhang X, Parisini T, Polycarpou MM. Adaptive fault-tolerant control of nonlinear uncertain systems: an information-based diagnostic approach. IEEE T Automat Contr 2004; 49: 1259–1274.