MULTI-MODEL APPROACH TO FAULT DETECTION, ISOLATION AND COMPENSATION: A CASE STUDY OF INDUSTRIAL PNEUMATIC CONTROL VALVE

BY

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The thesis work is dedicated to my parent and the love ones.

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THESIS ABSTRACT

NAME: Adegoke Muideen Adeniyi

TITLE OF STUDY: Multi-Model Approach to Fault Detection, Isolation and Compensation: A Case Study of Industrial Pneumatic Control Valve

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In recent years, a lot of studies has been done and going on, on fault detection, isolation, and compensation in a control system. These are due to high demand for good reliability and performance of plant or control system. Any unreasonable disturbance or performance of any kinds in any part of control systems can actually make the entire system unstable and this may lead to undesirable results such as a total breakdown of the entire system or plant. If necessary precaution or remedy is not taking into consideration on time this may lead to huge damage. Based on this, a great number of investigations are going on to detect the origin of the fault, identify the nature of the fault in the control system and ways to compensate it. This thesis work focuses on detection and isolation of fault, as well as compen-

sation of the faulty system. A case study of an industrial pneumatic valve is considered and the focus is mainly on STICTION (nonlinearity which resembles Backlash) since it is a major cause of oscillation in industrial control valve and because of its undesirable effect on quality of product, energy consumption including measurement oscillation. Multi-Model techniques combine with Constrained Kalman Filter (CKF) is utilized as a supervisory scheme to detect and isolate faults in a system (Pneumatic Control Valve as a Case Study) and new compensation methods are proposed based on optimization approach. These are employed to compensate stiction (a major cause of oscillation in a closed loop control valve) then the performance evaluation of the new method of fault detection, isolation with proposed compensation techniques are experimentally validated. In addition, the comparison between the existing control valve nonlinearity cancellation methods and the proposed methods are presented.

أطروحة مجردة

في السنوات الأخيرة، وقد تم ذلك الكثير من الدراسات ومستمرة، على الكشف عن خطأ، والعزلة، والتعويض في نظام التحكم. هذه هي نتيجة لارتفاع الطلب على موثوقية جيدة وأداء النظام مصنع أو السيطرة عليها. أي اضطراب غير معقول أو أداء أي نوع من أنواع في أي جزء من أنظمة التحكم يمكن أن تجعل في الواقع النظام بأكمله غير مستقر وهذا قد يؤدي إلى نتائج غير مرغوب فيها مثل الانهيار التام للنظام بأكمله أو النبات. إذا قائي أو علاج ضروري لا يأخذ بعين الاعتبار في الوقت المناسب وهذا قد يؤدي إلى ضرر بالغ. وبناء على هذا، فإن عددا كبيرا من التحقيقات جارية للكشف عن أصل الخطأ، وتحديد طبيعة الخلل في نظام التحكم وسبل تعويض ذلك. يركز هذا العمل أطروحة على كشف وعزل خطأ، فضلا عن التعويض للنظام الخاطئ. تعتبر دراسة حالة صمام هوائي الصناعي والتركيز بشكل رئيسي على صةيثةيو (استقامة الذي يشبه رد الفعل) نظرا لأنه هو سبب رئيسي من التذبذب في صمام التحكم الصناعي وبسبب تأثير غير مرغوب فيه على جودة المنتج، واستهلاك الطاقة بما في ذلك قياس التذبذب. تقنيات متعددة نموذج تتحد مع مقيدة كالمان تصفية (ثكذ) يستخدم كنظام رقابي لكشف وعزل الأعطال في نظام (هوائي صمام التحكم كدراسة حالة) وطرق تعويض الجديدة المقترحة على أساس النهج الأمثل. ويعمل هؤلاء لتعويض ستحُتـن (سببا رئيسيا من أسباب التذبذب في صمام التحكم حلقة مغلقة) ثم تقييم أداء طريقة جديدة لاكتشاف الخطأ، والعزلة مع تقنيات التعويض المقترح يتم التحقق تجريبيا. بالإضافة إلى ذلك، قدم مقارنة بين أساليب إلغاء القائمة صمام التحكم استقامة والأساليب المقترحة.

CHAPTER 1

INTRODUCTION

1.1 Motivation

Production plants like Petrochemical plant, Cement plant, Petroleum plant, Soft drink plant etc. in the process industry today are the vital tools for the production of a product for sales. These plants made up of hundreds if not thousands of loops of control valves working together as a group or network to achieve an objective or a group of objectives which is usually to produce an acceptable quality of a product for sales at minimum cost for better production profit. Each of these loops or control valves is meant to maintain vital process variable such as flow, pressure, level, temperature etc. to achieve the aforementioned objective(s) of the plant, meanwhile, the loop is being disturbed internally as well as other control loops which indirectly affecting process variable desired value. To eliminate or reduce this disturbance effect to an acceptable level, sensor and transmitter are usually used to collect information about the variable in question and compare it with a desired value or set-point. A controller (e.g. PID) is usually used to process the signals from sensor and transmitter to make a decision on what to do to recover the process variables back to their desired values where they should be after load disturbance occurs. When all the manipulations have been done by the controller (PID) then the final control element has to carry out the strategy selected by the controller. One of the final control elements that are commonly used is CONTROL VALVE, sometimes referred to as valve or control valve assembly or pneumatic control valve. The valve carries out the assignment such as manipulation of the flow of fluid such as steam, gas, water or chemical compounds (in chemical plants) to the desired set-point or an acceptable value close enough to the process variable setpoint. Therefore, from this, a control valve can be described as one of the vital final control elements in process control plant in today's industrial production plant set-up. An important issue does not lie in the name given to valve, either it's called valve, control valve, control valve assembly or industrial pneumatic control valve, but lies in the recognition that the control valve is a critical(vital) part of the control loop that must be healthy for better task performance. The control valves like other electrical/mechanical devices have their associated faults (an unwanted phenomenon which can cause huge damage to any control system especially in an environment where safety is significant such as in safety critical system like production plant). The major or the most commonly found pneumatic control valve problem or fault of valves in the process industry is stiction. Stiction in the valve causes oscillations which can cause an undesirable effect like a poor overall quality of product, increase in energy consumption, increase in downtime due to the unnecessary shutdown of the plant due to stiction for maintenance purpose. Due to this, stiction has caught the attention of researchers both in the academic environment and industry, this prompt researcher to work on it. A lot of scholarly work has been done on stiction such as its model, detection, and compensation methods but this model, detection methods, as well as compensation methods have one or more drawbacks that need to be addressed which called for this thesis work to embark on. This drawback ranges from unrealistic assumptions in stiction models, Complex detection methods with little or no isolation methods, aggressive and not fully automated compensation methods etc. For instance, Knocker based or Dithering methods [1],[2] of compensation, compensate at a cost of aggressive movement of the valve stem resulting in reduced or short life span of the valve due to quick wearing out of a valve which is not economical. This can be called short-term solution, therefore, it's required an almost permanent solution if not permanent solution more details will be provided in the literature review. Moreover, in the aspect of stiction models, these models are useful to carry out a simulation to simulate sticky control valve. It is important to mention that major work on valve stiction focus on its detection and modeling, there is little or no work on identification of a closed loop process with a sticky valve using mathematical definition or representation. This could be attributed to sticky valve non-linear features such as static friction, dead-band etc. Looking at it critically with the industrial perspective it is difficult to separate stiction model from control valve model. Therefore, it is important to model a sticky valve or sticky closed loop process to be able to study valves suffering from stiction effectively and design well suitable controller or compensation methods. In this work, we proposed to tackle all the aforementioned range of issues related to sticky industrial pneumatic control valve using Multi-model approach based on weighted constrained Kalman filter. More details of previous work on control valves, such as stiction model, detection and compensation methods and their drawbacks will be discussed in the next chapter which is the literature review. Also, some applications of the multi-model approach will be provided. In addition, Chapter 3 discusses the preliminary results and the implementation of multi-model using weighted constrained Kalman filter. Moreover, Chapter 4 talks about the optimization approach used in the development of the proposed stiction compensation method. Also, Chapter 5 presents results for different scenarios tested in the implementation of the proposed stiction compensation method. Besides, in this chapter, comparison between the previous method of valve stiction compensation and the proposed one in Chapter 5 is presented which then leads to proposed another new method of stiction compensation. In Chapter 6, an improved stiction compensation method based on the combinations of FIR filter, Least Mean Square(LMS) algorithm, and Gravitational Search Algorithm(GSA) is proposed and validated using experimental setup. Other chapters discuss summary, recommendation, and conclusion.

1.2 Problem Statement

Research problem for this thesis work is based on a relation between input and output of a system such as: Given an input, output data of a process plant and ask to detect and isolate the fault in the process as well as to compensate the faulty system for proper closed-loop process performance.

1.3 Thesis Objective and its justification

Based on literature survey, it is clear that stiction is an unwanted phenomenon which can cause huge damage to any control system especially in an environment where safety is significant like in a safety critical system (airplanes, production plants). Fault determination is usually referred to as fault detection and knowing its kind including its location is normally called Fault Detection and Isolation (FDI). Therefore, because of undesirable nature of the fault as stated above this call for the proper method of its detection, isolation, and compensation. For instance, in a closed loop control plant where valves are looped together to attain certain goals, proper closed loop monitoring is needed to prevent any severe disturbances that can lead to escalation of fault from one loop to another. Stiction in the valve is the cause of oscillation which can cause negative effects like a poor overall quality of product, increased energy consumption and increased production downtime. Some notable work on valve studies such as Knocker based stiction compensation method or Dithering method [2] compensates at a cost of aggressive movement of a valve stem resulting in reduced or short-life span of the valve due to quick wearing out of the valve which is not economical. A better method that is friendly to the control valve is therefore needed. Hence, the objectives of this thesis work are:

- Identification of a Sticky Valve in a closed loop process using both the input and output data (data-driven approach) of a system.
- Implementation of weighted constrained Kalman filter using multi-model approach to detect a fault in a control valve.
- Implementation of weighted constrained Kalman filter using multi-model approach to isolate a fault in a control valve.
- To propose and implement new methods of stiction compensation based on optimization approach to compensate control valve or process suffering from stiction.
- Evaluation of the proposed method with the other existing stiction compensation technique like LMS-FIR compensator or Knocker method.
- Validate using experimental setup.

1.4 Methodology-Approach

In part of achieving the aforementioned objectives, this thesis work is divided into different parts which involve theoretical formulations of the problem, simulation, and the experimental study. The software packages such as Matlab, Simulink, and

LabVIEW are utilized to carry out this investigation. In addition, experimental data are collected from a healthy valve and from abnormal ones for modeling purposes. Other approaches used in this work are explained as follows:

1.4.1 Matlab Simulation

In simulation section of this thesis work, most of the work is done by making use of both combinations of Matlab and Simulink packages. Besides, data used for simulation purposes is obtained from existing stiction model from literature survey and mathematical representation of the valve employed for the studies is obtained through the existing valve/plant model in literature while the whole plant process that is, both the healthy and abnormal process are formed by integrating the stiction model and the pilot plant (a plant transfer function) found in literature. Besides, intelligent methods such as Neural Network, Functional-network etc are then used to create models which describe the system behavior for different scenarios when stiction phenomenon is acting on the integrated system. Further investigation are carried out through experimental study. More details of this will be dealt with in other chapters of this thesis work.

1.4.2 Experimental Set-up

The rest of the work is based on experimental approach. In this part, a single closed loop level control process having a real healthy valve is used for the rest of studies, different stiction models are used in introducing fault into this control valve through the help of National Instrument(NI) Compact Control Processor. In addition, some other tests are performed on a real valve suffering from stiction. The closed loop process used is interacted with via human machine interface developed using LabVIEW package.

CHAPTER 2

LITERATURE SURVEY

2.1 Overview

Fault such as stiction is a highly undesirable phenomenon in industrial settings especially in a case/situation where safety is of almost important such as in a flight control system, petrochemical, petroleum plant, for instance, valve stiction is an unwanted phenomenon in any closed loop process having a pneumatic control valve, therefore, its detection, isolation, and compensation is critical. Generally, if there is intolerable deviation of one or more parameter/characteristics of a system from its default (normal) condition then such a situation is referred to as fault. In general, there are a lot of fault detection, isolation, and compensation methods and in particular, there are methods of detecting and compensating valve stiction (industrial pneumatic valve problem) found in the literature on its own. Looking at stiction diagnosis methods, it can be divided into subgroups which are KNOCKERS BASED, PID TUNING BASED, ADAPTIVE INVERSE

METHODS and MODEL INVERSE METHOD. This chapter deals with literature survey on different stiction studies such as modeling, detection and compensation methods.

2.2 Stiction Models

Stiction model is an important model in a closed loop valve process control especially in an area of closed-loop performance monitoring because it provides an avenue whereby real system suffering from stiction can be investigated in a simulation environment. There are many stiction models proposed in the literature, these models are of two types which are: Physical and Data-driven types. From literature survey like in Choudhury et al [3], it is shown that physical model of a pneumatic control valve requires a lot of parameters to be known which is a disadvantage to this model when compared to the other type of stiction models available. This kind of stiction model can be found in [4] introduced by Karnop. Equation (2.1) shows the general equation describing physical model of a valve stiction

$$M\frac{d^2x}{dt^2} = \sum Forces = P_a + P_r + P_f + P_p + P_i \tag{2.1}$$

where M represents the mass of the moving part, x in the equation describes relative stem position, P_a is the force of pneumatic actuator which is defined as P_a=Aa_{pr} where A is the diaphragm area while a_{pr} stands as air pressure of the actuator or input signal to the valve. The spring force of a valve is represented by P_r in the equation. This spring force is a function of spring constant k and relative stem position x. The equation describing their relation is shown as $P_r = -kx$. $P_p = -\alpha\Lambda$ represents the force due to fluid pressure drop where α is the plug unbalance area, Λ is the fluid pressure drop across the valve. The needed extra force to push the valve to be into the seat is denoted as P_i, friction force of the valve is P_f in the equation. P_f is further defined as in Equation (2.2).

$$P_f = \begin{cases} -P_c sign(v) - vP_v & \text{if} \quad v \neq 0; \\ -(P_a + P_r) & \text{if} \quad v = 0 \; and \; |P_a + P_r| \leq P_s \\ -P_s sign(P_a + P_r) & \text{if} \quad v = 0 \; and \; |P_a + P_r| > P_s. \end{cases} \tag{2.2}$$

In Equation (2.2), P_s represents maximum static friction, more detail explanation on each of the symbols in Equation (2.2) can be found in [4] and [5]. Both P_c and v represent coulomb friction and stem velocity respectively. Equation (2.1) can be rewritten as:

$$M\frac{d^2x}{dt^2} = \sum Forces = Aa_{pr} - kx + P_f - \alpha\Lambda + P_i \tag{2.3}$$

where P_f is as shown in Equation (2.2) and P_i is the extra force required to force the valve to be into the seat. The other form of stiction model is a data-driven type, this is used often as found in literature survey to carry out studies such as stiction detection, quantification, and compensation than the other type of stiction model. This model has an advantage over the physical model type because it has one or two parameters that define it which means it only requires a fewer number of parameters when compared to physical model type and also, in term of formation, the data-driven type is simple to form. There is a single parameter data driven model and two parameters data-driven model, both require specification of parameters such as dead-band plus sticky-band, slip jump and an input signal. For more details check [3]. An example of a single parameter data-driven stiction model and its mathematical description can be found in [6]. The commonly used two parameters stiction models are Choudhury-model, He-model, and Kano model. These models were proposed by Choudhury et al [3], [7], He et al [8] and Kano et al [9] respectively. Figures 2.1, 2.2, and 2.3 show the detail flowchart of the each of these models, in these figures both J and S represent slip-jump and dead-band plus stick-band respectively. In Figure 2.2, f_s and f_d denote static and dynamic friction respectively. Variable u_r in the flow-chart is the residual force acting on the valve which has not materialized into a valve moves. It is important to note that in the Figure 2.2, if the value of the cum_u is large enough to overcome the static friction (f_s), the valve position u_v will be the controller $u(t)$ offset by the dynamic friction f_d. Otherwise, the valve position will not be changed and cum_u equals to the residual force on the valve to be utilized in the next control instant. Different stiction behaviors can be simulated by varying these two parameters (J) and (S) [10]. The relationship among J , S, static friction (F_s) and dynamic friction (F_d) are shown in Equation (2.4) and (2.5).

$$J = \frac{F_s - F_d}{2} \tag{2.4}$$

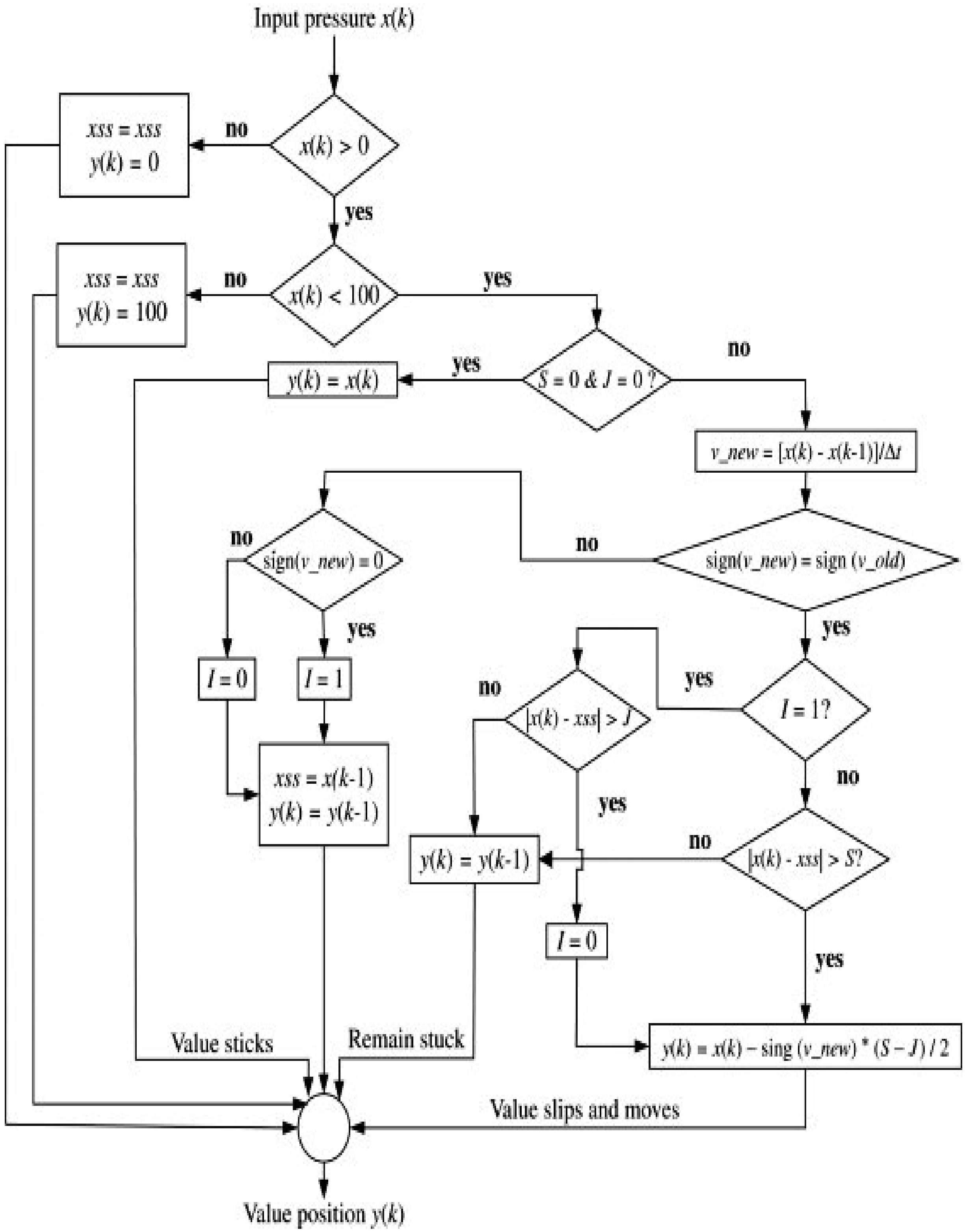


Figure 2.1: Flow-chart of the Choudhury Stiction Model [7]

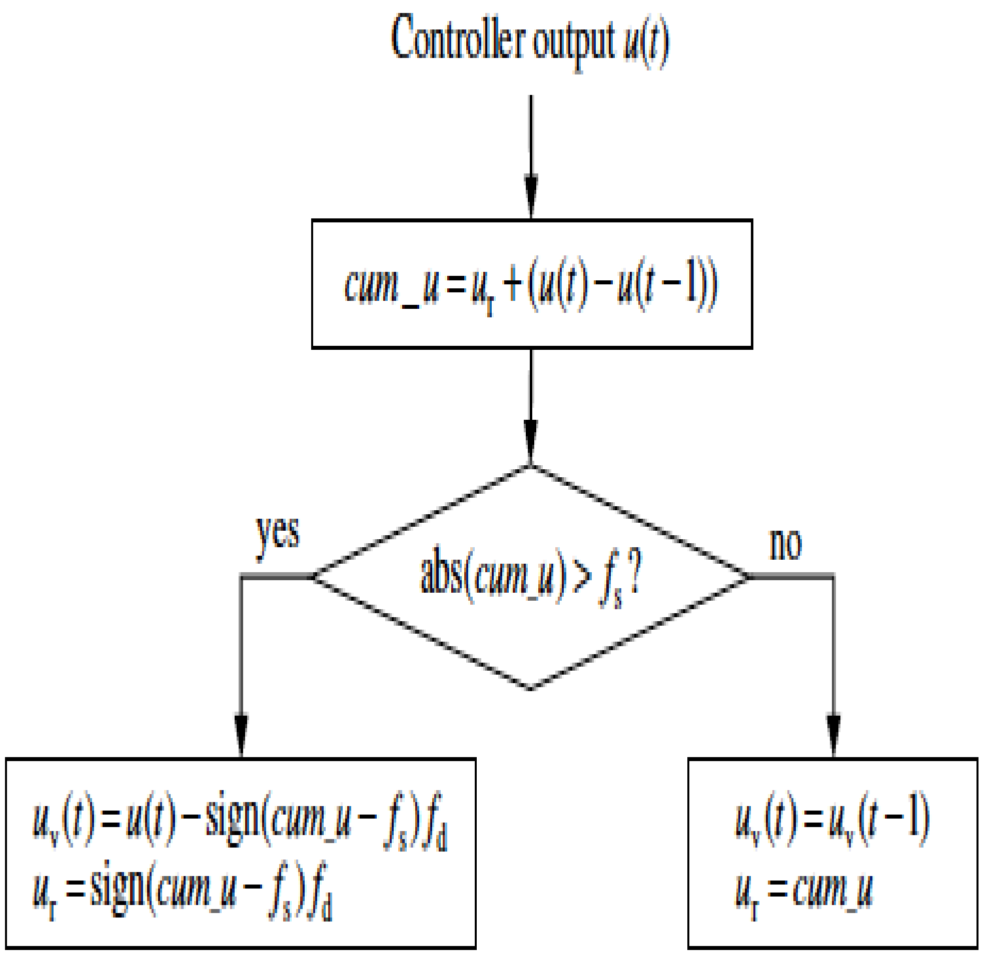


Figure 2.2: Logic and Flowchart of He model [8]

and

$$S = \frac{F_s + F_d}{2} \tag{2.5}$$

2.3 Stiction Detection and Compensation Methods

The work which prompt research in control loop system performance assessment and monitoring is Haris [11], work that was done in 1989 which dealt with control loop diagnosis. A lot of work on stiction has been carried out such as stiction detection, quantification (stiction estimation), and compensation by Horch [13], Ruel [14], and Ingimundarson et al. [15]. In the beginning, friction/stiction related problems studies were performed for servo positioning system and also for machines (H. Olsson [5],[16]) but recently valve stiction studies has become manifested because of its highly undesirable nature especially in pneumatic valve control in petrochemical plant. The valve stiction studies includes its elimination, isolation, and compensation. A model-based approach running in an offline mode, one of the Stiction detection methods proposed by Stenman et al [6], based on the information from Sabih [10], Stenman et al.[6] suggests the uses of an alarm device to determine/detect pronounce peak which is found in histogram when the valve jumps. Besides, a work by Taha et al., [17] proposed a new automatic way in which oscillation occurring in control loop either as a result of high friction, poor PID tuning or presence of external disturbance can be diagnosed automatically

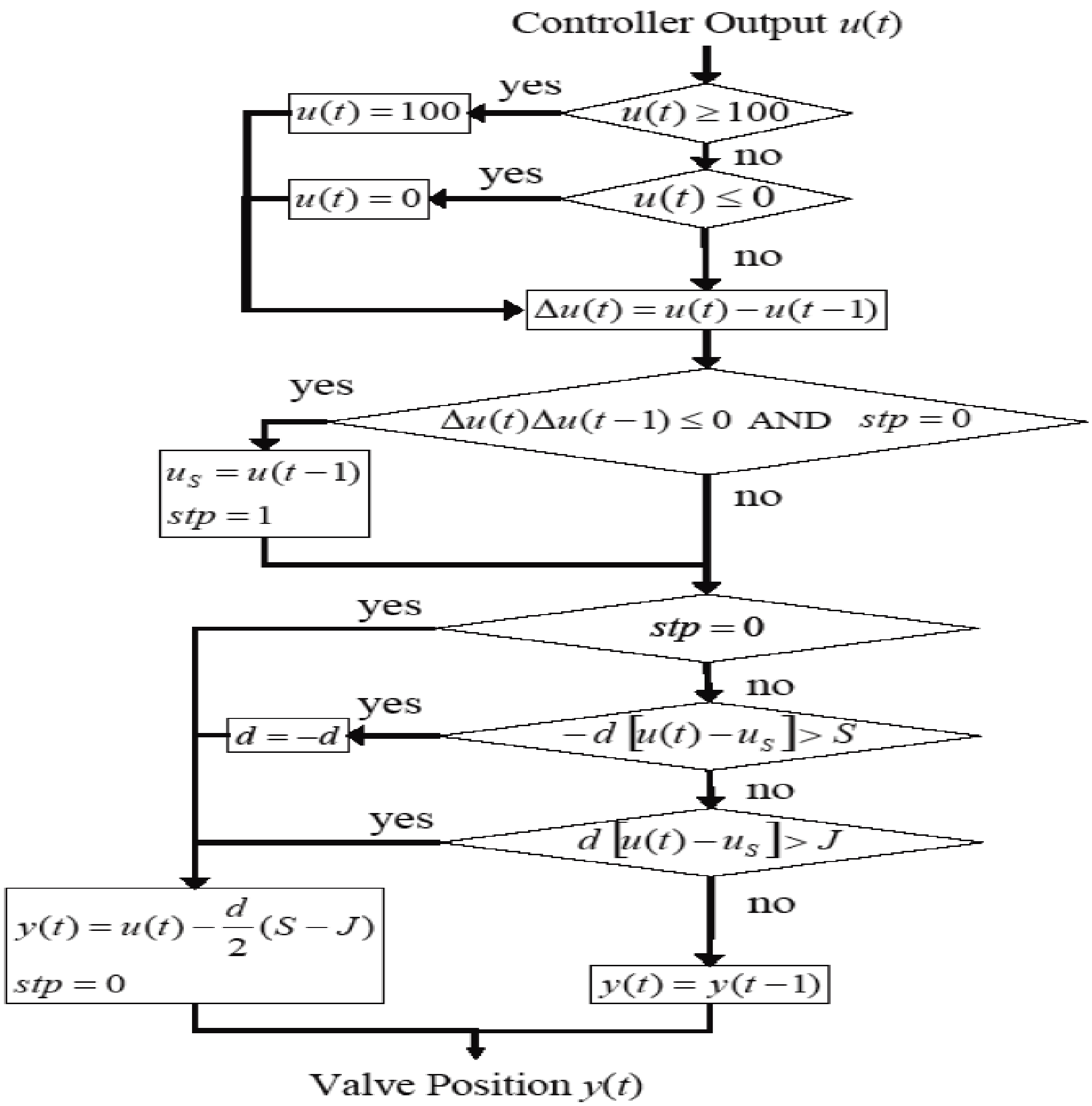


Figure 2.3: Flow-chart of the Kano model [9]

but this method is unable to differentiate oscillations due to stiction from those from others causes of oscillation like poor PID tuning. In their work [17], three major possible causes of oscillation in a closed-loop process were stated which are high friction (Stiction, Hysteresis), poor PID tuning and presence of an external disturbance. This is concord with a statement from [12] that both stiction in control valve and insufficient controller tuning are the two major causes or sources of control loop performance degradation. Furthermore, Choudhury et al [7], [3], [18], Kano et al [9] proposed stiction model and also developed stiction detection algorithm. The stiction detection method presented by Choudhury [18] which is bi-coherence method based on higher order statistics in his PhD dissertation uses two indexes to detect stiction, the indexes are Non-Gaussian index and Non-linear index, the issue with this kind of detection methods lies in index calculations, it involves a lot of manipulation and steps which may not be suitable for on-line mode. The model used for this stiction detection study is the Choudhury model, the model drawback was pointed out by Kano et al. that the model is not compatible with deterministic and stochastic signals and the improved version was introduced by Kano et al. [9]. A three parameters stiction model was proposed by Srinivanasan [19] but the model is a complicated one especially in carrying out stiction diagnosis and compensation studies and more details can be found in Sabih [10]. In addition, an in-depth study was carried out by Scali et al in [20] on automatic valve stiction detection in flow control system using qualitative shape approach (techniques) or relay techniques curve fittings as used by Rossi and Scali in [21]. Scali et al. analysis and explanation were based on loop dynamic, type of valve and control loop system setup (arrangement). His work is an improved version of the one in Yamashita [22]. His work circle around the relations between valve position (MV) and valve input (OP) data whereas MV data hardly available in practice. In another study by N. Ulaganathan et al [23] a one parameter stiction model was used in order to identify and isolate stiction from the external disturbance in a non-linear process, claiming in his working that all previous approaches in detecting stiction are based on linear process. In this work, a known system is considered and the validity of the proposed method is based on simulation only and no experimental test is performed to check the effectiveness of this method. Some other works on stiction detection methods like correlation analysis proposed by Horch [13] can be found in Sabih [10] and the references therein. The correlation analysis method of stiction detection is simple but gives the wrong detection often and also some conditions need to be met before it can work effectively in some cases. Such assumption/conditions includes but are not limited to these, the process does not have integral action, an oscillating loop has been detected as being oscillating with a significant large amplitude and then the process must be controlled by PI controller. In the work of Jelali [24], combination of genetic algorithms (GA) and separable least square was used in stiction quantification. Meanwhile, it involves a lot of computations, therefore, this method may not well suitable for an on-line mode. The work used an auto-regression moving average exogenous input (ARMAX) model to represent the linear part of the system, Hammerstein model as non-linear part, and then GA is used to determine the parameters of the non-linear part which are stiction parameters and separable least square method for the part represented by ARMAX model. The work is validated with different simulation scenarios and industrial data from control loop was also employed for validation.

Recently, the other area of valve stiction studies which caught the attention of researchers in the area of closed-loop process performance monitoring is stiction compensation. Although there are reasonable works in the literature concerning stiction compensation but the area has not been really developed. Among those found in the literature, they can be grouped into Knocker Based Methods, PID Tuning Methods, Adaptive Inverse Methods, Inverse of Model Methods and last but not the least is the Two Move Approach Methods. Starting with Knocker Based Methods, in this, three parameters (amplitude, pulse width, sample interval) dependent pulse signal is designed by H$\ddot{a}$gglund [25] to compensate for valve stiction. Since friction is preventing the stem in the valve to move then a pre-designed signal of a pulse of equal amplitude and duration is added to control signal in order to knock (overcome) out the friction preventing the valve stem movement. The work suggested how to determine the values of these parameters for the pulse signal and this is based on the experimental investigation carried out by H$\ddot{a}$gglund but this method of stiction compensation minimize stiction at the expense of aggressive movement of a valve which can shorten the lifespan of the valve through wearing. Series of simulation was performed for the proposed

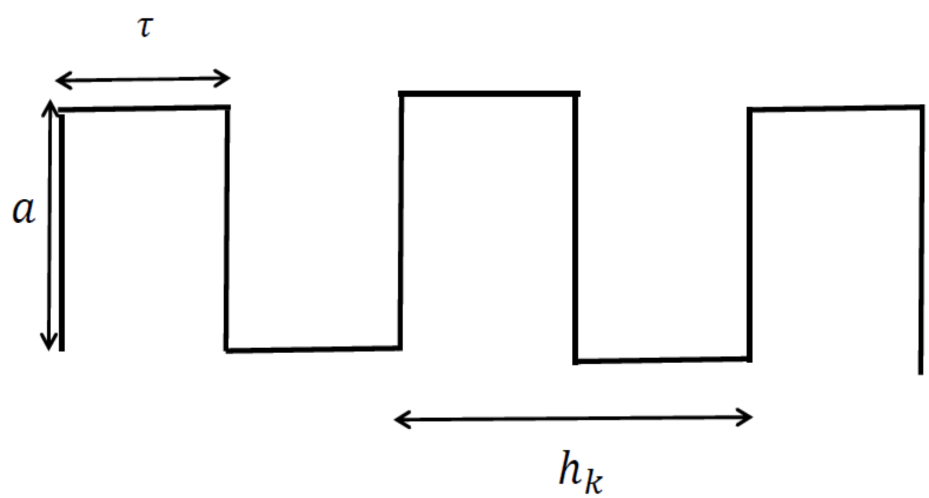


Figure 2.4: A shape representation of Knocker Signal

compensation method validation and its validity was also tested in an ABB distributed control system and the conclusion was that the compensation was able to reduce the amplitude as well as the oscillation period in control system compared to when no compensation is implemented. Figure 2.4 shows representation of the knocker signal where **a** stand for **Signal Amplitude**, τ denotes **pulse width** and h_k represents **time between pulses (period)**. Another form of stiction compensation which shares the same approach as Knocker method is Dithering method [2] but, in this case, the signal may not necessary be a pulse in shape. It could be sinusoidal or triangle in shape. In term of performance, Dithering method is more suitable for tracking and gives better smooth response compared to Knocker method. This method of compensation can as well be classified under Knocker-based method, therefore, it has the same issue as Knocker method, it compensate for stiction at the cost of valve wearing. Furthermore, a constant reinforcement (CR) method of stiction compensation was presented by X. Ivan et al. [26] the view resemble that of Knocker, the name (CR) came from the fact that a pre-design amount of additive signal is added to the control signal but the sign of the signal to be added is determined by the direction of the control signal but in a case where control signal remain constant (not changing direction) then no additional signal will be added to the control signal (controller output). The drawback of this approach is that the method cannot eliminate or reduce the extra movement of the valve. The mathematical representation of the constant reinforcement (CR) method is shown in Equation (2.6). In this Equation, a_{cr} denotes a predefined value of the signal to be added, $\triangle u$ is the change in control signal, sign represents *signum* function and d_{cr} is the constant reinforcement signal. The functionality of the technique (CR) is tested using a simulation example. The other form of stiction compensation different from the mentioned stiction compensation above is two moves approach presented by Srinivasan and Rengaswamy [27].

$$d_{cr} = a_{cr} sign(\triangle\, u) \tag{2.6}$$

This mainly focused on maintaining the stem of the valve at a steady position (state) claiming that in order to achieve steady state valve position maintenance, then, at least, two moves in the direction opposing (face each other) is required. The method employed a parameter stiction model for performance evaluation, in their work optimization based compensation method was also presented but in this case, stiction is sometimes not compensated for because the evaluation of the objective function trapped in local minimal, and suggest to use evolution optimization method which may require more computation for On-line practice. In addition; another stiction compensation method was introduced in 2009 by Sabih [10] in which an idea of inverse approach is introduced where approximate inverse of dynamics of stiction is inserted between the conventional controller (PID) and the sticky valve but because there is no ideal inverse of stiction as a result of its non-linearity nature and not only that but also because of its slowly changing in pattern, then inverse of the backlash is used as a stiction inverse, therefore stiction cannot be completely eliminated. Details of backlash, dead-band, hysteresis and their inverse are discussed in Abdeen [28], Sabih [10]. Another stiction compensation method is also presented by Sabih [10] called adaptive inverse control(AIC) which employed the use of Least Mean Square (LMS) and Finite Impulse response Filter (FIR), he referred to this combination as LMS_FIR. In this method, adaptive inverse methodology introduced by Bernard-windrow et al.,[29] is used and combined with LMS filter to minimize the objective function set up for the problem, in this work the weight of the filter used is determined using the method of steepest descent. The capability of the technique is checked using simulation case study. Adaptive inverse differential evolution compensation method was introduced and implemented using both simulation and experiment by Abdeen in his MSc thesis work [28]. This compensation method may be regarded as an advanced form of adaptive inverse stiction compensation proposed by Sabih [10] in his MSc thesis work. The main contribution of Abdeen in this compensation method is that differential evolution (DE) is used to optimize the weight of Filter applied in AIC method of Sabih for better performance instead of method of steepest descent utilized in adaptive inverse LMS method in [10] which has the tendency to be trapped in local optimum. Comparisons among Adaptive inverse differential evolution method, Adaptive inverse LMS and other stiction compensation methods like Knocker compensation was presented and a conclusion was made by Abdeen [28] from the result obtained that adaptive inverse DE out-performed others. More details can be found in [28]. Meanwhile, this method also has its own disadvantages, for instance, in his experimental validation of the proposed technique, the method of getting or updating the weights of the filter is not fully automated. It is done manually and the author suggests looking for a better objective function that can eliminate this issue. In addition, the method uses more time for computation of the global solution but in general, the method looks promising by checking the simulation results.

2.4 Multi-Model Approach and Applications

It is equally important to mention some previous work on the multi-model approach for fault detection and isolation since this is one of the approaches we intend to use to achieve some of the objectives of this thesis work. Multi-model approach technique is an alternative to the conventional approach to monitoring, modeling and identification of nonlinear process or systems. The method combines several models in a way where each model contributes to the system output with a certain degree of validity. Each sub-model can be regarded as a possible representation of the system within the operating space under either varying operating point or due to a fault. Any kind of model can be used to represent a system in multi-model approach either linear, non-linear, gray-box or black-box modeling approach. In general, fault determination and isolation methods in literature can be classified into two, model free and model-based approach but in this thesis work, the previous model-based technique is surveyed. Model-based approaches employ the use of an analytical method to analyze the model of the system to be diagnosed. Many methods under this categories analyze the consistency by generating the residual between the nominal model and the real system, both working in parallel. The residual generation can be achieved through different approaches such as state observers, parity equations, and parameter estimation methods or through the combination of one or more of this [30]. One drawback that is common to the aforementioned model-based approach is that it requires an accurate model of the system to be studied which is usually difficult sometimes to get basically because of the non-linear, parameter uncertainty and complexity nature of the real system under study. Based on this, the identification techniques in S. Simani and coworkers [30], [31], [32] as well as Multi-model approach applied in Wolfram [33], Z. Abbasfard [34] are often used to generate a nominal model of the real system. In system identification techniques which are data-driven, the mathematical model of the system is obtained through the input and output data from the system while in the multi-model implementations the multi-models are used to represent the system. Common multi-model FDI approach set-up usually consist of a bank of fault diagnoses, one will represent healthy operation mode of the system and the others will represent series of fault system's mode. The fault diagnosers can be in the form of multiple filters as in K. Takahisa et al.[35] or Multi-model like in Z. Vanini et al., [36] and V. F$\ddot{u}$vesi [37]. In general, the overall multi-model FDI framework is divided into two steps, the first is the residual generation (Fault Diagnose) and the second is residual evaluation (Supervisor design). However, different methodologies/algorithms have been employed in achieving the two steps for instance; recently, Artificial Neural Network (ANN) had been used as fault diagnosers in a non-linear system due to its ability to capture complex nonlinearity, the details can be found in Z. Vanini et al.,[36], V. F$\ddot{u}$vesi [37] and K. Patan et al., [38] but the drawback of this ANN is that it requires a large amount of data that is scarcely available in practice. On the other hand, different supervisor designs have been employed for evaluation of generated residuals. In K. Patan et al., [38] a simple residual threshold technique was engaged as supervisor while a probability threshold technique was employed in [36]. A dynamic Bayesian Network was proposed in H. Cho and J. Knowles [39] for fault detection and isolation (FDI) of induction motor control system. Other methods include the decision tree in Y. Kourd [40], ANN classifier by V. F$\ddot{u}$vesi [37] and residue approach by A. Karoui and M. Ksouri [41]. The main common drawback of these supervision techniques is the lack of accounting for modeling uncertainty and measurement noise. Also, the threshold methods are restrictive and assigning suitable threshold is a difficult task more detail can be found in S. Rahme and N. Meskin [42]. In this research work, multiple model approach using constrained Kalman filter is utilized which takes into account the model uncertainty, measurement noise, and neglect the uses of threshold methods to prevent the disadvantage coming with threshold methods of fault detection and other commonly used techniques.

CHAPTER 3

PRELIMINARY RESULTS AND IMPLEMENTATION OF MULTI-MODEL APPROACH USING CONSTRAINED KALMAN FILTER

3.1 Introduction

Implementation of multi-model approach in fault diagnosis and isolation basically involves having models describing fault-free and faulty system so that the condition of a complex dynamic system can be monitored through them. In general, based on literature survey for instance in the section 2.4, implementation of multi-model techniques require two major steps which are residual generation and residual evaluation. The description of the method used in generating residue from the system that this thesis work employed as a case study and the method utilized in evaluating the residue are presented in this chapter. It is also important to mention that the method of residual evaluation considered in this thesis work takes into account the model uncertainty and measurement noise unlike other multi-model approaches such as [37], [40], [41], and [42] which do not take into consideration model uncertainty and measurement noise. The remaining part of this chapter describes the formation of nominal(fault-free) and faulty system models of a closed loop process having a real industrial pneumatic control valve considered for this thesis work. In addition, it also describes algorithm applied as a supervisor scheme which serves as a residual analyzer. This residue is the error generated by the real system output and the output of the models representing the different behavior of the real system under study for various cases considered in this work. Furthermore, the results obtained during the experimental validation of this method (Multi-model approach using weighted constrained Kalman filter) are presented and reference is also made to the simulation results obtained in the validity of this method.

3.2 Validity Computation and Process Identification

There are many works on multi-model techniques in literature as stated earlier with examples of some of them mentioned in section 2.4 but this thesis work discusses the real time implementation of a multi-model approach using constrained Kalman filter(MMCKF). In the implementation of this method, the errors generated between the multiple models for different behaviors of the real system and the real system under study itself are evaluated using validity estimation method called CKF. This CKF was initially introduced and used in [43] and its performance was tested using simulation examples meanwhile in this thesis work, its practical implementation to fault detection, isolation is investigated (using control valve suffering from stiction as a case study) after that new stiction compensation methods are proposed. We chose to use MMCKF for fault detection, isolation because of its superior performance over the other commonly used validity computation methods. Table 3.1 shows the algorithm describing the validity computation used in this Multi-model technique. Subsection 3.2.1 explains in details Table 3.1 algorithm's formation.

Table 3.1: Constrained Kalman Filter (CKF) model validity computation algorithm

1: Initialize $\Phi = [\phi_1, \ldots, \phi_m]$, P (3.1a)
Define Q, R

2: Compute unconstrained estimate Φ^{est} of Φ

$$\begin{aligned}
\Phi^{est-}(k) &= \Phi^{est-}(k-1) \\
P^{-}(k) &= P^{-}(k-1) + Q(k-1) \\
K(k) &= P^{-}(k)\mathbf{y}^T(k)[\mathbf{y}(k)P^{-}(k)\mathbf{y}^T(k) + R(k)]^{-1} \\
\Phi^{est}(k) &= \Phi^{est-}(k) + K(k)[y(k) - \mathbf{y}(k)\Phi^{est-}(k)] \\
P(k) &= [I - K(k)\mathbf{y}(k)]P^{-}(k)
\end{aligned} \tag{3.1b}$$

3: Compute equality constrained estimate, Φ^{est*} of Φ

$$\begin{aligned}
K^*(k) &= \mathbb{W}^{-1}\beta^T[R + \beta\mathbb{W}^{-1}\beta^T]^{-1} \\
\Phi^{est*}(k) &= \Phi^{est}(k) + K^*(k)[1 - \beta\Phi^{est}(k)] \\
P^*(k) &= [I - K^*(k)\beta]\mathbb{W}^{-1} + Q
\end{aligned} \tag{3.1c}$$

4: Truncation of $\Phi^{est*}(k)$

$$\phi_i^{est**}(k) = 0 \;\; \text{If } \phi_i^{est*}(k) < 0 \tag{3.1d}$$

5: Finally normalized $\phi^{est**}(k)$

$$\phi_i^{est***}(k) = \frac{\phi_i^{est**}(k)}{\sum_{i=1}^{m} \phi_i^{est**}(k)} \tag{3.1e}$$

6: The final estimated validities at k is

$$\Phi^{est***}(k) = [\phi_1^{est***}(k), \ldots, \phi_m^{est***}(k)]^T \tag{3.1f}$$

3.2.1 Constrained Kalman Filter(CKF) Validity Computation Overview

Given a dynamic system (Ds) having an output y_i where $i = 1, 2, \ldots, M$ denote various or different mode of the output of the system. Each of these models M_i corresponding to the output y_i can be represented by either a state-space or an input-output form of the discrete time system. This model M_i can as well be a linear or non-linear model depending on how complex the system under study is. Besides, the model of this dynamic system can be derived or formed by means of system identification methods or can be an analytical model.

In multi-model concept, a weighted sum of the output of all the models used to represent the various behavior of a dynamic system is used as the output of the diagnosed system. That is, the diagnosed system can be estimated by a combination of M number of models defined as

$$y(k) = \sum_{i=1}^{M} y_i(k)\phi_i(k) + v(k) \tag{3.1}$$

where y denotes the diagnosed system's output, ϕ_i is the weight or validity of the model M_i corresponding to output y_i and $i = 1, 2, \ldots, M$. v stands as measurement noise which is commonly present in real life processes.

In the implementation of this algorithm(CKF) throughout this thesis work, M_1 represents the Fault-free model of a dynamic system and M_i with $i = 2, \ldots, M$ corresponds to fault mode or behavior that can be experienced by the dynamic system that is models that describe the behavior of system during fault conditions.

The weight of the model or its validity (ϕ) defined the contributions of each model M_i to the output of the diagnosed system. To ameliorate the reading of the models, the weight(validity) satisfy the convexity property [44].

$$\sum_{i=1}^{M} \phi_i(k) = 1 \quad \forall k \tag{3.2}$$

$$0 \leq \phi_i \leq 1 \quad \forall k,\ \forall i \in 1, 2, \ldots, M \tag{3.3}$$

The validity(weight),ϕ, of the model denotes an essential or a key decision making in multi-model based fault detection and isolation using constrained Kalman filter and therefore, its computation plays a vital role in the efficiency of the FDI scheme. To determine the validity(weight) of the model in Equation (3.1) underlying the MM based FDI, the vector form of the Equation in (3.1) is shown as follows:

$$y(k) = \bar{\mathbf{Y}}(k)\Phi(k) \tag{3.4}$$

where $\bar{\mathbf{Y}} = [y_1, y_2 \ldots, y_m]$ is a known vector of outputs of the models $M_1, M_2 \ldots, M_m$ in the model bank and $\Phi = [\phi_1, \phi_2, \ldots, \phi_m]^T$ is the unknown vector of the validity of the models. Each corresponding to each output of the models that is $(\phi_1, y_1, \phi_2, y_2, \ldots, \phi_m, y_m)$. This formulation can be cast or transformed into a parameter estimation problem of the form

$$\Phi(k+1) = \Phi(k) + w(k) \tag{3.5}$$

$$y(k) = \bar{\mathbf{Y}}(k)\Phi(k) + v(k) \tag{3.6}$$

where $\Phi(k)$ is the vector of unknown parameters(weights) to be estimated and $v(k)$ is the measurement noise at time k with $w(k)$ stands for process noise and the model mismatched noise with covariance R. Also, Q defined to represent the covariance of the measurement noise $v(k)$.

Furthermore, considering the convexity of Φ, the equality and inequality constraints in Equation (3.2) and (3.3) need to be included. Hence, the full estimation problem is given as follows:

$$\Phi(k+1) = \Phi(k) + w(k) \tag{3.7}$$

$$y(k) = \bar{\mathbf{Y}}(k)\Phi(k) + v(k) \tag{3.8}$$

$$\text{such that} \qquad \beta\Phi(k) = 1$$

$$0 \leq \phi_i(k) \leq 1$$

where β is a row vector of $[1, 1, \ldots, 1, 1]$. The problem is then formulated, assuming given an Equation like that of the Equations in (3.7), (3.8) and the equality and inequality constraints, as minimizing the mean square error (MSE) of the estimate of the state $\Phi(k)$

$$\begin{aligned} &\min_{\Phi} \ \mathbb{E}[(\Phi(k) - \Phi^{est}(k))^2] \\ &\text{such that} \\ &\beta\Phi(k) = 1 \\ &0 \leq \phi_i(k) \leq 1 \end{aligned} \tag{3.9}$$

with $\mathbb{E}$ represents expectation operator, β is the row vector of $[1, 1, \ldots, 1, 1]$, Φ is the unknown parameters and Φ^{est} is the estimated ones.

The above problem is solved by CKF algorithm in two steps. First step, the equality constraint is solved by utilizing the projection techniques [45], [46] where the unconstrained estimate, $\Phi^{est}(k)$ is projected onto the constrained space by minimizing:

$$\min_{\Phi} \mathbb{E}[(\Phi(k) - \Phi^{est}(k))^T \mathbb{W}(\Phi(k) - \Phi^{est}(k))] \tag{3.10}$$
$$\text{such that} \quad \beta\Phi(k) = 1$$

$\Phi(k)$ is $[\phi_1(k), \phi_2(k), \ldots, \phi_m(k)]^T$ and $\mathbb{W}$ is a positive definite matrix. The problem solution is given as (Equation 3.1c of Table 3.1:

$$\begin{aligned} K^*(k) &= \mathbb{W}^{-1}\beta^T[R + \beta\mathbb{W}^{-1}\beta^T]^{-1} \\ \Phi^{est*}(k) &= \Phi^{est}(k) + K^*(k)[1 - \beta\Phi^{est}(k)] \\ P^*(k) &= [I - K^*(k)\beta]\mathbb{W}^{-1} + Q \end{aligned} \tag{3.11}$$

where Φ^{est} represents the unconstrained estimate, $\Phi^{est*}(k)$ is the updated equality constrained estimate that satisfy equation (3.2) and $\mathbb{W}$ is the positive definite matrix weight or symmetric positive definite weighting matrix. In this thesis work, there are two settings of $\mathbb{W}$ used in the implementation of this algorithm, which are:

i. Setting $\mathbb{W} = P^{-1}$ as in Equation 3.11 results in minimum variance estimate.

P is the covariance matrix of the standard Kalman filter algorithm estimate.

ii. Setting $\mathbb{W} = I$ gives least square estimate of $\Phi(k)$ [47],[48]

In the first setting where $\mathbb{W} = P^{-1}$, the algorithm is named as $CKFP$ and in the second setting where $\mathbb{W} = I$ the algorithm is named as $CKFI$ where P denotes covariance matrix of standard Kalman filter algorithm and I stands as an identity matrix. In the implementation of both settings, the unconstrained problem is first solved using the standard solution of Kalman filter and then, the obtained unconstrained estimates,Φ^{est}, is used to update the equality constrained estimate shown in (3.11).

In summary, given the observation $y(k), y(k-1), \ldots, y(1)$ and the model outputs $\bar{y}(k), \bar{y}(k-1), \ldots, \bar{y}(1)$, the unconstrained estimate,Φ^{est}, can be computed using the standard Kalman filter algorithm as shown in Equation (3.1b) of Table 3.1. The obtained unconstrained estimate,Φ^{est}, is used to update the equality constraint,Φ^{est*}, as in equation (3.1c) of Table 3.1. This is followed by truncation and normalization of the validity(weight).

In the next step, truncation, and normalization [49] are adopted for the inequality constraint. The truncation serves to readjust each element of Φ^{est*} such that inequality constraint in (3.9) will not be violated.

$$\phi_i^{est**}(k) = 0 \quad \text{if } \phi_i^{est*}(k) \leq 0 \tag{3.12}$$

As in Equation 3.1d of Table 3.1.

Lastly, Φ^{est**} is normalized to prevent violation of inequality constraint in Equation (3.2) and to satisfies the other part of the inequality constraint, Equation (3.3).

$$\phi_i^{est***}(k) = \frac{\phi_i^{est**}(k)}{\sum_{i=1}^{m} \phi_i^{est**}(k)} \tag{3.13}$$

The final estimated weights or validity computations at time 'k' is shown in equation 3.1f of Table 3.1, for further details on the algorithm and simulation's results obtained when CKF is tested on simulated or analytical model of a three tank dynamic system from [50], check [63].

In this thesis work, in the experimental implementation of multiple models (MM) concept, model banks are created consisting of system identification models of normal system mode and the two fault modes, the outputs of these models are compared on-line with the real system output to detect the existence of a fault and the kind of fault. The next subsection explains the models formation for both normal mode and two fault modes of the dynamic system used in this work.

3.2.2 Process Identification

In multiple model approach to fault detection and isolation, accurate model which represents the behavior of a dynamic system at different conditions is an important part of any multi-model techniques, because of this, functional network(FN) [51] is used in forming the mathematical model (Polynomial family) of the form in Equation (3.14) and its mathematical equation is shown in Table 3.2 representing fault-free and fault-mode of a closed loop level control process having a pneumatic

Table 3.2: Model Representation

Generalized Model For Both Normal and Faulty System
$y(k) = a - b(y(k-1)) - c\sqrt{(y(k-1))} - d(u(k-1)) - e\sqrt{(u(k-1))}$

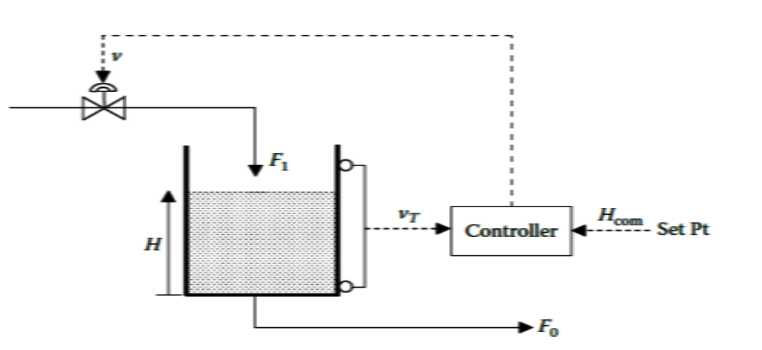


Figure 3.1: Schematic of a Process Set-up

control valve. It is the generalized model for both normal and faulty system. For different mode or behavior of the system, the values of the parameter a, b, c, d and e as shown in the Table 3.2 will be different.

$$\{1, x^1, x^2, \ldots, x^n\} \tag{3.14}$$

The parameters of the model that is a,b,c,d, and e of the Table 3.2 were obtained through the well-known least square procedures. The schematic of the process setup is shown in Figure 3.1.

Functional network(FN) introduced by Castillo et al [51] is an alternative to Neural network. It uses domain knowledge as well as data knowledge in learning functions which is an advantage over Neural network. It is a new modeling scheme and has been used in prediction and classification problems, also, it is generally useful in solving problems in engineering, function estimation or approximation and in statistics. Due to the fact that functional network is not the topic of this thesis work therefore for more details on its architecture, formulation, and comparison with other methods such as Neural network(NN), General Regression Neural-network(GRNN), Cascade Correlation Neural network (CCNN) etc., check [51],[52],[53],[54].

The first stage in data-driven or system model formation is the data collection, in what follows, input and output data of a closed-loop dynamic water level control system are collected from Process control laboratory at King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia. The data collected namely OP and PV which are the input (output of a PID Controller) and output of the level control loop process at the aforementioned laboratory and this was done via the aids of LabVIEW interface and National instrument compact Controller processor.

The model performance evaluation or model accuracy and suitability for the task are evaluated using root mean square error(RMS), the mean square of error (MS) and the correlation coefficient(CC) between the desired response and the estimated response. Root mean square error (RMS) and mean square error (MS) is defined as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2} \tag{3.15}$$

$$MS = \frac{1}{N}\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2 \tag{3.16}$$

where y is the measured/observed data from the system, $\hat{y}$ is model response value and N denotes the number of data points observed. Both the RMS and MS can have the values with an optimal value equal to zero which indicate a perfect match of model value and desired system value whereas, in the case of the correlation coefficient, a value of one indicate a perfect match between data and model. The models which describe different behaviors the closed loop liquid level control process utilized in this work exhibited are formed as follows:

a. Nominal Model(Fault free model)

At this point, based on the input-output data collected from a level control system at the lab mentioned earlier. A quantitative dynamic model of a closed loop system is formed in the presence of healthy control valve(label E in the Figure 3.2) that is without any stiction disturbance. Throughout the data collection and the experiment, the desired set-point is set to 15cm. 1000 data points are collected for both OP and PV from the system showing in Figure 3.2. The simulation is carried out using MATLAB R2013b on a Dell intel Core i5 laptop for modeling the system after the data collection. The responses obtained for the model are depicted in Figure 3.3, 3.4 and the corresponding mathematical model shown in Equation 3.17 along side its performance evaluation in Table 3.3. The data collected both OP and PV is divided into two sets, the first set is 800 data points for training the functional Network and the remaining 20 percent of the data is used for validation of the model.

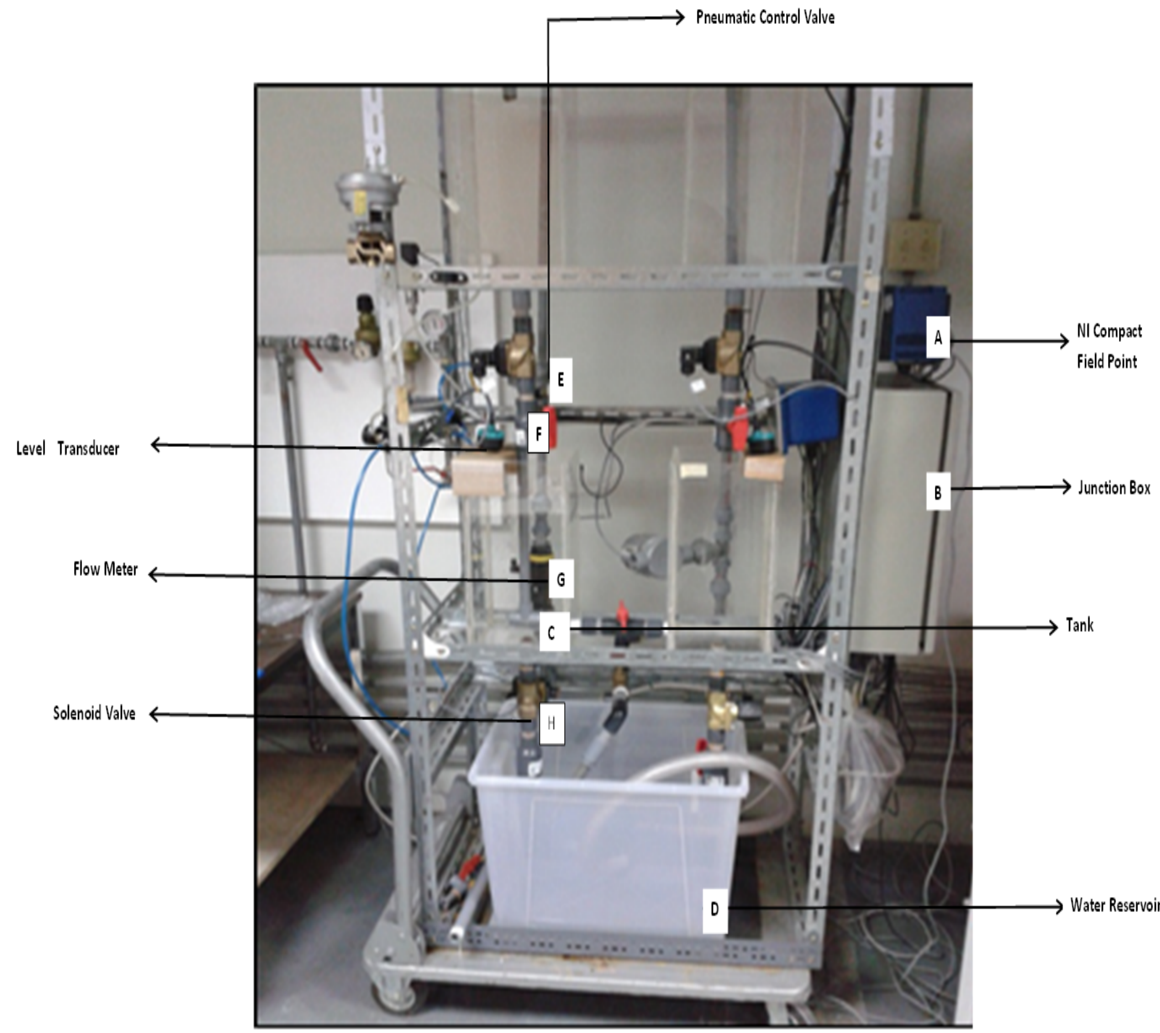


Figure 3.2: A closed loop level control process

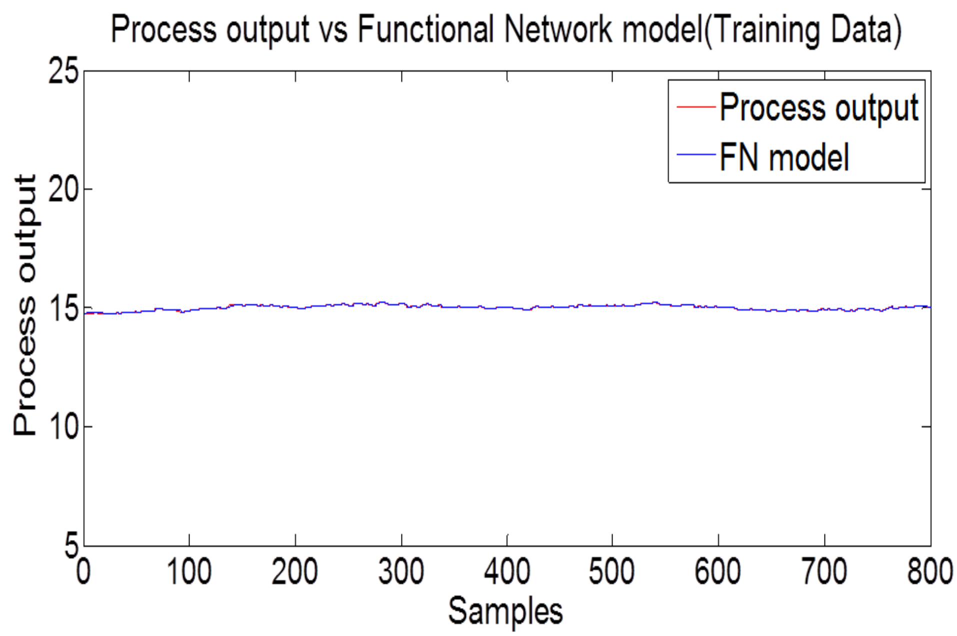


Figure 3.3: FN Model for the Process with Normal Mode (Training Data)

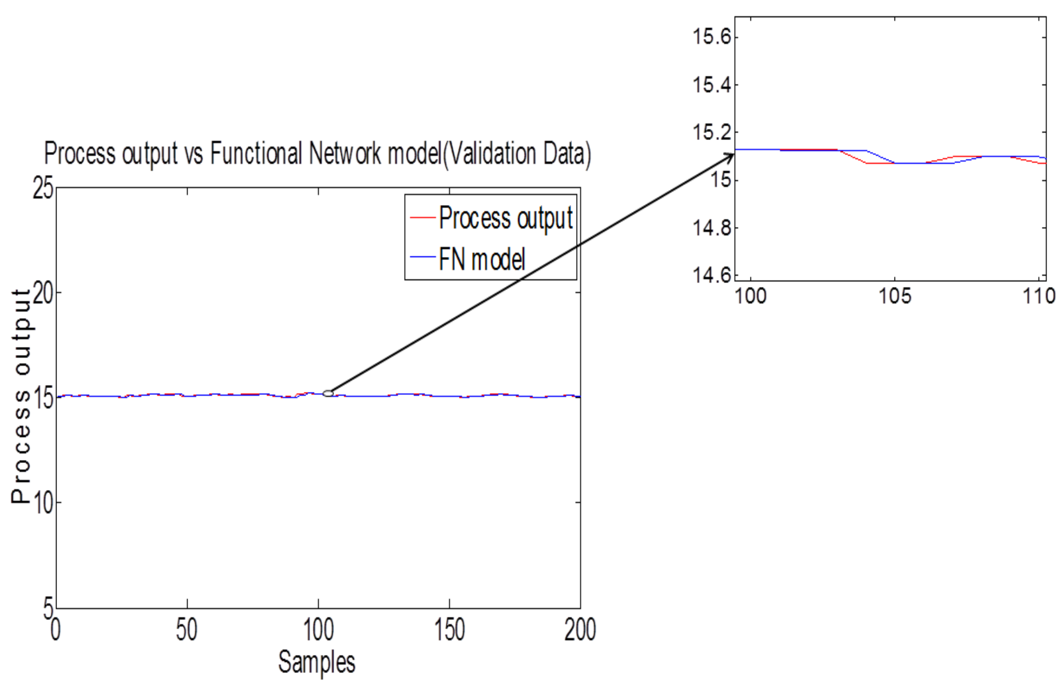


Figure 3.4: FN Model for the Process with Normal Mode (Validity Data)

Table 3.3: Performance Evaluation result for Nominal Model

	RMS	MS	CC
Training Data	0.0214	4.5636e-004	0.9813
Testing(Validation)	0.0203	4.1106e-004	0.8637
Model Coefficient	a= 14.7200,b=-1.9387 ,c= 7.436, d=0,e=0		
PV is output of the system and OP is input to the system			

$$PV(k) = a - b(PV(k-1)) - c\sqrt{(PV(k-1))}\dots$$
$$+d(OP(k-1)) + e\sqrt{(OP(k-1))} \tag{3.17}$$

It is clear from the figures and the table that the model response perfectly match the process response with an acceptable error as it is obvious from the RMS, MS, and Correlation coefficient values present in the Table 3.3 which shows the accuracy of the model formed.

b. Fault Mode Model

In this part, two models are formed which describe the fault behaviors of a dynamic system and this is done by introduced stiction to the healthy control valve in a closed loop level control process via soft-element (Kano model) coded into a National instrument(NI) compact field processor. After introducing different amount or degree of stiction by varying the two parameters J and S which define stiction phenomenon, then 500 data points were collected for each scenario of stiction introduced via LabVIEW interface, 80% of the data collected is used to train the functional network and the remaining 20% is utilized for the model

Table 3.4: Performance Evaluation of Faulty Model 1

Fault Type1 Parameters: $F_s = 25$ and $F_d = 5$			
	RMS	MS	CC
Training Data	0.1775	0.0315	0.9930
Testing(Validation)	0.1681	0.0283	0.9940
Model Coefficient	a1= 15.0210,b1=-3.3935,c1= 14.2714,d1=0.0794,e=0		
PV is output of the system and OP is input to the system			

Table 3.5: Performance Evaluation of Faulty Model 2

Fault Type 2 Parameters: $F_s = 60$ and $F_d = 10$			
	RMS	MS	CC
Training Data	0.3203	0.1026	0.9952
Testing(Validation)	0.2847	0.0810	0.9961
Model Coefficient	a2= 11.1697,b2=-2.2217,c2= -8.0321,d2=0.0233,e2=0		
PV is output of the system and OP is input to the system			

validation in each case. The relationship among the J, S and static friction F_s and the dynamic Frictional Force F_d is shown in Equation (2.4) and (2.5).

The details of the value of the parameters used and performance evaluation of each scenario in each case are shown in Tables 3.4 and 3.5. Also included are the mathematical model, Equation (3.18) and (3.19). In addition, the responses of the models for each type of behavior the system exhibited when the stiction phenomenon is introduced are shown in Figures 3.5, 3.6, 3.7, 3.8. It is obvious from the figures that the water level deviates from the set-point of 15cm as a result of stiction introduced. The RMS, MS and the correlation coefficient (CC) values in the Figures 3.4, 3.5 show the accuracy of the model representing the two fault mode or behavior of the dynamic system.

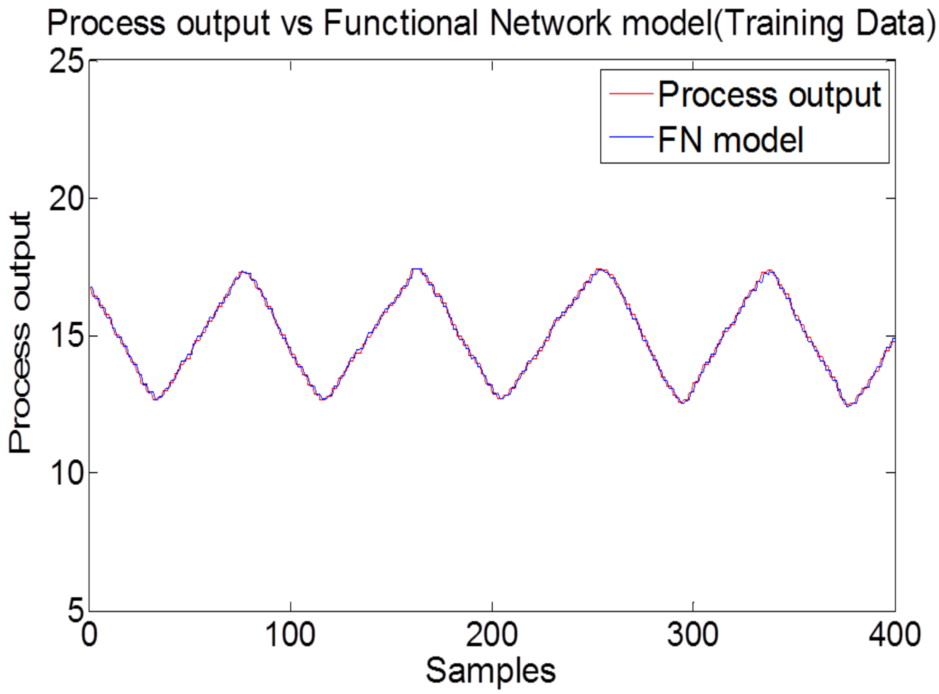


Figure 3.5: FN Model for the Process with Fault 1 (Training Data)

$$PV(k) = a1 - b1(PV(k-1)) - c1\sqrt{(PV(k-1))}\dots$$
$$+d1(OP(k-1)) + e1\sqrt{(OP(k-1))} \tag{3.18}$$

$$PV(k) = a2 - b2(PV(k-1)) - c2\sqrt{(PV(k-1))}\dots$$
$$+d2(OP(k-1)) + e2\sqrt{(OP(k-1))} \tag{3.19}$$

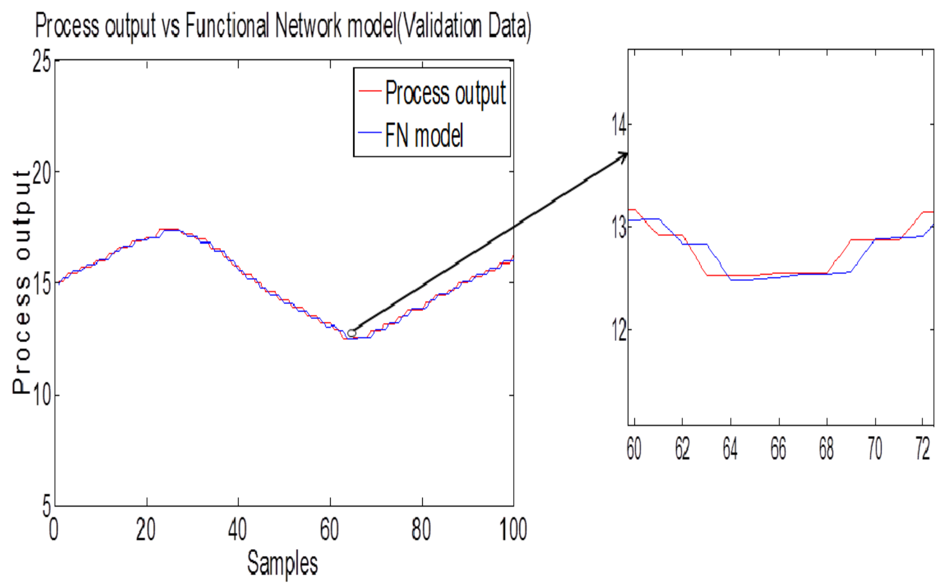


Figure 3.6: FN Model for the Process with Fault 1 (Validation Data)

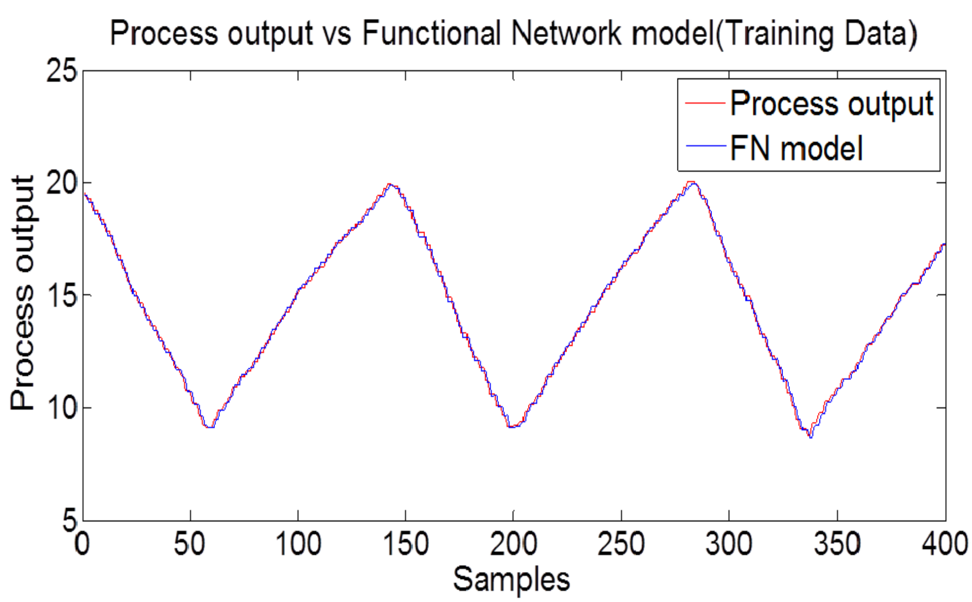


Figure 3.7: FN Model for the Process with Fault 2 (Training Data)

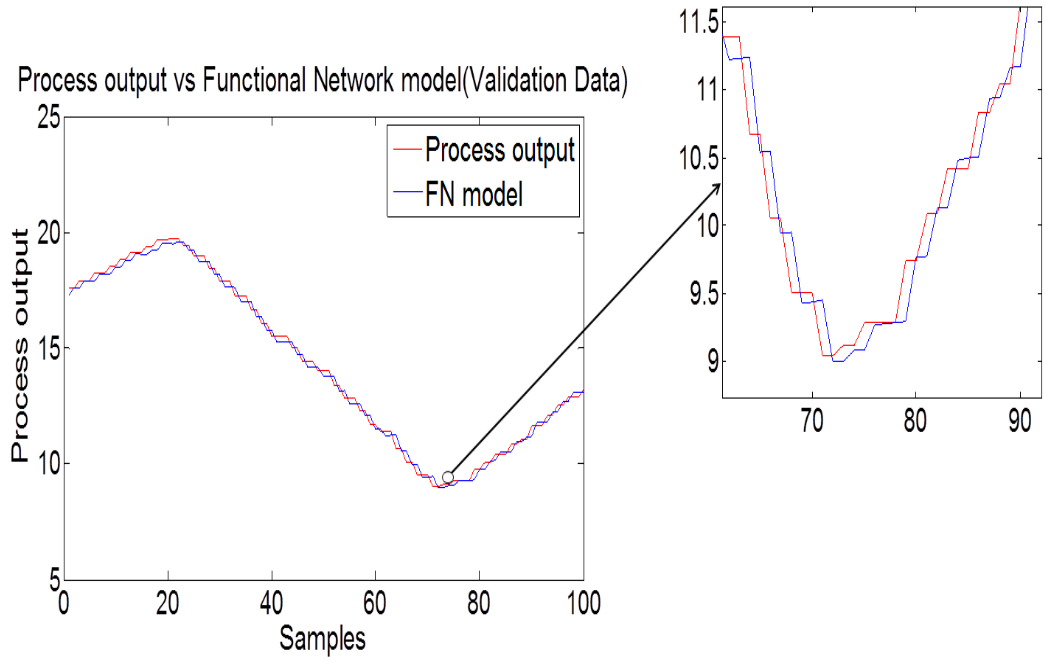


Figure 3.8: FN Model for the Process with Fault 2 (Validation Data)

3.3 Implementation of CKFP and CKFI for Fault Detection and Isolation

In the implementation of both forms of constrained Kalman filter for validity computation (CKFP and CKFI) explained earlier to detect and isolate the fault in a closed loop process having a pneumatic control valve, an experimental setup of a closed loop level control system is utilized. The setup is made up of a healthy control valve, sensors, transmitters, LabVIEW interface(HMI), NI Compact RIO programmable automation controller, embedded real-time/FPGA, tanks, Leo APm37 AC peripheral pump, and water reservoir etc., as shown in the diagram setup figure 3.2. The techniques are tested on a level control loop (LC) in order to detect a fault and isolate its fault types. The algorithms (CKFP and CKFI) were used

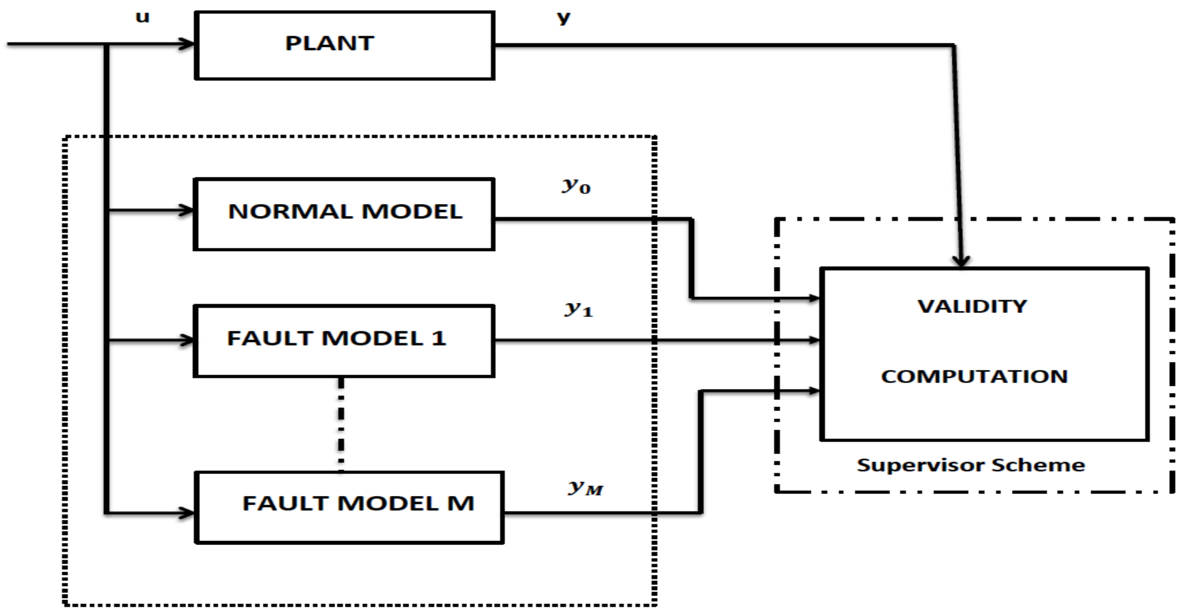


Figure 3.9: Multi-Model Fault Detection and Isolation Scheme For Level Control Loop (LC)

experimentally to diagnose stiction phenomenon. The multi-model fault detection, isolation scheme for the level control loop is therefore shown in Figure 3.9.

In this experiment, there are four cases considered for the closed loop process, namely:

- Stiction free process
- Process with fault mode 1
- Process with fault mode 2
- Process with fault mode 1 and mode 2

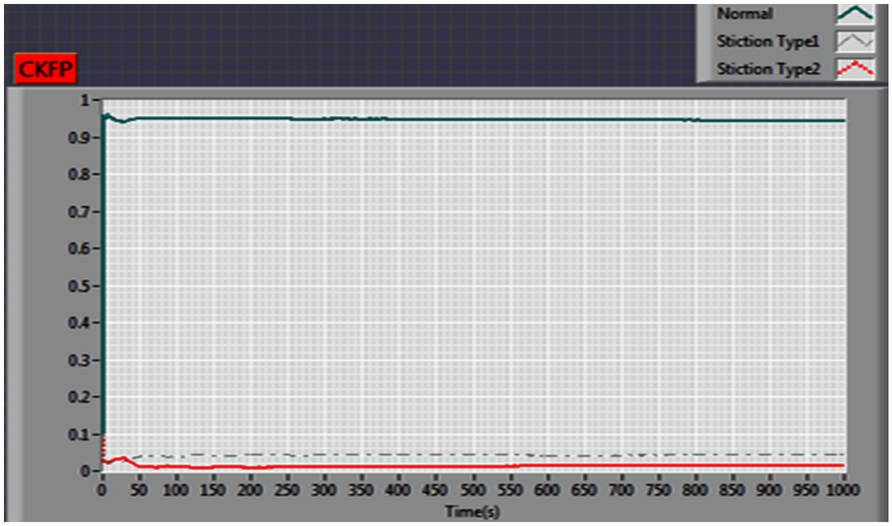


Figure 3.10: Normal condition detection using MMCKFP with $\mathbb{W} = P^{-1}$

Stiction free process: In the first case which is Stiction free process, after the whole setup, the process is allowed to run normally using PI controller without any stiction disturbance introduced then both techniques allowed to run in parallel with the process setup as shown in Figure 3.9. In this first case, the aim is to check if the scheme will able to detect if there is no problem with the process. Figures 3.10, 3.11, 3.12, and 3.12 show the responses obtained when both CKFP and CKFI were utilized for both detection and isolation of fault in the experimental setup.

In all the figures, it is clear that the multi-model approach using both CKF('P' and 'I') able to isolate and detect that the process set-up does not suffer from any fault. There are three models in the model bank, M1 is the normal mode of the dynamic system, M2 and M3 represent the two fault behaviors that the system (process setup) will exhibit if the stiction phenomenon is introduced. Each of these shows their contribution to the description of the condition the dynamic

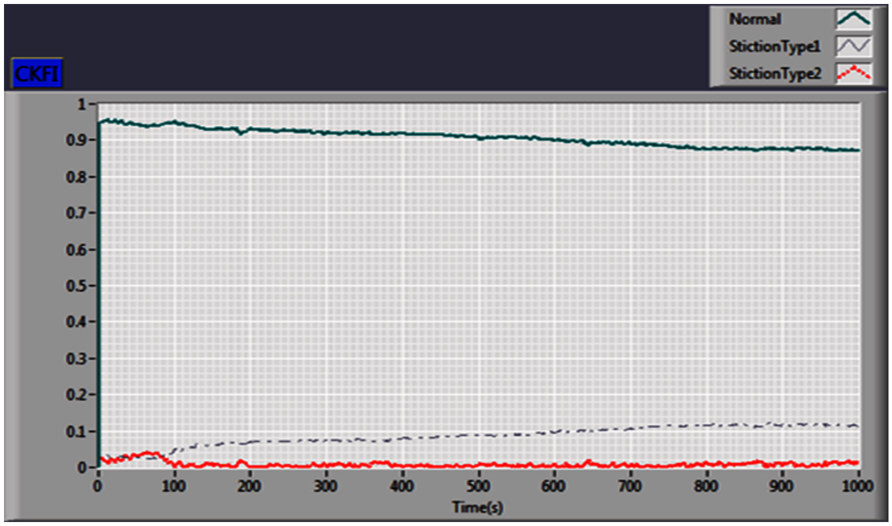


Figure 3.11: Normal condition detection using MMCKFI with $\mathbb{W} = I$

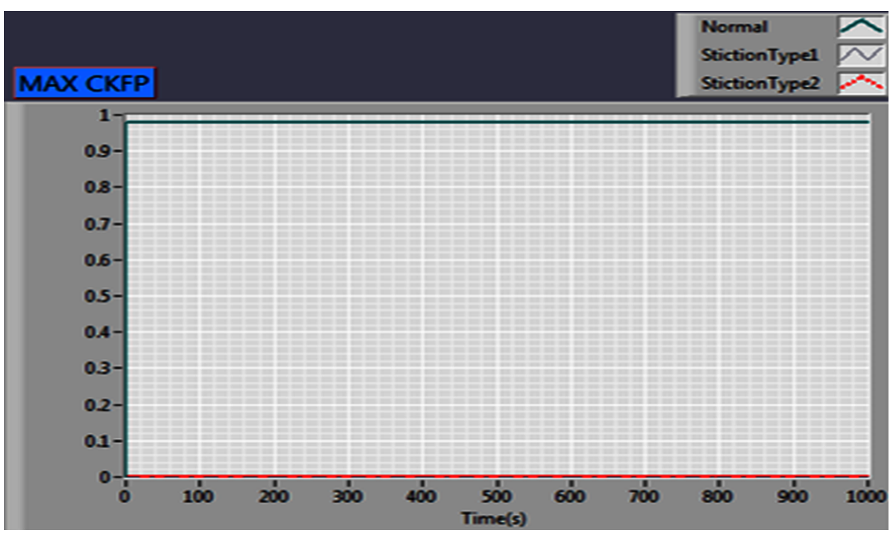


Figure 3.12: Fault Isolation Case 1: Normal condition detection/Isolation using MMCKFP with $\mathbb{W} = P^{-1}$

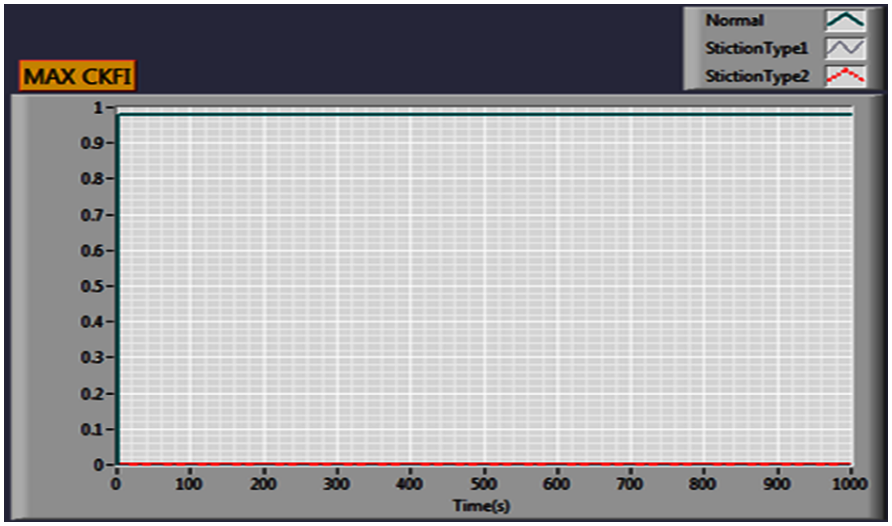


Figure 3.13: Fault Isolation Case 1: Normal condition detection/Isolation using MMCKFI with $\mathbb{W} = I$

system exhibited using the validity(weight),ϕ_i. In Figures(3.10, 3.11,3.12,3.13) we could see that the green line is showing that the system is almost 100% ok and the others almost equal zero. This is telling us that the process is working fine with the validity of almost 100%. In order to investigate further if the scheme will able to detect the condition of the plant in fault modes, further tests are performed.

Process with fault mode 1: In this case, the process setup is allowed to run in parallel with the both scheme (CKFP and CKFI) as shown in the figure 3.9. Initially, no stiction effect was introduced to the process before the instance of time 500s, before this time, both CKFP and CKFI able to detect that no fault occurred to the process. At the exact instance of time 500s, the stiction phenomenon of parameter $F_s = 25$ and $F_d = 05$ corresponding to fault type 1 is introduced into the process, both techniques(CKFP and CKFI) detect that the process is suffering from fault type 1. This is shown in Figures 3.14, 3.15, it is obvious from

Figure 3.14: Case 2: Fault Type1 detection using MMCKFP with $\mathbb{W} = P^{-1}$

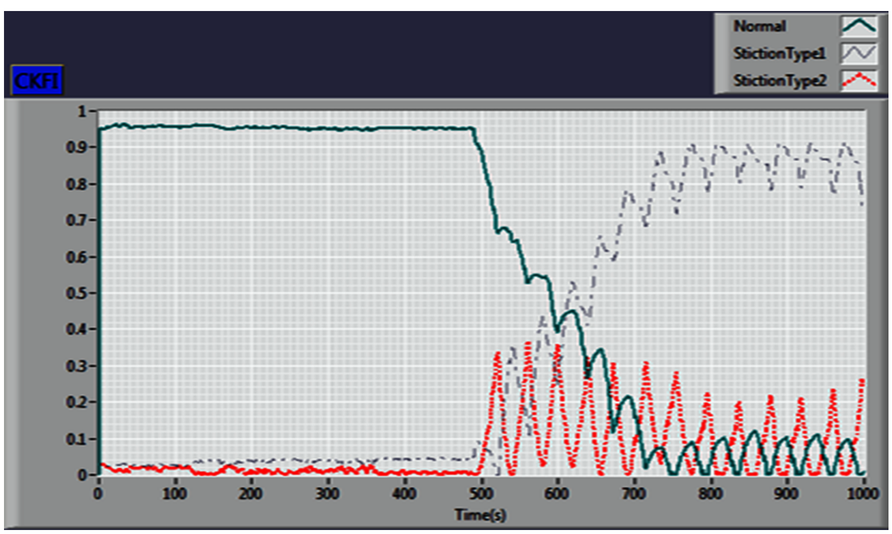


Figure 3.15: Case 2: Fault Type1 detection using MMCKFI with $\mathbb{W} = I$

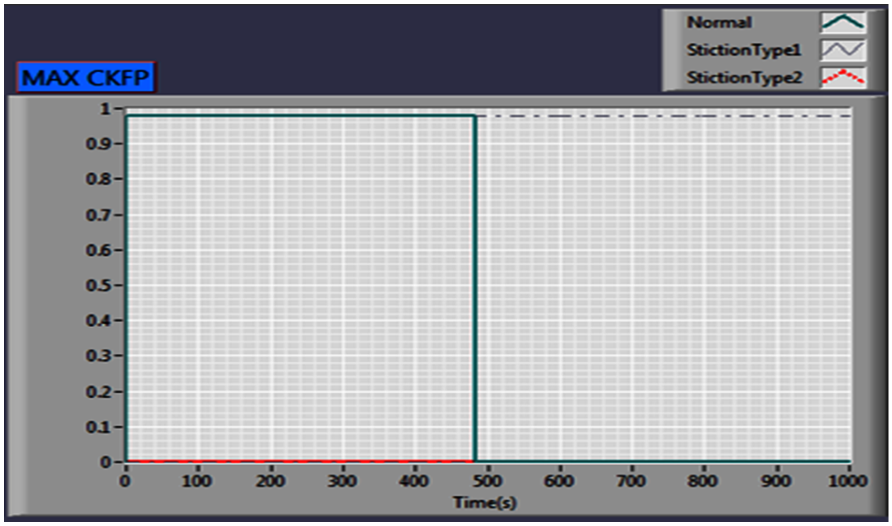


Figure 3.16: Fault Isolation Case 2: Fault Type 1 detection/Isolation using MM-CKFP with $\mathbb{W} = P^{-1}$

the figures that the validity of the normal model(green line) start decreasing, that of model-three (M_3) remain closed to zero and that of model-two (M_2) start rising showing that the process/system start having an issue. Figures 3.16, 3.17 show the corresponding isolation scheme responses, it is clear from these figures that the process is suffering from fault type 1. Based on the model in the model bank, the isolation scheme able to isolate clearly the fault type 1 that the process setup is suffering from, from other modes of faults that the process could suffer from, therefore, this will help and enhance in applying the best compensation method to correct the problem.

Process with fault mode 2: In this test, stiction phenomenon with parameter $F_s = 60$ and $F_d = 10$ equivalent to fault type 2 was introduced into the closed loop process described earlier, this results in the responses shown in the figures 3.18, 3.19, 3.20, 3.21 which reveal that the algorithms CKFP and CKFI able to

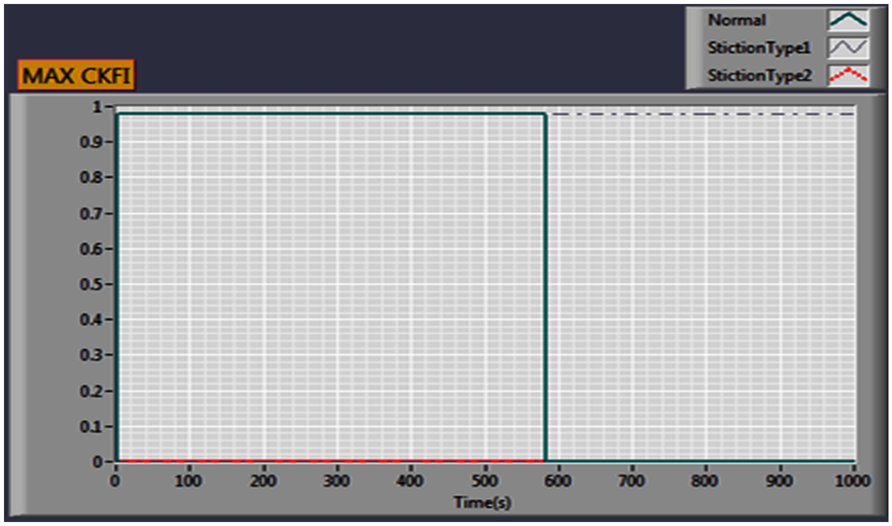


Figure 3.17: Fault Isolation Case 2: Fault Type 1 detection/Isolation using MM-CKFI with $\mathbb{W} = I$

detect and isolate the fault type occurring in the process. Stiction was introduced at the instance of time equals 490s and the fault detection took place for the $CKFI$ AND $CKFP$ at approximately 490s but there was an acceptable delay in fault isolation for both $CKFI$ and $CKFP$ which is approximately equal to 20s and this does not affect the performance of both techniques to detect and isolate faults occurring in the process.

Process with fault mode 1 and mode 2 : In this last part of this experiment, stiction type 1 and 2 ($F_s = 25$, $F_d = 05$, $F_s = 60$, and $F_d = 10$)were introduced at different instant of time to experimentally test the validity of the algorithms, the results obtained is satisfactory. As it can be seen from the figure 3.22, 3.23,3.24,3.25 both CKFP and CKFI able to detect fault type 1 and 2 at the time instance approximately 300s and 850s when the stiction phenomenon was introduced respectively, for the fault isolation part there was delay in isolating

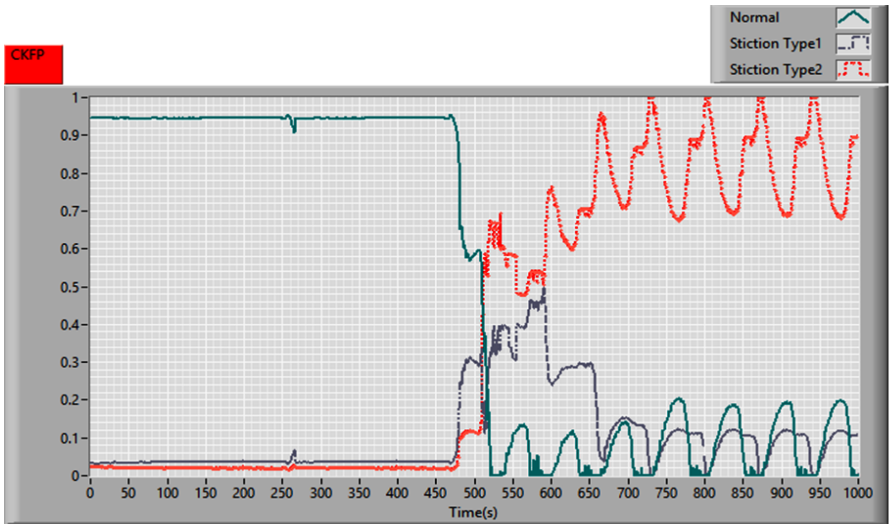


Figure 3.18: Case 3: Fault Type 2 detection using MMCKFP with $\mathbb{W} = P^{-1}$

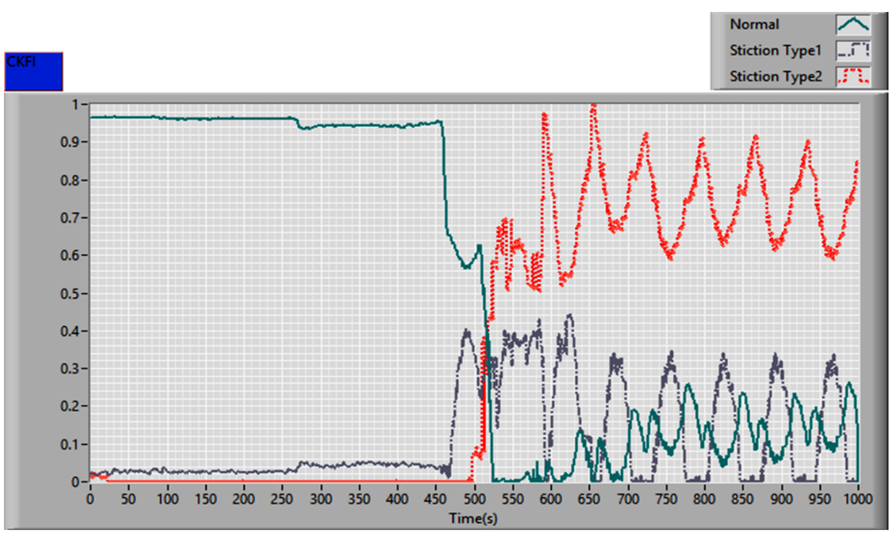


Figure 3.19: Case 3: Fault Type 2 detection using MMCKFI with $\mathbb{W} = I$

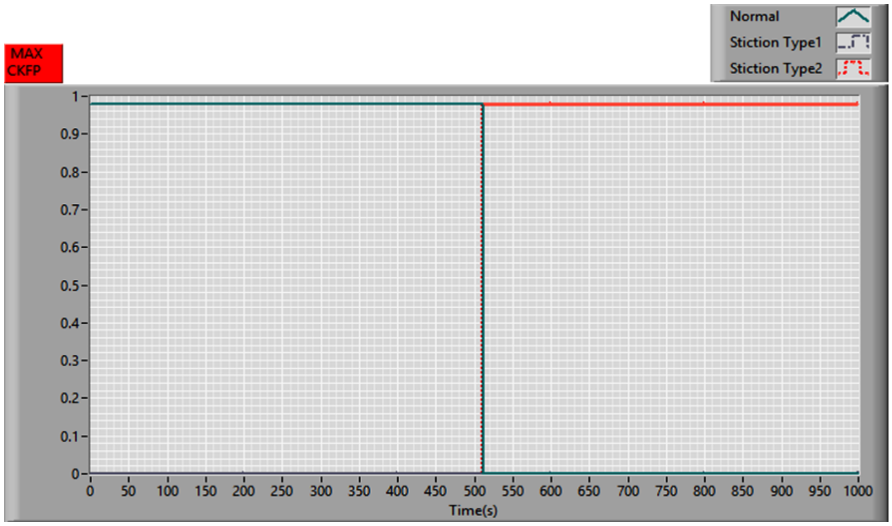


Figure 3.20: Fault Isolation Case 3: Fault Type 2 detection/Isolation using MM-CKFP with $\mathbb{W} = P^{-1}$

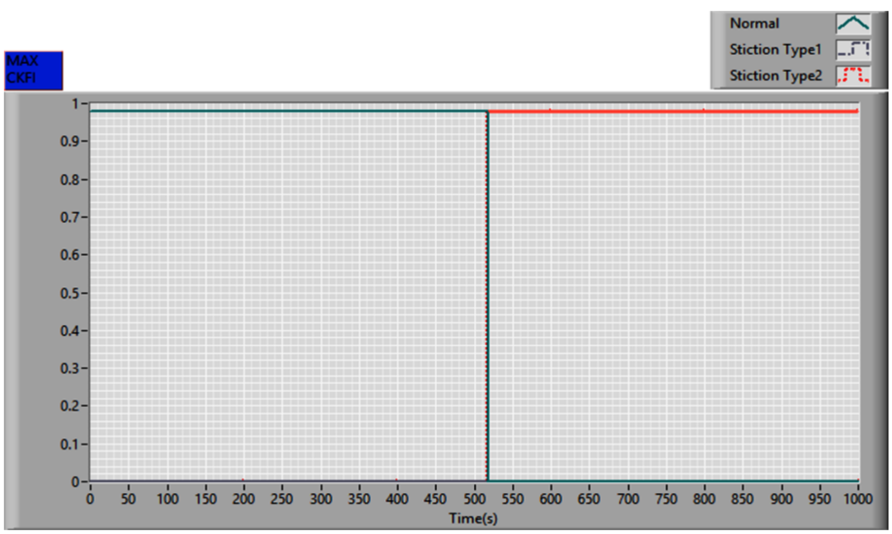


Figure 3.21: Fault Isolation Case 3: Fault Type 2 detection/Isolation using MM-CKFI with $\mathbb{W} = I$

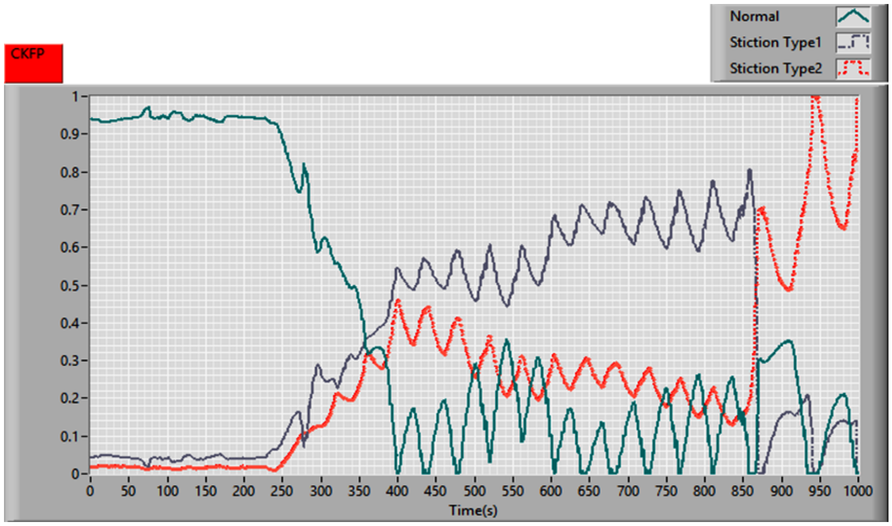


Figure 3.22: Case 4: Fault Type 1 and 2 Simultaneous detection using MMCKFP with $\mathbb{W} = P^{-1}$

fault type 1 for both techniques CKFP and CKFI, however, this does not affect the performance of scheme to detect and isolate fault. Also, in the case of isolating fault type 2 both algorithms able to isolate it at the exact time when the fault occurred.

3.4 Summary

In this Chapter, several detection and isolation of faults for different cases in a closed loop level control process having a pneumatic control valve have been investigated, emphasizing the valve stiction. The experiment carried out confirm the validity or the efficiency of the multi-model approach using constrained Kalman filter to detect and isolate faults in a dynamic system. Therefore, this work has provided an alternative approach to detect and isolate faults in a process with sticky valve and this can be used in designing a better controller or compensation

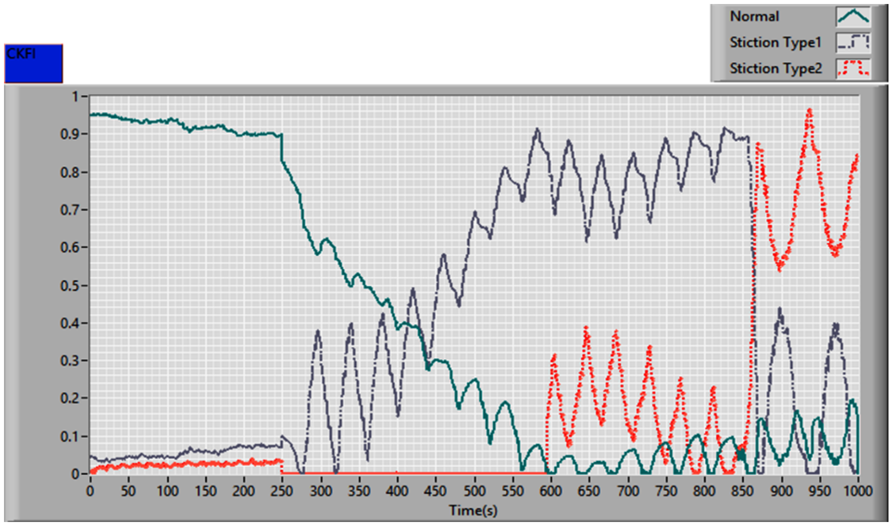


Figure 3.23: Case 4: Fault Type 1 and 2 Simultaneous detection using MMCKF with $\mathbb{W} = I$

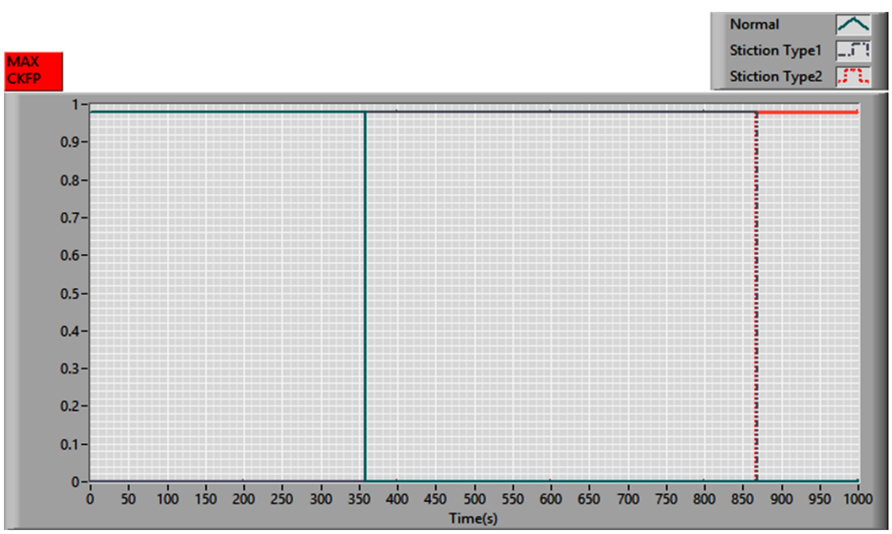


Figure 3.24: Fault Isolation Case 4: Fault Type 1 and 2 Simultaneous detection/Isolation using MMCKFP with $\mathbb{W} = P^{-1}$

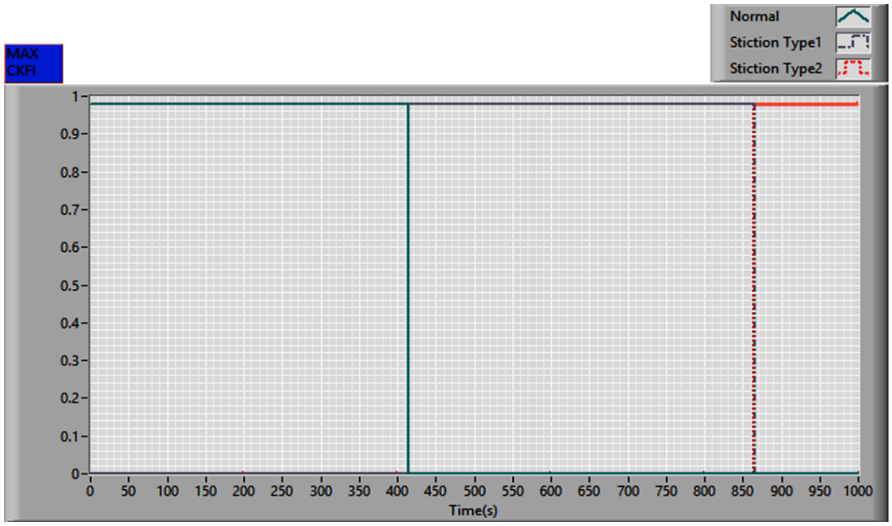


Figure 3.25: Fault Isolation Case 4: Fault Type 1 and 2 Simultaneous detection/Isolation using MMCKFI with $\mathbb{W} = I$

method to eliminate the closed loop process oscillation resulting from a sticky valve or any other faults. In addition, some of the remaining chapters in this thesis work discuss the proposed sticky valve compensation methods based on an optimization approach.

CHAPTER 4

STICTION COMPENSATION METHOD BASED ON OPTIMIZATION TECHNIQUE

4.1 Introduction

The main focus of this chapter is based on valve stiction compensation technique. As explained in literature survey that stiction in a control valve and insufficient controller tuning are the two major causes or sources of control loop performance degradation[12]. Therefore, in order to minimize or eliminate negative effect coming with a closed loop process having a sticky valve then such a process need to be compensated. There are different stiction compensation methods proposed in the literature, some of these have been surveyed which are grouped as stated in the literature survey of this work meanwhile in this thesis work a new stiction compensation method based on an optimization approach is proposed and implemented on both simulated and experimental system setup. The proposed technique is friendly, simple to use and easy to combine with the MMCKF explained earlier to detect and isolation faults in a closed loop process.

There are a lot of heuristic optimization proposed in the literature, this field has not been fully employed in valve stiction compensation. However, Sivagamasundari et al., [55] used particle swamp optimization (PSO)[56], one of the available heuristic optimization methods for stiction quantification. Also, Jelali in [24] used a global search algorithm (Genetic algorithm)[57] and Srinivasan et al.[58, 59] employed optimization approach to jointly estimate stiction and process parameters. In addition, in [60] Mohd Sazli Saad et al., implements Differential evolution and Genetic algorithm to tune PID controller to control a higher order, time delay, and non-minimum phase system and the results obtained were compared with that of conventional PID tuning (Ziegler-Nichols) method with better performance obtained when both GA and DE were implemented. In this present work, a recently heuristic optimization method, Gravitational Search Algorithm (GSA), is used to find the global optimum weights of adaptive filtering element (FIR filter) which are then used to perturb the conventional controller's (PI controller) signal applied to control valve suffering from stiction to remove or mitigate the degradable effects of stiction in a closed loop process control. Furthermore, Choudhury et al stiction model and first order plant transfer function are used to validate the presented method through simulation in both Matlab/Simulink. Also, an experimental set-up monitored through the human-machine interface (HMI) of LabVIEW is used to experimentally test the method. Besides, both mean square error (MSE) and integral absolute error (IAE) of the errors between the process setpoint (SP) and process variable (PV) are used as the fitness function for GSA to check its performance as stiction compensator.

4.2 Pneumatic Control Valve

Figure 4.1 shows the general structure of industrial pneumatic control valve.

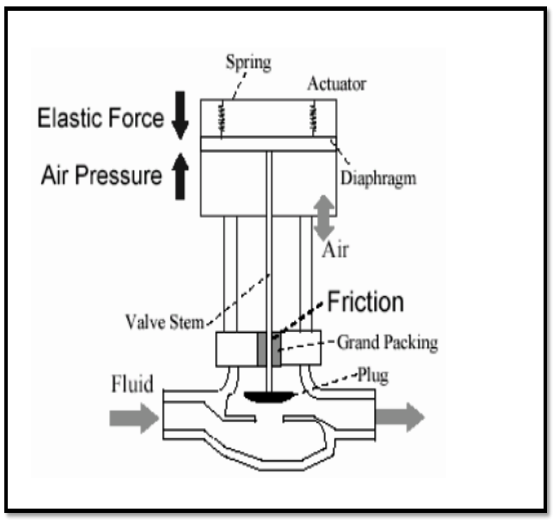


Figure 4.1: General Structure of Industrial Pneumatic Control Valve

Whenever there is a reluctance to smooth movement of the valve stem through the excessive static friction at the packing areas of the valve then stiction results. The abrupt change or sudden slip of the stem after which the signal from the controller out-weigh static friction usually causes an unacceptable effect of the control loop. The input-Output behavior of a sticky valve is shown in Figure 4.2. In this figure, the dotted line which passed through the origin represents an ideal condition of

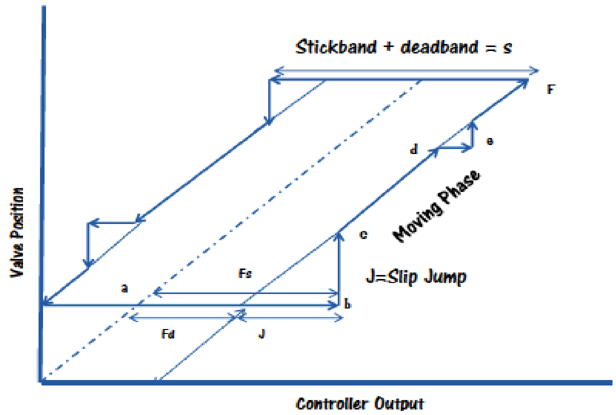


Figure 4.2: Typical Features of a Valve Suffering from Friction or Stiction

a valve in the absence of stiction. As pinpoint in [7], stiction consists of moving phase, stick-band, dead-band, and slip jump. For a stick control valve resting at point **a**, the valve position remains the same until when the controller output signal overcomes static friction F_s, after this the valve starts moving. A slip jump with a value J occurs at point **b** when the valve starts moving due to excessive accumulation of control signals from the controller as a result of static force F_s. After this jump, it follows by kinetic force F_d which leads to smooth movement of the valve stem until point **d** where valve jump could occur again and follow by smooth movement. At point **F** where valve stem change direction similar scenario occurs and the cycle continue until the process plant is stopped. In this work, Choudhury model shown in Figure 2.1 is used in stiction compensation study in simulation aspect and both He and Kano model described in [8],[9] respectively are used in the experimental case study. These models are flexible in simulating different stiction scenarios by varying both parameters value S and J. Besides, they can handle both deterministic and stochastic signals.

4.3 Gravitational Search Algorithm (GSA)

Unlike other traditional optimization methods which work based on the method of gradient descent, GSA is a heuristic optimization algorithm such as PSO[56], GA [57] etc. This optimization approach (GSA) works based on Newton law of gravity [61]. In GSA, agents denote objects like a population of individuals in GA, particles in PSO and the fitness of the agents is measured by their masses. These agents are move or attract each other by the force of gravity between them. This force results or leads to a global movement of all the objects towards those with the heavier masses. Therefore, masses interact through gravitational forces as a direct form of communication. In this algorithm, there are four major specifications namely:

- Position : This corresponds to problem solution
- Inertia mass: This is determined by a fitness function
- Active gravitational mass : This is defined based on fitness(objective) function
- Passive gravitational mass : This is determined as well based on an objective function

In general, GSA could be addressed as an isolated system, a small artificial world of masses obeying the Newtonian law of gravity and motion [61]. Let us consider a system with a N population of available agents(masses). The position of the ith agent is defined by:

$$X_i = [x_i^1 ... x_i^k ... x_i^n] \tag{4.1}$$

where $i = 1, 2, \ldots N$. N is the total number of population of agents in a kth dimension, n represents the dimension of the agents which is problem dependent. Therefore, x_i^k denotes ith agent position in the kth dimension.

At a specific time(t), the force acting on a mass at position i from mass at a another position j is defined as :

$$F_{ij}^k(t) = \frac{G(t) * M_{pi}(t) * M_{aj}(t)}{R_{ij}(t) + \epsilon} * (x_j^k(t) - x_i^k(t)) \tag{4.2}$$

In Equation (4.2), M_{aj} denotes active gravitational mass related to agent in position j, M_{pi} is passive gravitational mass related to agent i. $G(t)$ is the gravitational constant which is iteration/time dependent. It is related as defined in Equation (4.3)

$$G(t) = G(t_0) * e^{(\frac{-\alpha * t}{max_{it}})} \tag{4.3}$$

where $G(t_0)$ represent gravitational constant at time t_o, α denotes decay constant, max_{it} is the maximum iteration and ϵ is a small constant number. Also, R_{ij} is the Euclidean norm of the distance between agent i and j defined as:

$$R_{ij}(t) = \|X_i(t) - X_j(t)\|_2 \tag{4.4}$$

Total force acting on agent i in a dimension n is given as randomly weighted sum of the kth component of the forces acting on the ith agent from other agents:

$$F_i^k(t) = \sum_{j=1 j \neq i}^{N} r_j * F_{ij}^k(t) \tag{4.5}$$

This Equation (4.5) gives a stochastic character to the algorithm which prevent it to stuck in local optimum. Here, r_j denotes a random number in the interval $[0, 1]$ that is $r_j \in (0, 1)$. Based on the law of motion, the acceleration $a_i^k(t)$ of the agent(mass) i at a particular iteration or time (t) in a direction kth, is define as shown in Equation (4.6):

$$a_i^k(t) = \frac{F_i^k(t)}{M_{ii}(t)} \tag{4.6}$$

where $M_{ii}(t)$ represents inertia mass of the ith agent. The next velocity of the agent(mass) is taken or considered as a fraction of its current velocity added to its acceleration multiply by change in time (dt). Therefore, its position and velocity could be calculated as follows:

$$v_i^k(t+1) = a_i^k(t) * dt + [r_i * v_i^k(t)] \tag{4.7}$$

$$x_i^k(t+1) = x_i^k(t) + v_i^k(t+1) * dt \tag{4.8}$$

In these equations (4.7),(4.8) r_i is a uniform random variable in the range $[0, 1]$ that is $r_i \in (0, 1)$. This random number r_i in Equation (4.7) is adopted to give a randomized character to the search. Furthermore, gravitational and inertial mass in this algorithm is calculated by the objective function evaluation. The better agents (agents with heavier masses) have higher attraction and work more slowly. In this algorithm, gravitational and inertial mass are updated using the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i \tag{4.9}$$

where $i = 1, 2...N$

$$m_i(t) = \frac{OBJ_i(t) - worst(t)}{best(t) - worst(t)} \tag{4.10}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{4.11}$$

In Equation (4.10), OBJ_i is the value of the objective function of the agent i at the time t, $worst(t)$ and $best(t)$ are defined as:

- minimization

$$best(t) = min_{j\in(1...N)} OBJ_j(t) \tag{4.12}$$

$$worst(t) = max_{j\in(1...N)} OBJ_j(t) \tag{4.13}$$

- maximization

$$best(t) = max_{j\in(1...N)} OBJ_j(t) \tag{4.14}$$

$$worst(t) = min_{j\in(1...N)} OBJ_j(t) \tag{4.15}$$

To improve the performance of the GSA, in term of heuristic optimization's exploration and exploitation features then it is suggested in [61] to replace equation

(4.5) by the one in equation (4.16) so that only the K_{best} attract each other

$$F_i^k(t) = \sum_{j \in K_{best} j \neq i} r_j F_{ij}^k(t) \tag{4.16}$$

K_{best} is the set of masses (agents) with the best objective function values and the biggest masses.

4.3.1 Steps in GSA

The following are the summary of the steps in Gravitational Search Algorithm:

i. Search space identification : This is the upper and lower bound of the agent which is problem dependent

ii. Agent initialization $'X'$ (randomized initialization)

iii. Objective function evaluation (Fitness function of agents)

iv. Updates $G(t)$, $best(t)$, $worst(t)$ and $M_i(t)$ for $i = 1, 2...N$

v. Calculation of total force in different directions

vi. Calculation of the velocity and acceleration

vii. Updates agent's position

viii. back to the step **iii** until stopping criteria is satisfied

ix. end

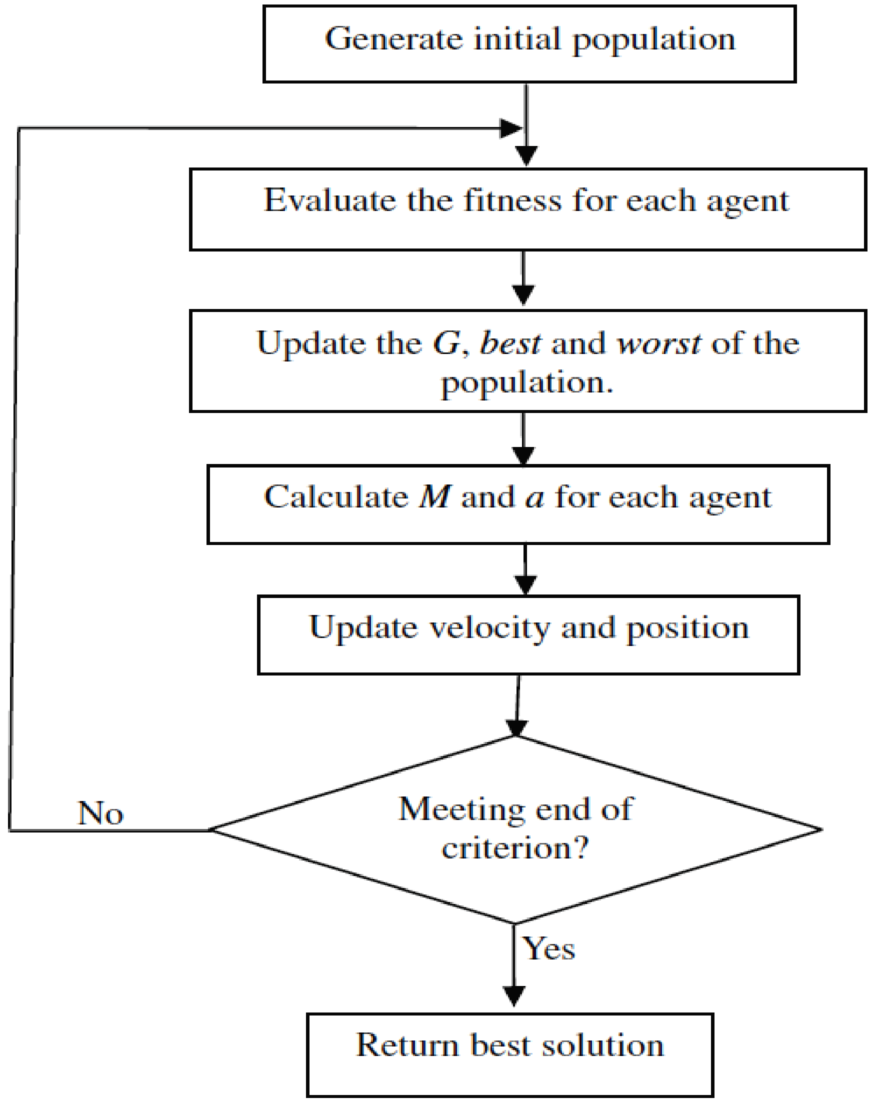


Figure 4.3: Flow chart showing general principle of GSA [61]

This summary is put together as a flow chart as shown in the Figure 4.3. The next chapter discusses the proposed stiction compensation method based on this heuristic optimization technique (GSA)

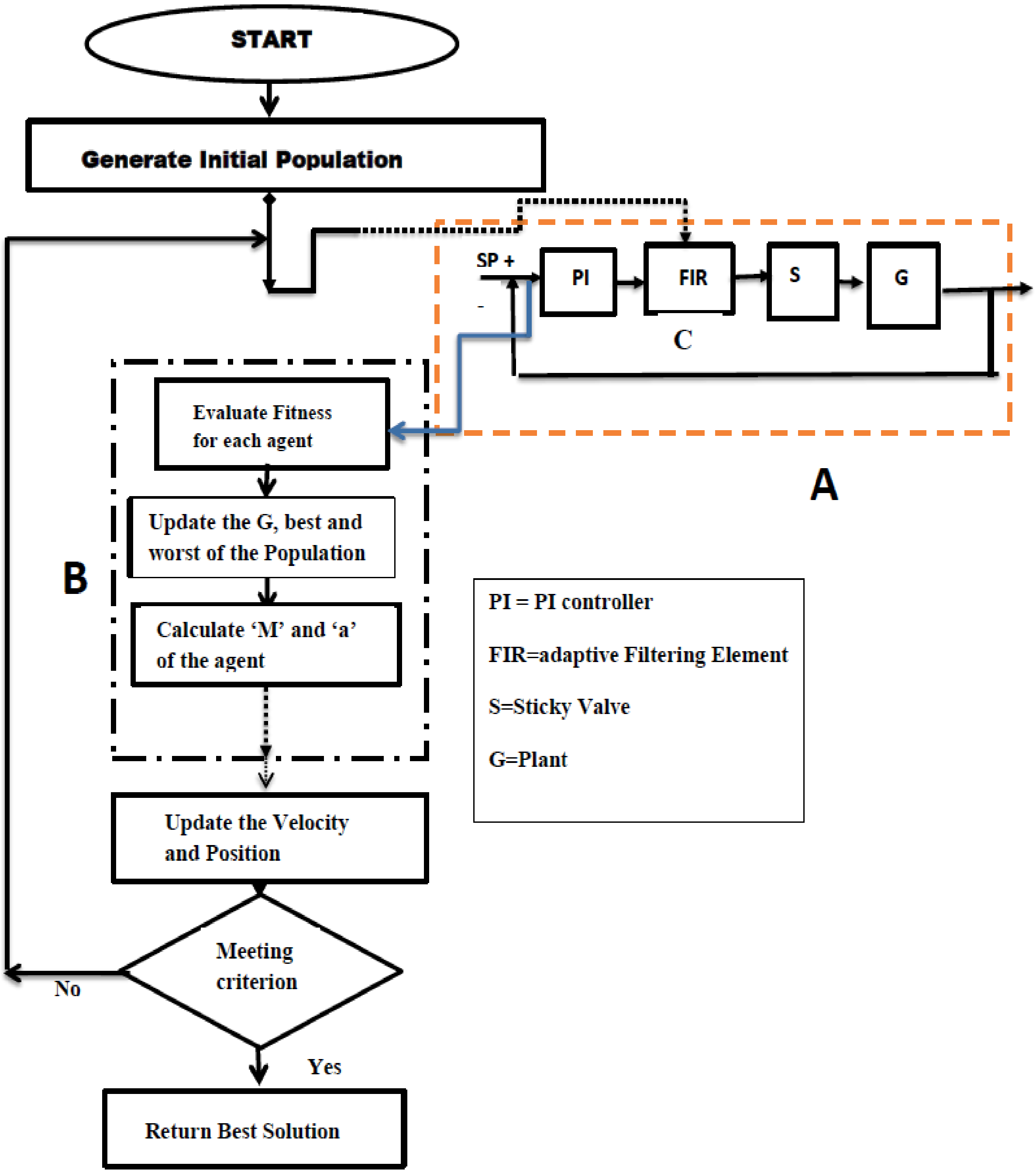


Figure 4.4: Generalized implementation of GSA as stiction Compensator

CHAPTER 5

GSA BASED CONTROL VALVE STICTION COMPENSATION: PROPOSED METHOD

5.1 Implementation of GSA as a control valve stiction compensation

The main purpose of this section is to describe and present how GSA could be implemented as a stiction compensator. Figure 4.4 shows the flow chart of how GSA is used for stiction compensation. As it can be seen from the figure, both the GSA and the closed-loop control system are integrated together. Hence, the followings describe implementation of gravitation search algorithm(GSA) in stiction compensation:

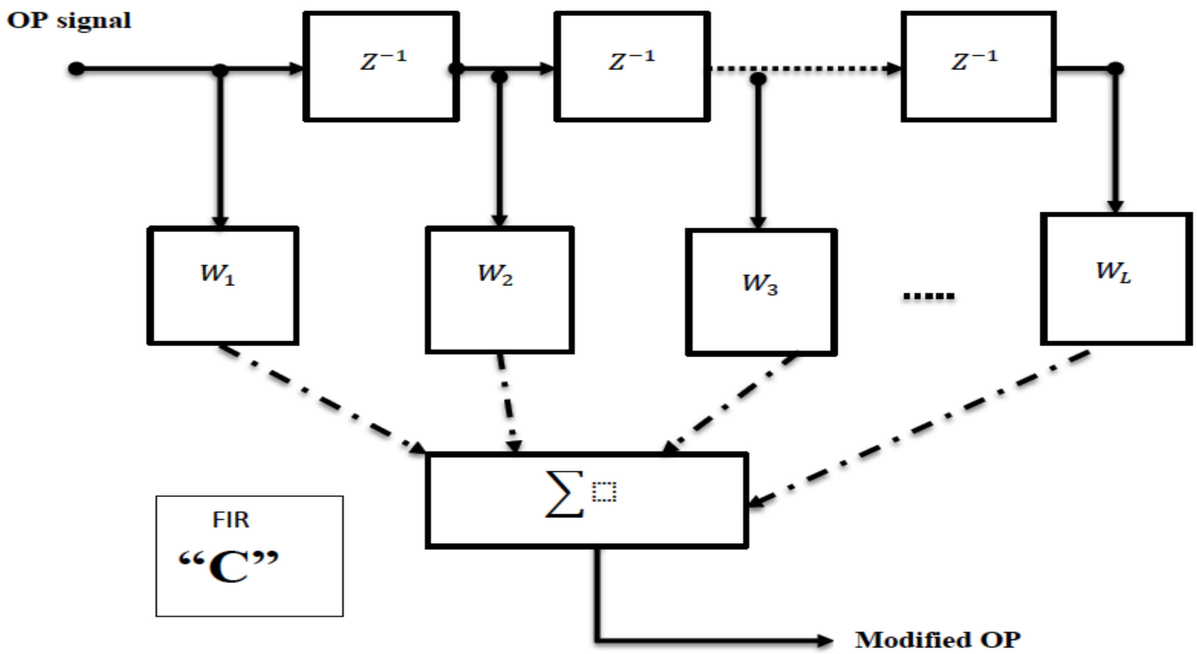


Figure 5.1: Details of Adaptive Filtering Element (FIR) in 'C' of Figure 4.4

i. Initialize the setting of GSA parameters and generate an initial population of agents: It is vital to implement small population (N) agents, this is needed in practice for small optimization time. In this work, the size of the initial population is set to 15 for simulation and experimental section. The dimension D/n of the agent's population is a problem dependent. In this study, a dimension of length 4 is used which means the number of optimized parameters of adaptive filtering element(Length(L) of the filter) employed in the fitness function is 4 as shown in Figure 5.1 for more details. Also, the upper and lower bound of the adaptive filter parameters used are $[1, 1, 1, 1]$ and $[-1, -1, -1, -1]$ respectively. These correspond to bounds of the filter weights.

ii. Fitness Function Evaluation: In Figure 5.2, each agent X_i of dimension

D/n is send to the plant as shown in $'A'$ and the fitness function for each agent is evaluated based on error between Set-Point (SP) and Actual output (PV).

$$fitness_{values} = f(X_i) \equiv OBJ_i(t)$$

where

$$f(X_i) = \frac{1}{T}\int_{t_o}^{t_f} (e(t))^2 dt, \qquad for \ldots MSE \tag{5.1}$$

and

$$f(X_i) = \int_{t_o}^{t_f} |e(t)| dt, \qquad for \ldots IAE \tag{5.2}$$

after the evaluation of each agent based on the errors obtained from plant (A) in Figure 4.4 through the fitness function (5.1) and (5.2) then, this is used to select the best and the worst of the population according to Equation (4.12) and (4.13) for minimization and (4.14) and (4.15) for maximization problems.

iii. **Updating the 'G', 'best' ,and the 'worst' of the population:** Here, 'G' is updated using Equation (4.3). Stiction compensation in this work is formulated as minimization problem therefore Equation (4.12) and (4.13) are employed to update both best and the worst of population respectively.

iv. **Calculating both M and a:** The moment of inertia M of the agents as well as their acceleration a is calculated using Equation (4.11)and (4.6)

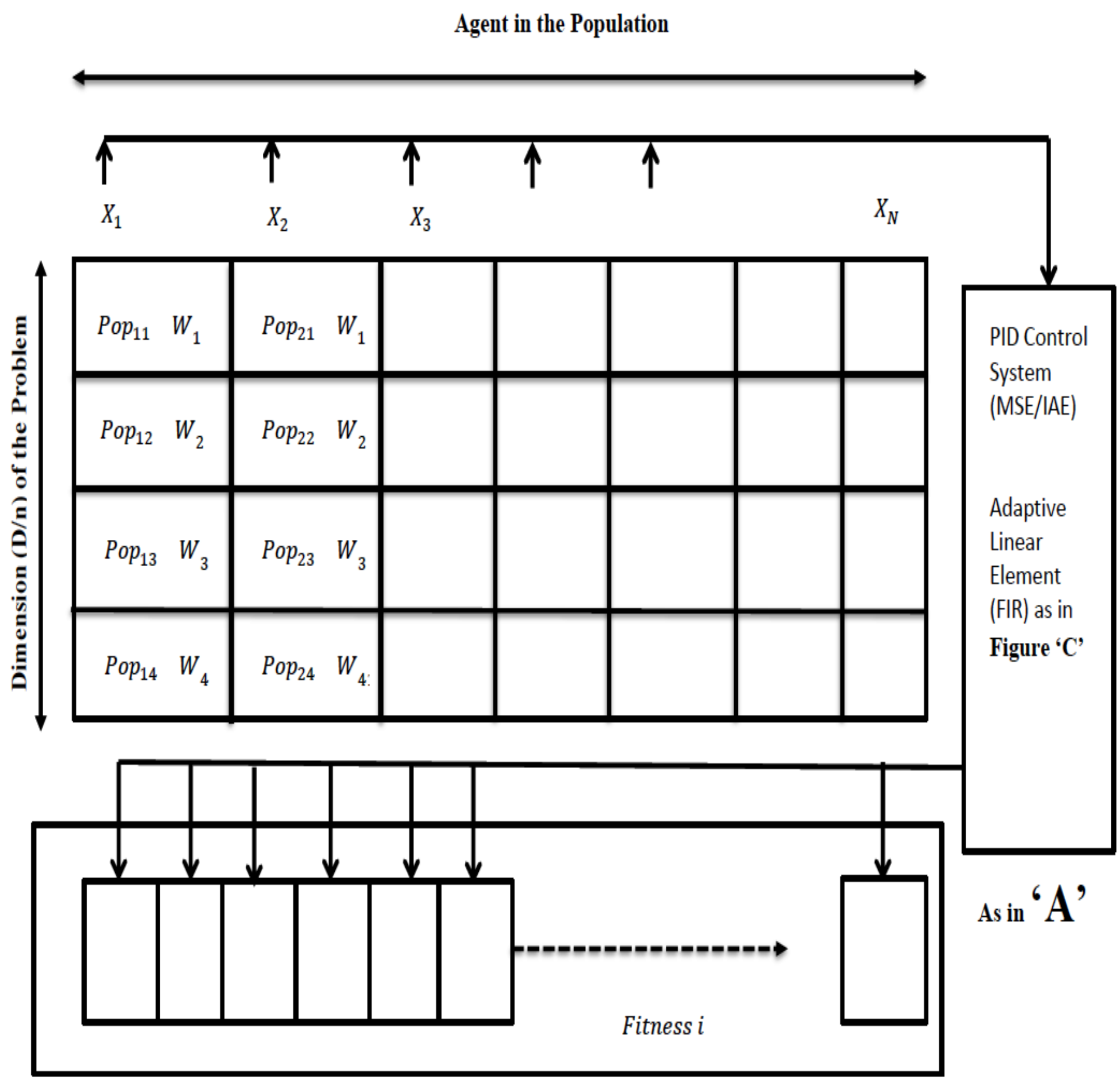


Figure 5.2: The block diagram for Population of Agents and their Corresponding Fitness Values

respectively.

v. Agent's Velocity and Position Update: In this step, both the velocity of the agents and their positions are updated using Equation (4.7) and (4.8) and the random number r_i in these equations is to give randomized character to the search which enhance the performance of the algorithm.

vi. Stopping criteria: These are the conditions set for the search process to terminate. These could be specified as follows:

- Terminate when no improvement is observed over a set of consecutive generations
- Terminate when there is no change in the population
- Terminate when an acceptable solution has been found.

5.2 Case Studies With Results and Discussion

5.2.1 Simulation

The typical process control block diagram with stiction behavior is shown in Figure 5.3. In this figure, stiction model is placed between the valve dynamic and controller to simulate stiction phenomenon. In this section, the accuracy/performance of the proposed method/scheme is tested on a sticky pilot plant model of Choudhury et al[3]. The Simulation block diagram of the model designed to investigate this stiction phenomenon using the proposed technique is shown in

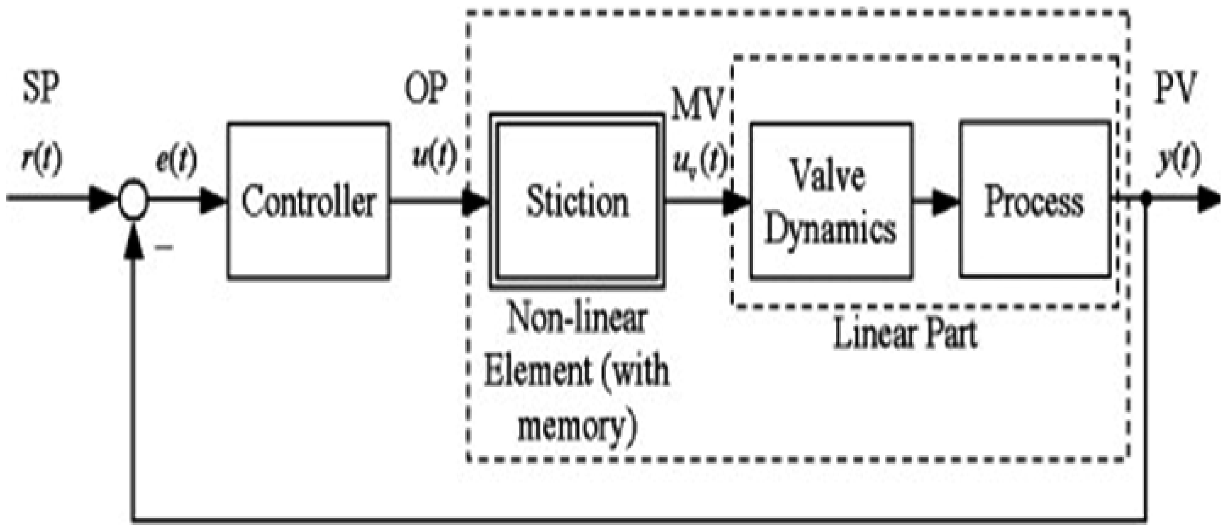


Figure 5.3: The typical process control block with stiction behavior

Figure 5.4. In this figure, adaptive filtering element is placed between the controller and valve input so that controller output (OP(t)) signal will be perturbed by the proposed compensator to give new signal named OP-perturb ($OP_p(t)$). This signal then goes into the sticky valve to give the required amount of signal to open or close the valve in a required quantity without aggressive movement of the valve stem. The equation describing the relationship between $OP(t)$ and $OP_p(t)$ is shown in Equation 5.3.

$$OP_p(t) = OP(t)*W_1+OP(t-1)*W_2+OP(t-2)*W_3+...+OP(t-L-1)*W_L \quad (5.3)$$

In this equation, GSA is utilized to search for the global optimum values of these weights ($W_1, W_2, \ldots W_L$) depending on the value of L)that when they are used to scale up or down the OP(t) signals, it will eliminate or reduce the stiction effect such as process oscillation to acceptable level. Based on this, the problem is formulated as an optimization problem and then, the objective functions Equation

Table 5.1: Stiction Scenarios

	Stickyband(S)	Jump(J)
Deadband($J = 0$)	3	0
Overshoot($J >$S)	3	4.5
Undershoot($J < S$)	5	2
No Offset($J = S$)	3	3

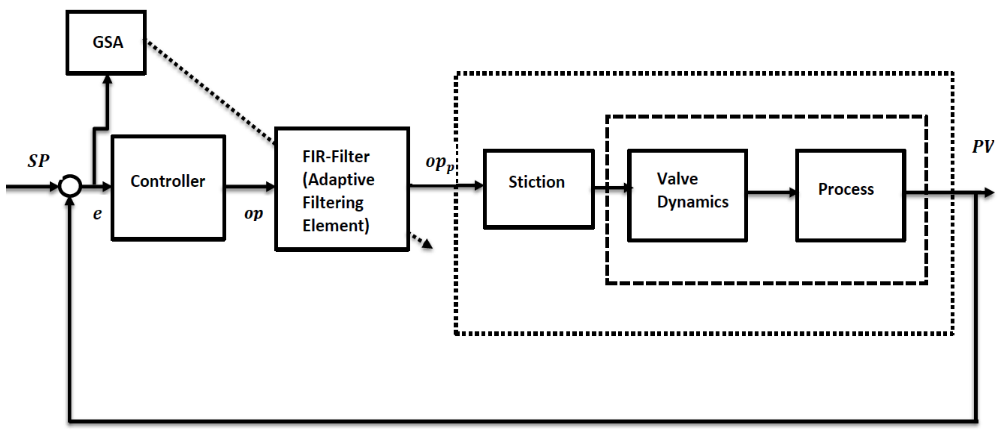


Figure 5.4: The Simulation-Link Block Diagram of the Proposed Scheme

(5.1) and (5.2) are used in this work as a guide for GSA to search for optimum values of these parameters. Different scenarios of stiction phenomenon are obtained by varying the stiction parameters as shown in Table 5.1. Figures (5.5,...,5.8) show the results of all the scenarios tested in this section. In these figures, it is discovered that the proposed scheme was able to completely eliminate the undesirable stiction effect when it was switched On at $250s$ instance as compared to when pure PI controller is used (from $0s \ldots 250s$). In addition, its performance was tested on step change disturbance for instance at time $500s$ the desired set-point was changed from $10cm$ to $5cm$ and it is noticed that the proposed scheme tracks and eliminates stiction in the present of this disturbance(set-point change).

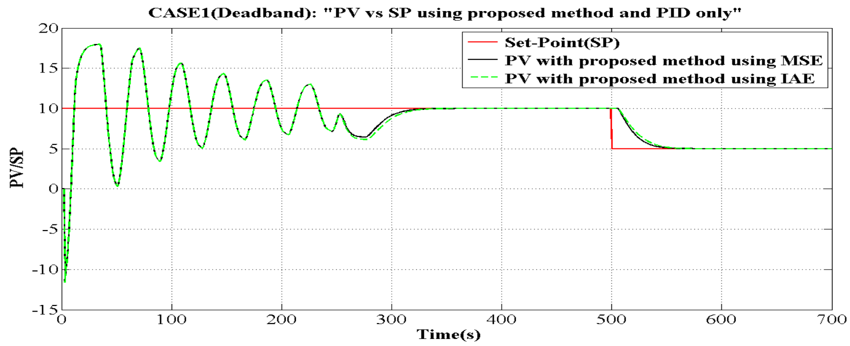


Figure 5.5: Closed loop response of the plant output in the case of deadband stiction using proposed approach(Proposed method switched On at 250s)

Furthermore, the corresponding control signals for all the cases of stiction phenomenon tested are shown in Figures 5.9. From this figure, It is seen that lesser amount of control signal is utilized when the proposed method switched On at the instance of time 250s when compared to that of pure PI controller that is between time 0s up to 250s. Therefore, for all the cases considered it is obvious that the proposed approach performed well by completely eliminates the stiction effect. For further investigation on the efficiency of the scheme presented in this section, this article considered a real-time implementation of the proposed techniques in the next section.

The objective function variation plots for all the cases considered using both mean square of error (MSE) and integral absolute error (IAE) for our proposed method are shown in Figure 5.10.

5.2.2 Experimental Set-Up/Real-time Implementation

The main point of this section is to test the efficiency of the proposed GSA based stiction compensation technique on experimental level control(LC) loop. The

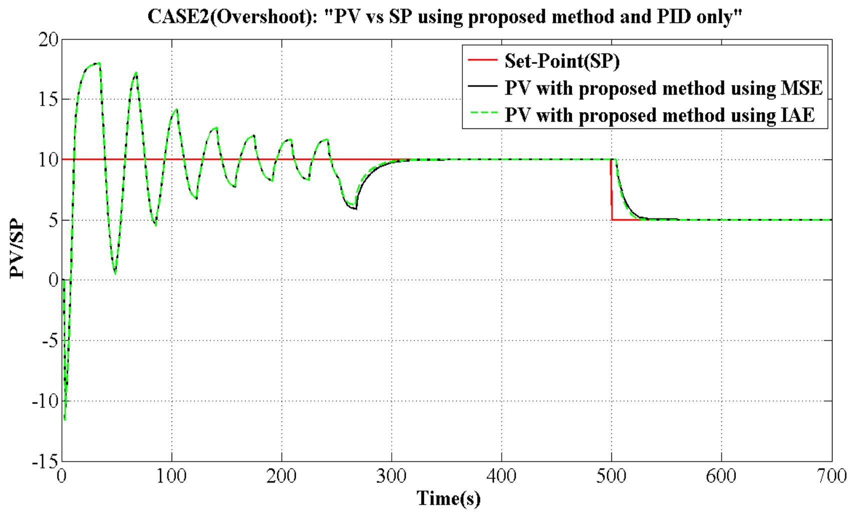


Figure 5.6: closed loop response of the plant in the case of overshoot stiction using the proposed approach (Proposed method switched On at 250s)

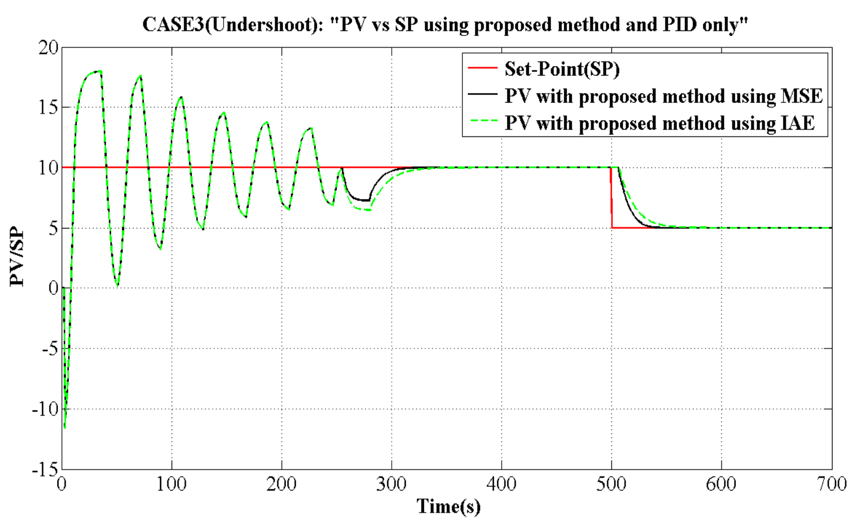


Figure 5.7: closed loop response of the plant in the case of undershoot stiction using the proposed approach(Proposed method switched On at 250s)

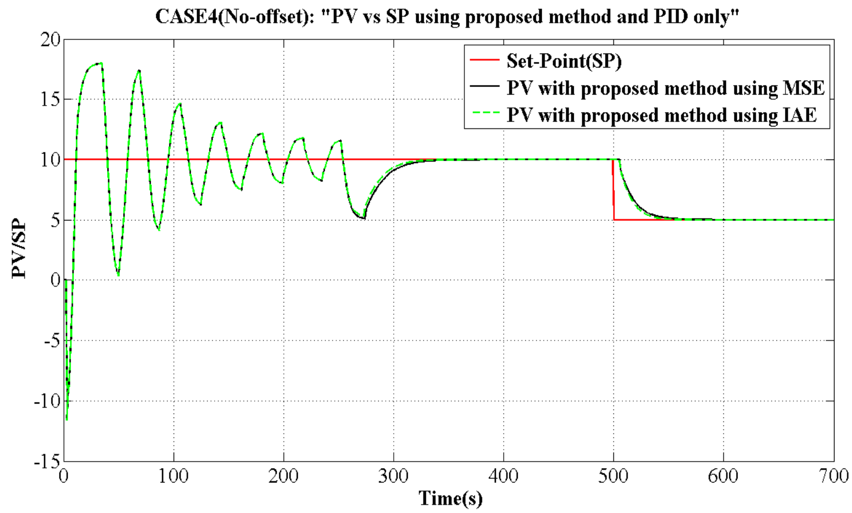


Figure 5.8: closed loop response of the plant in the case of no- offset stiction using the proposed approach(Proposed method switched On at 250s)

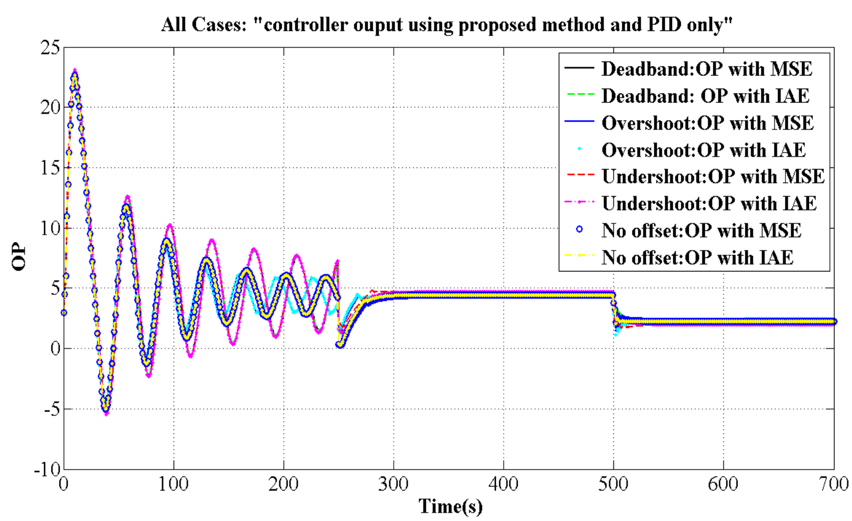


Figure 5.9: Closed loop response of the controller output in all stiction cases tested using the proposed approach(Proposed method switched On at 250s)

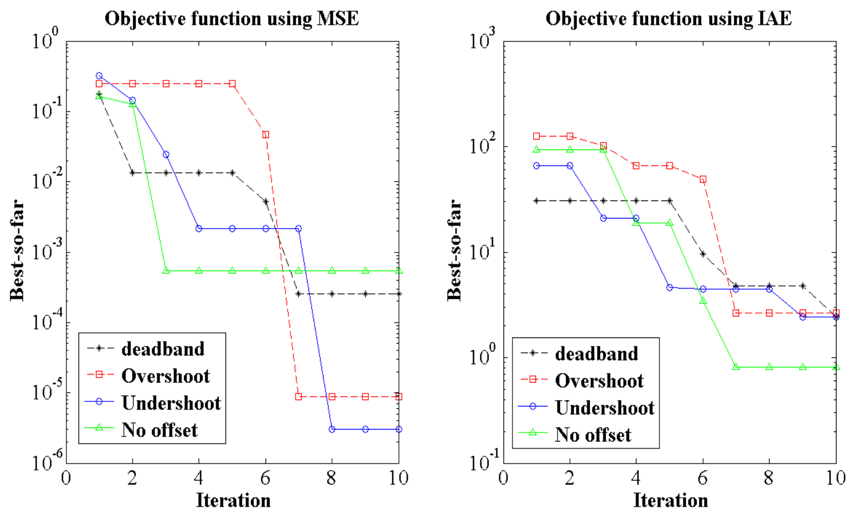


Figure 5.10: Objective function variations for all the cases of stiction tested

process diagram showing in Figure 5.11 is a single tank configuration and its experimental set-up. In this figure, the tank has an ON/OFF outlet valve switch to keep constant flow and inlet via a pneumatic control valve to control the level of the liquid in the tank. A level transmitter is attached to continuously measures the level of the liquid in the tank, which sends its signals to a PI controller programmed in NI compact Field point processor through the human machine interface(HMI) labVIEW software. Through the help of electrical current to pressure converter (I/P), the 4-20mA signal from the controller output triggers the pneumatic control valve. An HMI which made up of PI controller, set-point and other parameter settings such as stiction models and their associated parameter settings were developed by using a labVIEW software package such as the one shown in Figure 5.12. Here, it is important to mention that the full tank used in this experiment set-up was calibrated to be 32cm and the set-point was set to 15cm at the beginning of the experiment and changed to 18cm to test for load

Table 5.2: Stiction model's parameter values for both He and Kano model

	Kano Model	He Model
F_s	45	40
F_d	15	20

disturbance. At a later time, it was switched to $10cm$ to test for performance of the proposed scheme in load or step change disturbance. In order to test the validity of the proposed technique to remove completely or reduce stiction phenomenon to the barest minimum in the process, stiction behavior on the control valve was generated by software element using Kano-model[9] and He-model[8]. The algorithm was programmed in NI compact field point controller through the LabVIEW software. The detail of the stiction models parameter J and S values considered in this section is shown in Table 5.2. The relationships among the static friction(F_s), dynamic friction (F_d) , slip jump (J) and sticky band plus dead-band (S) are shown in Equation (2.4) and (2.5). In this experiment, series of tests are performed, some of the results achieved are reported here, Figure 5.13 shows the results obtained when Kano model stiction behavior using the values shown in Table 5.2 is introduced into the process without the proposed approach. In this figure, it is obvious that there is a big oscillation in the level of liquid in the tank, the level deviates greatly from the set-point of $15cm$, also looking at the corresponding controller output(color-green), it is clear that the conventional controller is unable to control the oscillatory effect of stiction. A similar result is obtained when the He model of stiction value as shown in Table 5.2 is introduced into the process, the response obtained is shown in Figure 5.15.

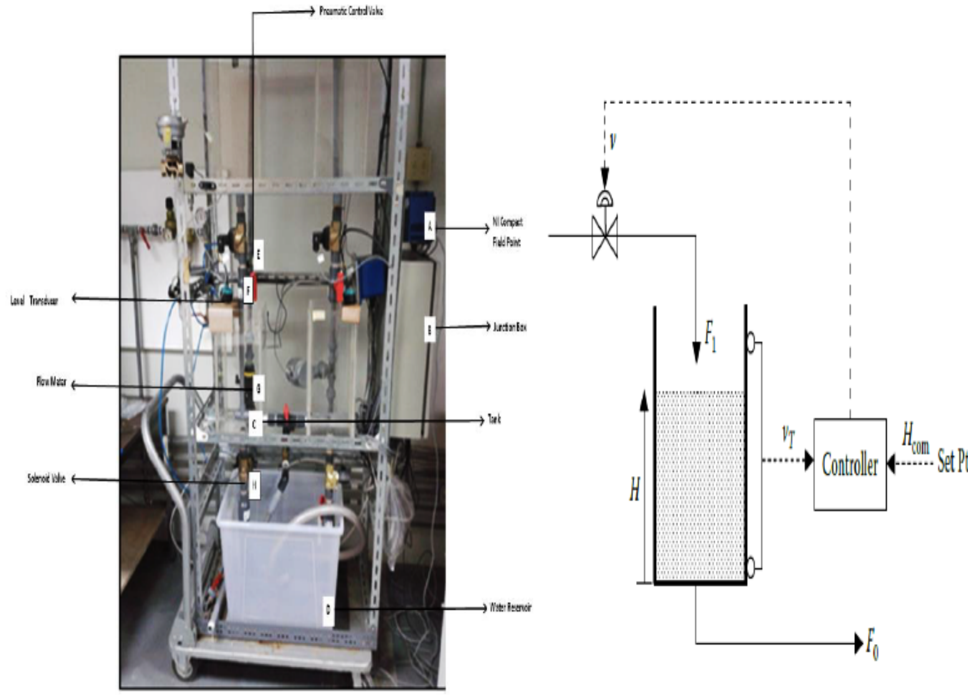


Figure 5.11: Experimental set-up for a single closed-loop level control process

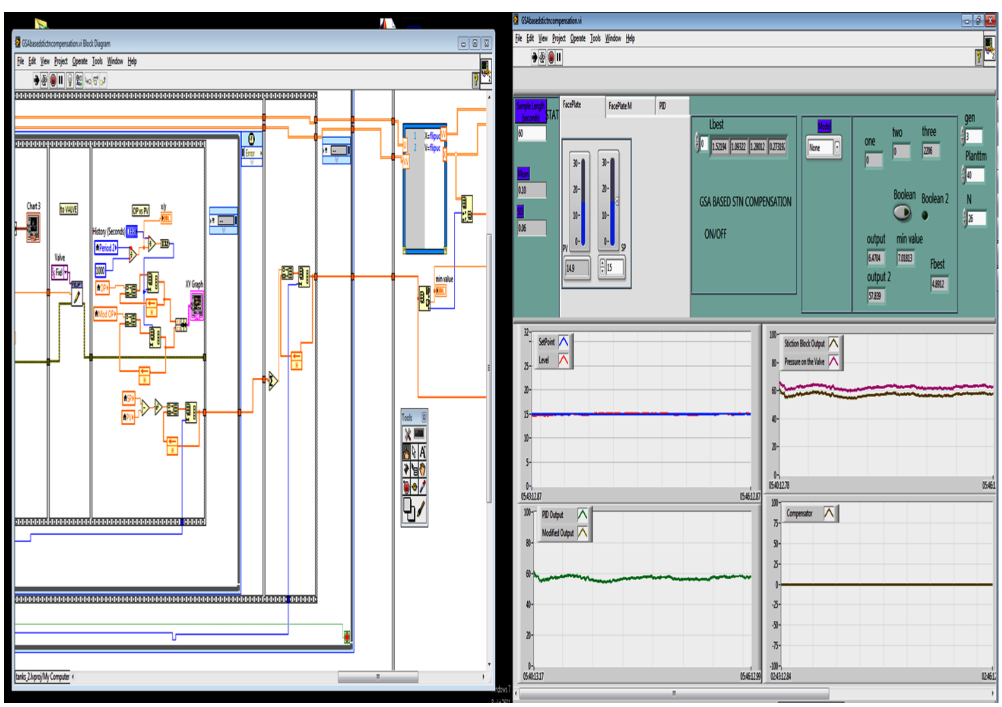


Figure 5.12: A Section of human machine interface of lab-view package used in experimental set-up

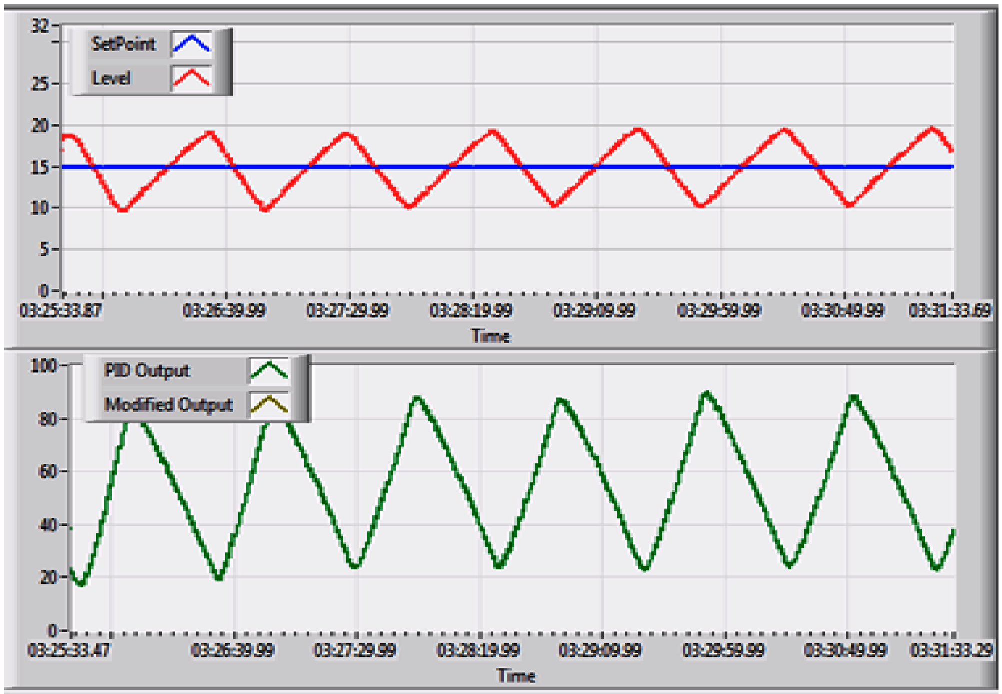


Figure 5.13: Sticky valve behavior using Kano model without compensation

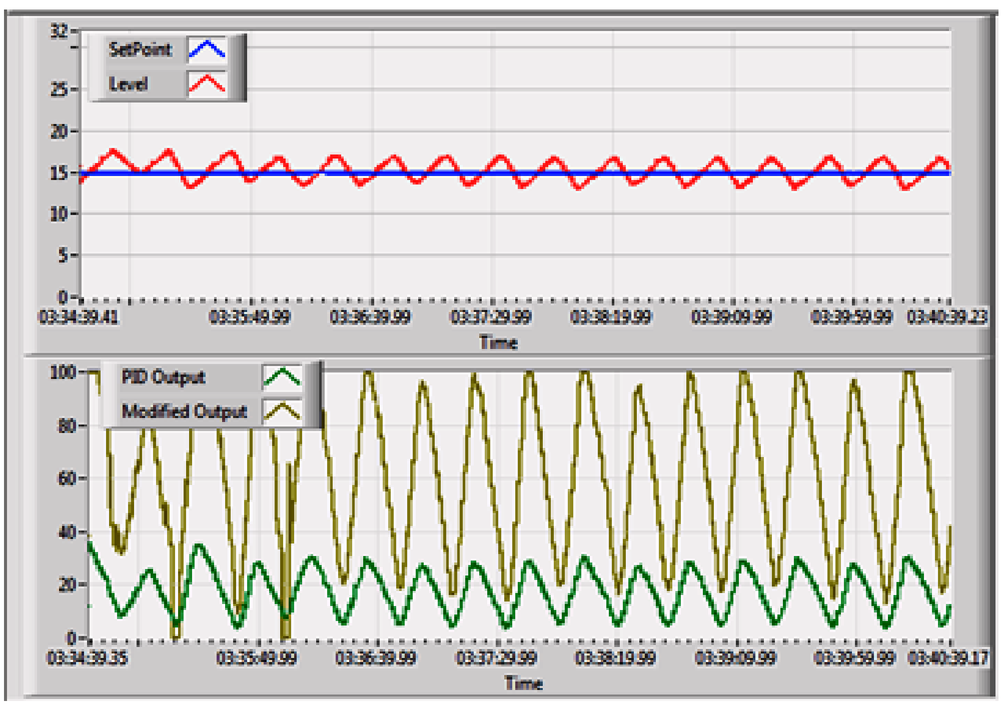


Figure 5.14: Process variable(color-red),Set-point(color-blue),Controller output(color-green) and its modified-output using proposed approach with Kano model

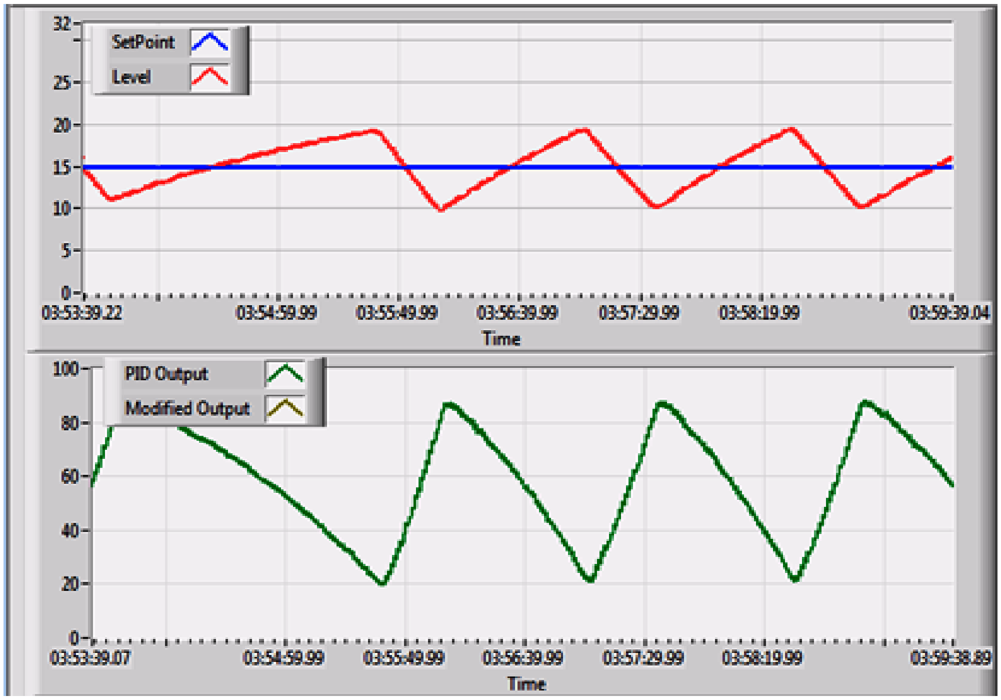


Figure 5.15: Sticky Valve behavior using He-model without compensation

The results obtained when the proposed approach is implemented are shown in Figure 5.14 and 5.16, from these, we could see that the amplitude of oscillation is greatly reduced when compared to that of a case when the conventional controller (Figure 5.13 and 5.15) is implemented. In addition lesser amount of control signal is required using proposed technique. Furthermore, further test is performed by introducing the load or step change disturbance to the process to test the efficiency of the proposed method on load change, from Figure 5.17 the set-point of $15cm$ is changed to $18cm$ at the time $(3h : 41mins : 03sec)$ and later to $10cm$ at the time instant of $(3h : 43mins : 37secs)$ and it is obvious from this figure that the proposed technique able to track the set-point, reduced the amplitude of oscillation and maintained the minimal amplitude oscillation that is acceptable with load disturbances.

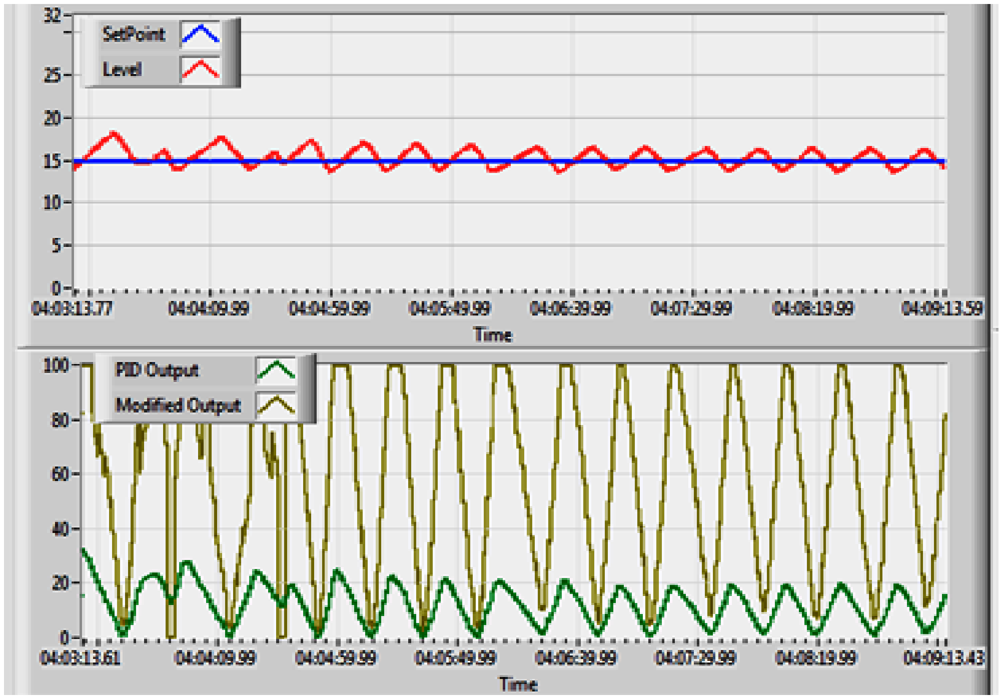


Figure 5.16: Process variable(color-red), Set-point(color-blue), Controller output(color-green) and its modified-output using proposed approach with He model

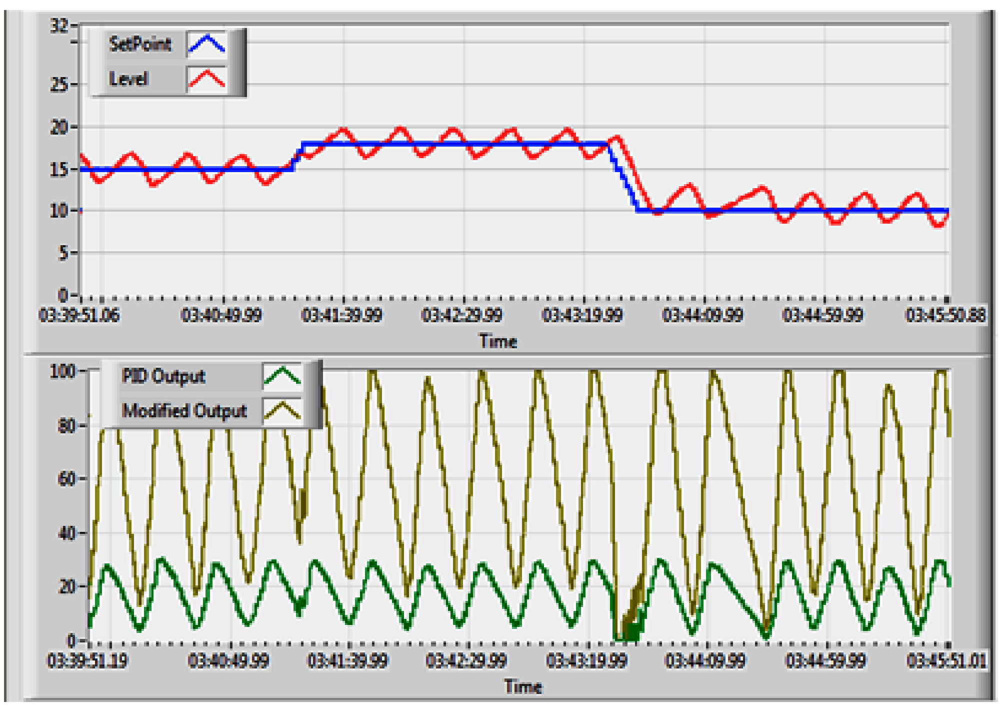


Figure 5.17: Process variable(color-red),Set-point(color-blue), Controller output(color-green) and its modified-output using proposed approach with Kano model during load disturbances

5.3 Comparison between LMS-FIR based method and proposed GSA based method

LMS-FIR method,(Finite impulse response filter tuned by Least mean square algorithm (LMS)), is an optimization based stiction compensation method that was introduced by M. Sabih [10]. This method is based on gradient descent optimization technique which uses the least mean square algorithm that was introduced by Bernard Windrow [29] to search for global optimum weight(Ws). This stiction compensation method has been compared by other commonly existing stiction compensation methods such as knocker based, constant reinforcement(Cr), an inverse method in [10] and it was shown that it outperformed the others. Therefore, In this work, LMS-FIR based and the proposed GSA based method are only compared. An improved version of this method (LMS-FIR) was implemented by M. Abdeen [28] using both Kano and He stiction models, the simulation set-up and the responses obtained by him using both stiction models are shown in Figures 5.18, 5.19 and 5.20.

In this research work, the same setting and parameter used in [28] are utilized using the proposed GSA-based stiction compensation method for comparison purpose between the LMS-FIR and GSA based compensator. Figures 5.21 and 5.22 show the obtained result using the proposed technique.

It is obvious from the Table 5.3, 5.4 and the responses(Figures 5.21 and 5.22) that the proposed technique outperformed the LMS-FIR based method by weighing their Integral Square Error (ISE), Maximum of the Integral Absolute Error

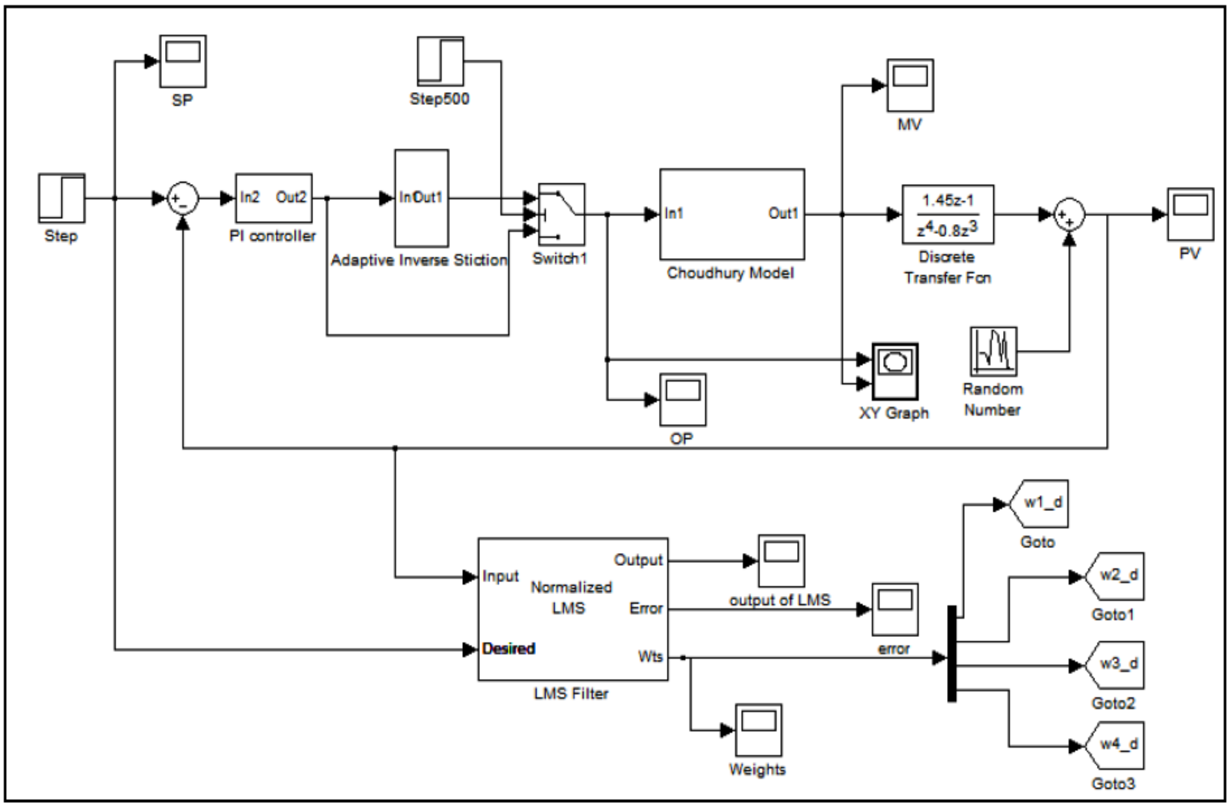


Figure 5.18: Simulink setup for Adaptive Inverse Control LMS-FIR compensator [28]

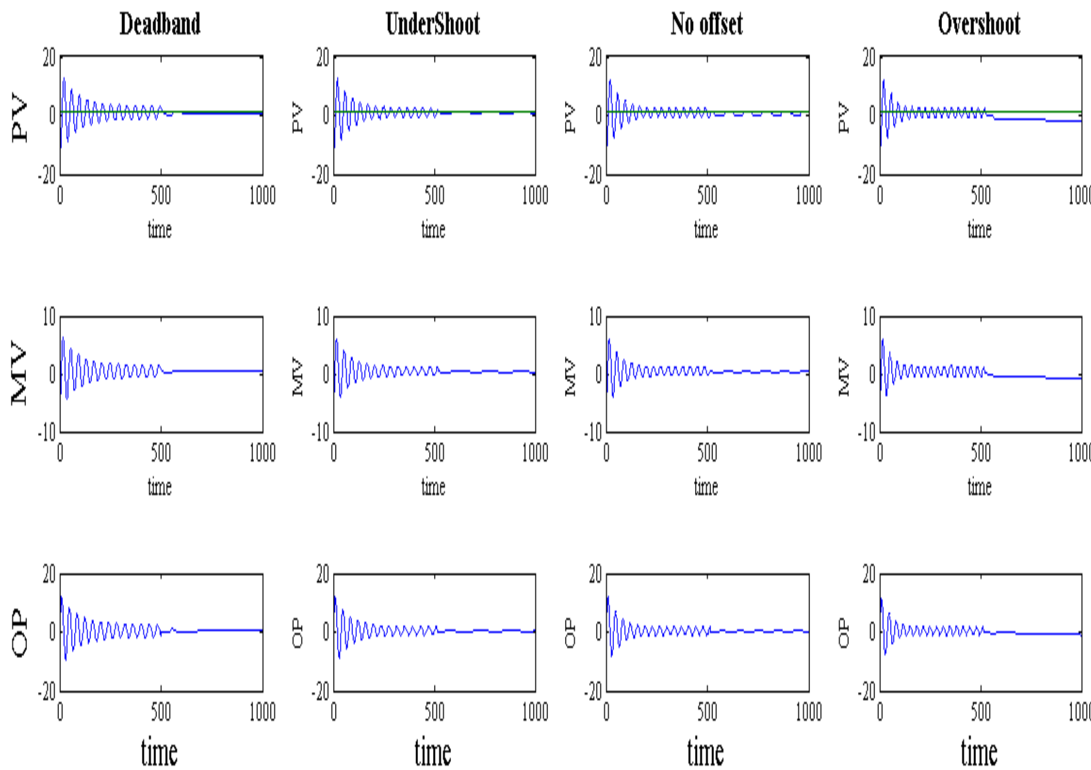


Figure 5.19: Response from Adaptive Inverse Control LMS-FIR compensator with Choudhury Mode

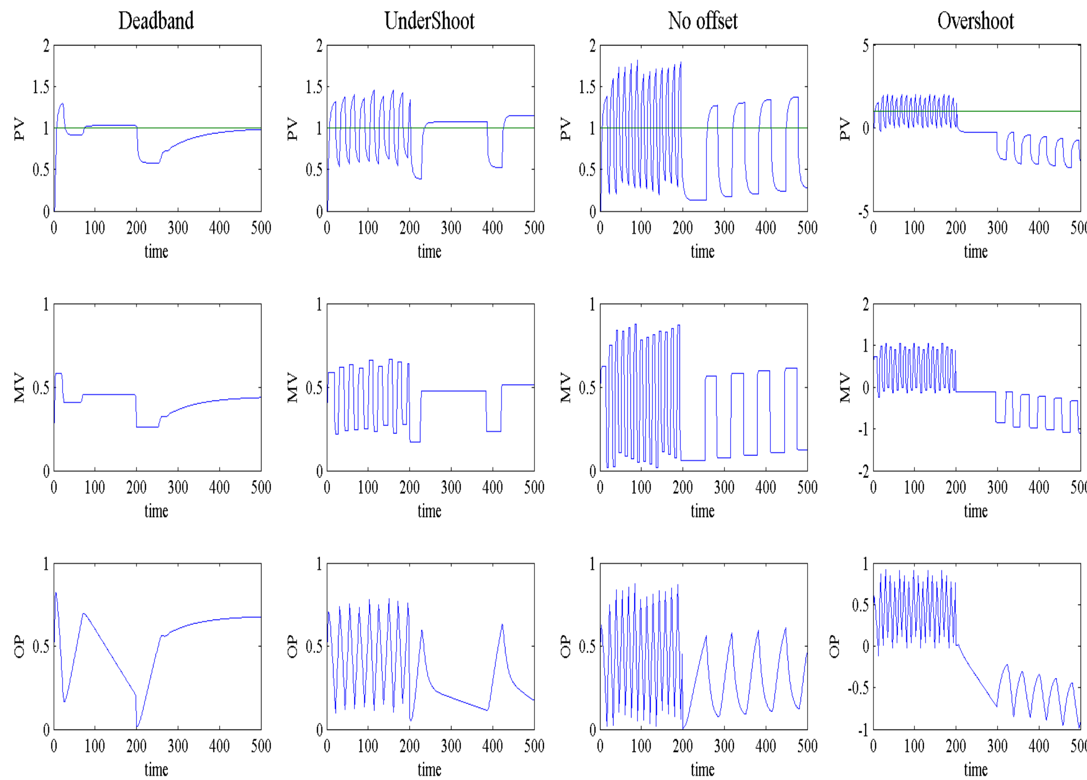


Figure 5.20: Response from Adaptive Inverse Control LMS-FIR compensator with Kano Model

Table 5.3: ISE, MAX_{error}, and Var of Error Obtained Using LMS_FIR Compensator and GSA-Based Compensator For Choudhury Model

	LMS-FIR Compensator			GSA Based Compensator		
Choudhury Model	ISE	MAX_{error}	Var	ISE	MAX_{error}	Var
Deadband	1.6864	0.1439	6.0066E-4	0.0937	0.0216	7.7422E-34
Undershoot	15.6685	0.3237	0.0783	0.0343	0.0131	0
No offset	59.8216	0.7516	.02793	0.1042	0.0228	3.0969E-33
Overshoot	1509.4	2.7889	0.0147	0.7785	0.0943	1.1149E-31

Table 5.4: ISE, MAX_{error}, and Var of Error Obtained Using LMS_FIR Compensator and GSA-Based Compensator For Kano Model

	LMS-FIR Compensator			GSA Based Compensator		
Kano Model	ISE	MAX_{error}	Var	ISE	MAX_{error}	Var
Deadband	1.5143	0.1949	0.0024	1.2142E-5	0.0014	5.2670E-8
Undershoot	9.263	0.4746	0.0463	0.0012	0.0024	9.2461E-16
No offset	66.0243	0.8307	0.2582	14.3371	0.8038	0.0715
Overshoot	1228.8	3.4064	0.5290	0.4658	0.0458	8.2650E-21

(MAX_{error}) and the Variance (Var) of the Table 5.3 and 5.4. Looking at the values of the ISE, MAX_{error} and the $Variance$ of the error between the plant set-point and its output, it is found out that ISE, MAX_{error} and the $Variance$ of errors for the cases tested for the proposed method are much lesser than that of LMS-FIR compensator. This shows that GSA based compensator outperformed the LMS-FIR compensator. This can as well be seen by comparing their responses.

This is so because the LMS-FIR method does trap in local optimum when searching for the best weight to remove stiction phenomenon. When investigate what could cause the LMS-FIR based stiction compensation method to trap in the local optimum, it is found out that, its performance depends on the initial starting point(initial weight)of the search and learning rate μ which are usually set manually. In order to improve this an improved version of LMS-FIR method is proposed using gravitation search algorithm. This is named as GSA-LMS-FIR

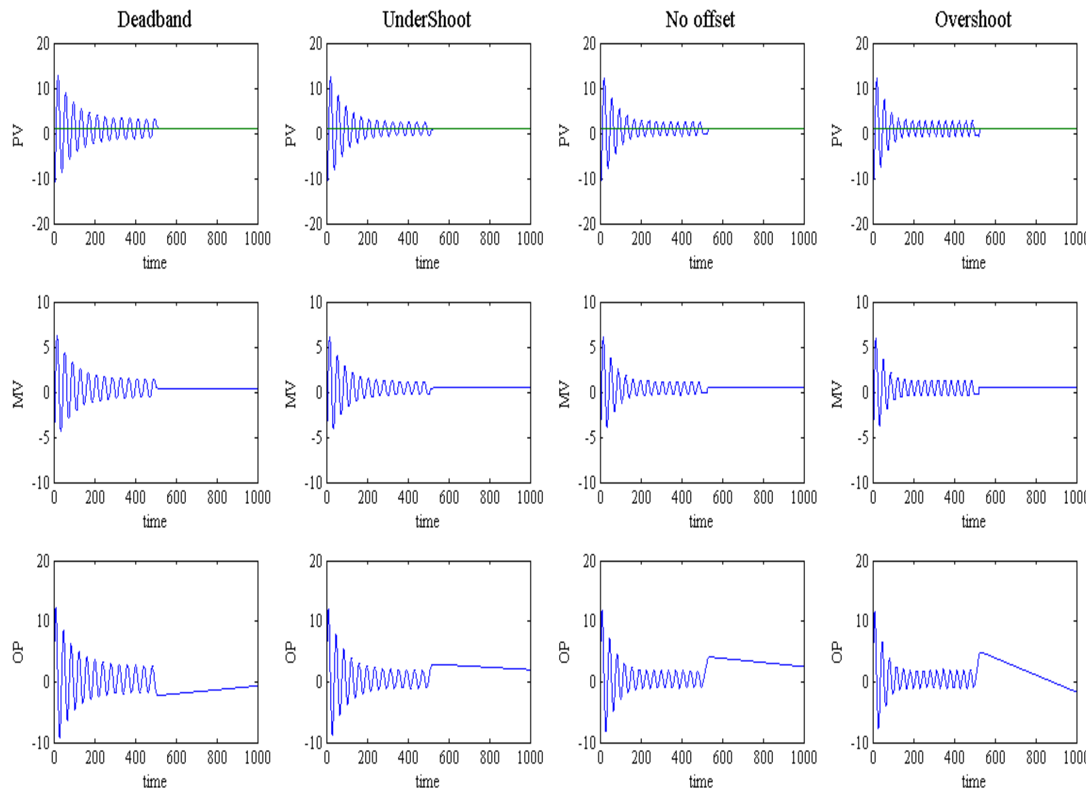


Figure 5.21: Response from Adaptive Inverse control GSA based compensator with Choudhury Model: The proposed method

based stiction compensation method and it is the topic of next chapter.

5.4 Summary

In this chapter, a new technique to compensate stiction, a fault in the closed loop level control process, is proposed based on an optimization approach. This method uses a gravitational search algorithm (GSA) to find global optimum weights(Ws) of an adaptive filtering element (FIR filter). These weights are used to perturb the signal from the conventional controller(e.g PI controller). The perturbed signal is then used as an input signal to the sticky valve which reduces or mitigates

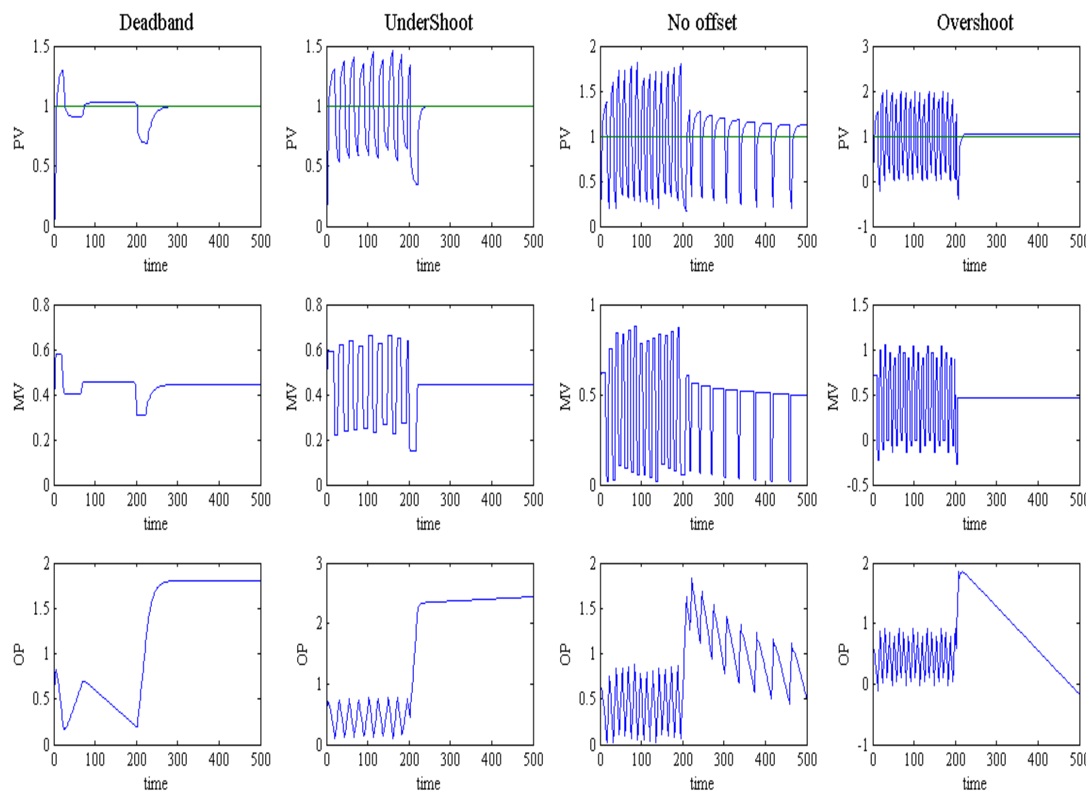


Figure 5.22: Response from Adaptive Inverse control GSA based compensator with Kano Model: The proposed method

the unacceptable effects of stiction such as an increase in energy consumption, increase in production downtime, oscillations in process variable like a fluid level in a level control systems etc. Simulations are carried out using Matlab/Simulink to investigate the validity of the proposed method. In addition, experimental case studies are presented. Besides, the performance of GSA is evaluated using Mean Square Error (MSE) and Integral Absolute Error (IAE) of the errors between the process variable (PV) and the setpoint(SP) of the plant.

Stiction has shown to be a major issue in the plant-wide oscillation and performance degradation in various control tasks, it also causes an increase in energy consumption. Therefore, eliminating or reducing this stiction effects in a control valve is a vital task to have a good end product of the production process in the control loop. Hence, in this work, a new stiction compensation based on optimization approach is presented. The proposed method improves control loop performance by utilized global searched optimal weights of adaptive filtering element(FIR filter of length 4). The use of this approach is friendly to the valve stem movement as it is not causing the valve wearing. Therefore, it will increase the production life cycle of the valve. The experimental case studies have shown that the compensation method proposed reduced greatly the amplitude of the oscillation compared to the conventional approach. Therefore, the proposed technique will yield a more effective production.

The unoptimized and optimized values of the weight of the adaptive element (FIR filter) used to perturb the control signal from the conventional controller

Table 5.5: Optimized FIR Filter weights(Ws) using both settings (MSE and IAE) for all the Four Cases in Subsection 5.2.1

	MSE Optimized Weight(Ws)				IAE Optimized Weight(Ws)			
	W1	W2	W3	W4	W1	W2	W3	W4
Deadband	0.4221	0.3262	0.0319	-0.6008	0.8860	-0.1472	-0.7160	0.1369
Overshoot	0.5407	0.4853	0.0903	-0.8852	0.9655	-0.0292	0.2423	-0.9156
Undershoot	0.6360	0.7064	-0.6229	-0.4805	0.7212	-0.0302	-0.0320	-0.4819
No offset	0.4291	0.1411	0.4204	-0.8193	0.7118	-0.1911	0.4402	-0.7689
Initial Ws; Lower bound: [-1,-1,-1,-1]					Initial Ws; Lower bound: [-1,-1,-1,-1]			
Initial Ws; Upper bound: [1,1,1,1]					Initial Ws; Upper bound: [1,1,1,1]			

which eliminates the degradable effect of stiction in this work is therefore shown in Table 5.5. The table shows the values of the optimized weight for both settings employed, Mean Square error (MSE) and Integral absolute error (IAE) for all the cases of stiction phenomenon investigated. Initial weights(unoptimized weights) upper and lower bound are $[1, 1, 1, 1]$, $[-1, -1, -1, 1]$ respectively.

Also, Comparison between the previous optimization based stiction compensation (LMS-FIR) method and the proposed GSA based method is provided and the possibility of improving the existing LMS-FIR based method by combine both GSA-FIR and LMS-FIR based method is research.

CHAPTER 6

AN IMPROVED LMS-FIR BASED STICTION COMPENSATION USING GSA: A PROPOSED METHOD

6.1 Adaptive Inverse Control (AIC)

AIC is a concept introduced by Bernard Widrow et al., [29] which is an important part of adaptive filtering theory. In this thesis work, adaptive filtering theory is utilized to proposed the adaptive inverse method for controlling valve non-linearity. In this chapter, an introduction to adaptive control technique, the least mean square (LMS) algorithm and an improved version of a stiction compensation method based on AIC proposed by Sabih [10] in 2009 are given.

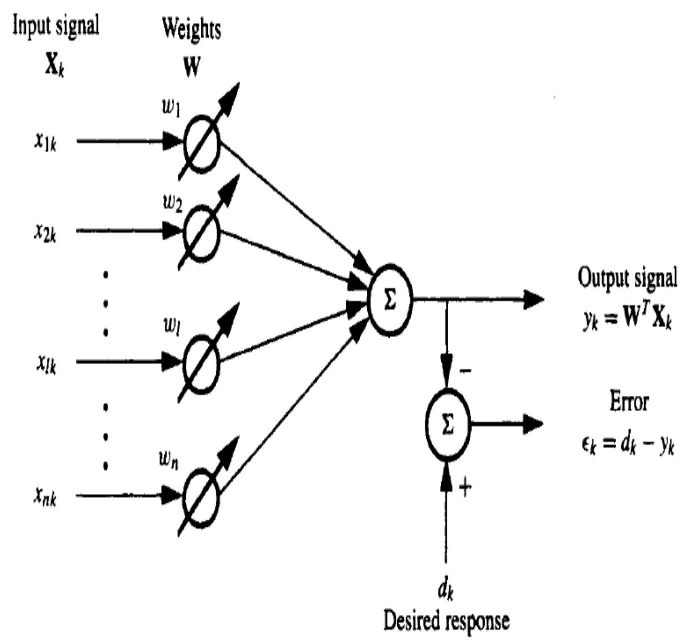


Figure 6.1: A causal linear adaptive filter [29]

6.1.1 Adaptive Least Mean Square (LMS) filter

The best linear square filters are the Wiener filters which are used for application such as prediction, estimation, signal and noise filtering, interpolation and so on. This kind of filters required a prior knowledge of suitable statistical properties which often not available. Therefore, due to this, adaptive filters are often employed to replace them.

Figure 6.1 is a causal linear digital filter (an adaptive filter) which has an input, an output, adaptive algorithm like LMS algorithm, desired response, adjustable weight and a vital signal called error ϵ_k which is essential in the learning process. The corresponding one having an adaptive algorithm is shown in Figure 6.2. The weight is an adjustable parameter which controls the filter impulse response. This is usually tuned by an adaptive algorithm (LMS). The most vital filter employ in

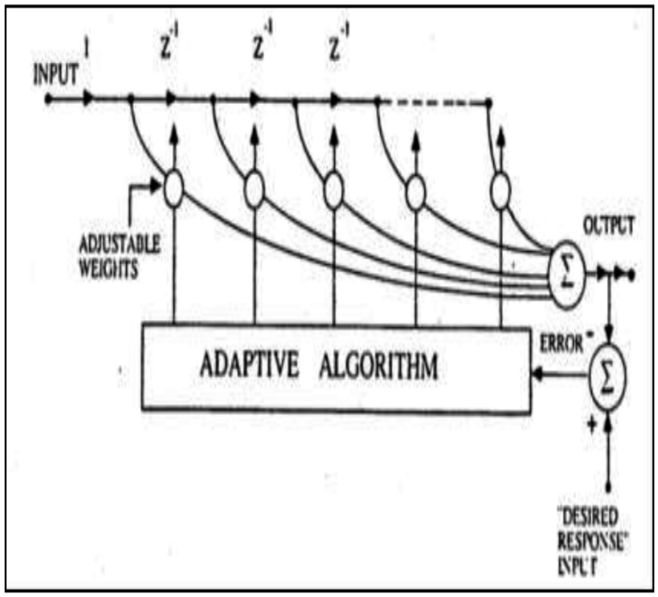


Figure 6.2: A causal linear adaptive filter with learning algorithm

adaptive inverse control is the FIR filter which has no pole but only zeros. The length of the FIR filter normally used for compensation usually of a few length like 4 or 6. This is so in order to minimize the computation time during the optimization process. What could be achieved using filter of longer length can as well be obtained using a few length of 4 or 6. Increasing the length of the filter has a disadvantage of increasing the computation time which is an unwanted in the practical implementation of the stiction compensation.

The adaptive filters are useful in so many application such as plant modeling, plant inverse modeling, they are also useful in plant-wide disturbance cancellation. In this work, adaptive filter is used to cancel non-linearity in a sticky control valve.

In Figure 6.1, the *kth* output signal equal to output signal of the adaptive filter is obtained as follows: Given a set of 'n' input signals, a weighted sum of the signal is formed to represent an output signal. The inputs to the adaptive filter occur simultaneously and discrete in time as shown in the figure. The kth input signals is given as:

$$X_k = [x_{1k}, x_{2k}, ..., x_{lk}, ..., x_{nk}]^T \tag{6.1}$$

The set of weights is designated by the vector W

$$W = [w_1, w_2, ..., w_l, ..., w_n]^T \tag{6.2}$$

Then, the k_{th} output signal is equivalent to:

$$y_k = \sum_{l=1}^{n} w_l x_{lk} = X_k^T W = W^T X_k \tag{6.3}$$

6.1.2 The Least Mean Square (LMS) Algorithm

The LMS algorithm is an application of steepest descent using either measured or estimated gradients.

$$W_{k+1} = W_k + \mu(-\nabla^{est}) \tag{6.4}$$

where the true gradient estimate is $\nabla^{est} = \nabla + N_k$, corresponds to the true gradient plus gradient noise.

The error (ϵ_k) in Figure 6.1 can be used to find a crude gradient estimate ∇^{est} by squaring the error (ϵ_k) and differentiating it with respect to weight w_l as if it were the mean square error:

$$\epsilon_k = d_k - y_k \tag{6.5}$$

$$y_k = W^T X_k \tag{6.6}$$

substituting Equation (6.6) into that of (6.5), squaring the resulting Equation and then differentiate with respect to the weight w_l will give the Equation 6.7.

$$\nabla^{est} = \begin{bmatrix} \frac{\partial \epsilon_k^2}{\partial w_1} \\ . \\ . \\ . \\ \frac{\partial \epsilon_k^2}{\partial w_n} \end{bmatrix} = 2\epsilon_k \begin{bmatrix} \frac{\partial \epsilon_k}{\partial w_1} \\ . \\ . \\ . \\ \frac{\partial \epsilon_k}{\partial w_n} \end{bmatrix} = -2\epsilon X_k \tag{6.7}$$

Substituting Equation (6.7) into (6.4) gives or yields the Least Mean Square (LMS) algorithm.

$$W_{k+1} = W_k + 2\mu\epsilon_k X_k \tag{6.8}$$

The following is a brief summary of the LMS algorithm: The Least Mean

Square algorithm for a kth order filter can be specified such as:

- Parameter(L) equivalent to the filter order
- μ the step size or the learning rate for the algorithm
- Initialization: In the implementation of LMS algorithm in adaptive filter, the initial weights $W_{k=0}$ must be specified by the user
- Computation: For $k = 0, 1, 2, 3, \ldots, n$

  $X_k = [x_k, x_{k-1}, \ldots, x_{k-L+1}]$

  $\epsilon_k = d_k - W^T X_k$

  $W_{k+1} = W_k + 2\mu\epsilon_k X_k$

6.1.3 Stability and Convergence of LMS Algorithm

LMS algorithm does use exact value of the expectation [62], therefore, the weights(Ws) would never reach the optimal value in the absolute sense. Also, if the variance at which the learning weights change is large, then the convergence in mean would be misleading. This kind of problem may occur if the value of the step-size or learning rate μ is not chosen properly. The main drawback of LMS algorithm is that it is sensitive to the scaling of its input values, this makes it difficult to select a correct learning rate that will boost or guarantee its stability, that is, the stability of the algorithm.

6.2 Proposed GSA-LMS-FIR Valve Stiction Compensator

In this section, an improved version of the LMS-FIR stiction compensator by [10] is proposed using the proposed GSA-based stiction compensator in chapter 5. After the comparison between the GSA-based stiction compensation and the LMS-FIR based method with other investigations such as tuning the initial weight and learning rate for LMS-FIR method by trial and error for a few number of time for series of cases, then it is found out that the efficiency of the LMS-FIR compensator could be improved if the following conditions are met, although there could be possibility of other ways of improving its efficiency:

i. If the initial weights are selected in such a way that they are close enough to the global optimum weights: This could be solved by using the global search algorithm such as GSA to find the weights that are very close to the global optimum weights and use LMS algorithm for the rest of the job. That is, both gradient descent and evolutionary algorithm can be integrated together to compact non-linearity in control valve.

ii. If the learning rate μ of the LMS algorithm is assigned a small value, this can prevent the misalignment and improve the stability of the algorithm, although this may converge very slow and this could be solved using the condition as mentioned in i. above.

The parameters, initial weight (Ws) and learning rate μ in LMS-FIR stiction compensation method are normally set manually meanwhile in the proposed GSA-LMS-FIR compensator, combination of the two conditions (mention earlier) are employed to improve the performance of the algorithm, that is, in the improved version of LMS-FIR stiction compensator, GSA algorithm described in section 4.3 is used to search for the initial weight in LMS algorithm and learning rate μ is given a small value of .0001. After this, LMS algorithm introduced by Bernard Widrow [29] utilized by Sabih [10] for stiction compensation is employed in this work to tune FIR filter starting with initial weight searched by GSA [61]. In summary, GSA-LMS-FIR stiction compensator is an integration of GSA, LMS algorithm, and FIR filter to cancel control valve stiction non-linearity.

6.3 GSA-LMS-FIR compensator for a control valve non-linearity cancellation

In this section, validity of this proposed approach is performed. A first order closed loop water level control process described in Subsection 5.2.2 is taken as a pilot plant to validate the efficiency of the proposed GSA-LMS-FIR stiction compensation. All the real-time implementations of the presented technique are done on the LabVIEW. The LabVIEW code/block used in the setup (GSA-LMS-FIR) is shown in Figure 6.3. Both He and Kano stiction models are used to introduce the stiction behavior into the process.

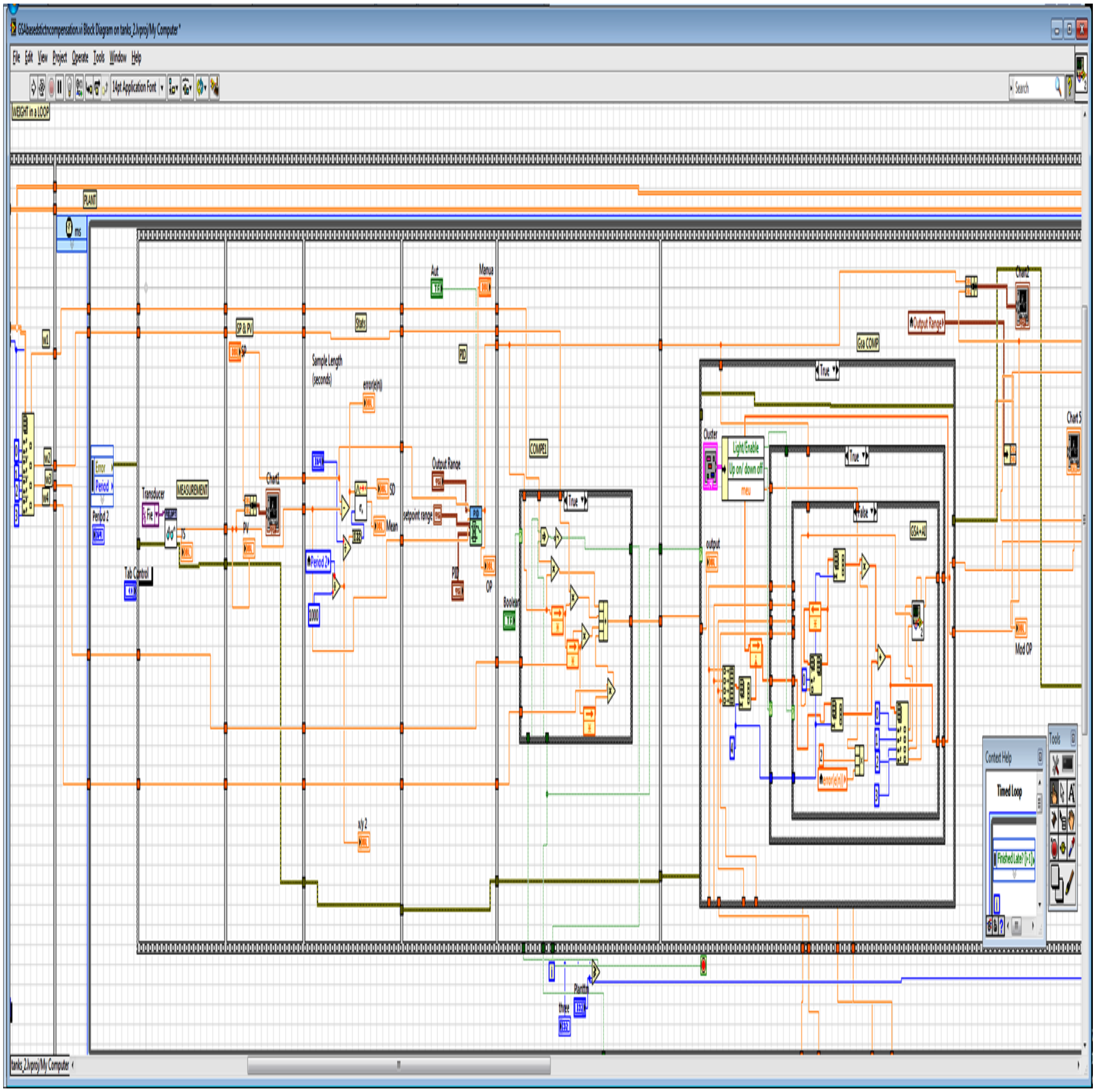


Figure 6.3: Part of GSA-LMS-FIR LabVIEW code/block utilized in the closed loop setup

Table 6.1: Values used for Kano and He Stiction Models

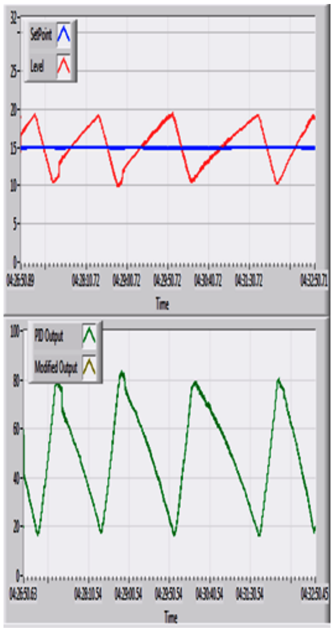
	Kano and He model			
	F_s	F_d	J	S
Undershoot	40	15	32.5	12.5
Dead-band	40	40	0	40
Offset	30	0	15	15

Table 6.2: Key to the Figure (6.4)

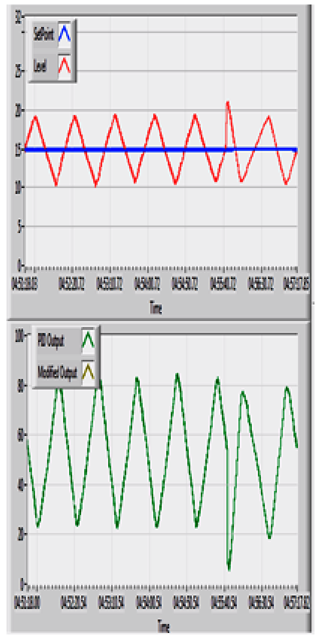
	a	b	c	d	e	f
J	32.5	32.5	0	0	15	15
S	12.5	12.5	40	40	15	15

Table 6.1 shows the values of stiction phenomenon utilized. The corresponding responses using PI controller are shown in Figure 6.4 (for values of the parameter used check Table 6.2) and that of the case when the proposed method is applied are showing in the Figure 6.5

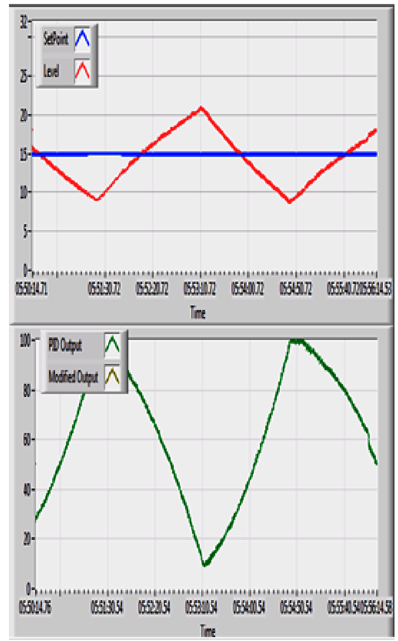
It is clear from the responses that the techniques greatly reduced the damaging effect of stiction. Looking at the amplitude of the oscillation when the proposed method is applied is greatly reduced compared to when it is not used. Also, the effect of the proposed method on the control signal is that it reduced the amount of the control signal exploit to mitigate the stiction oscillatory effect unlike when the stiction compensation is not applied. This will reduce the energy consumption, minimize the production downtime and most importantly it will improve the overall quality of a product. Therefore, all the proposed stiction compensation methods in this work and multi-model constrained Kalman filter for detection and isolation of fault utilized in this work to detect a fault, isolate its type could be integrated together to work as a single system to detect, isolate and compensate fault such as stiction in a closed loop control process.



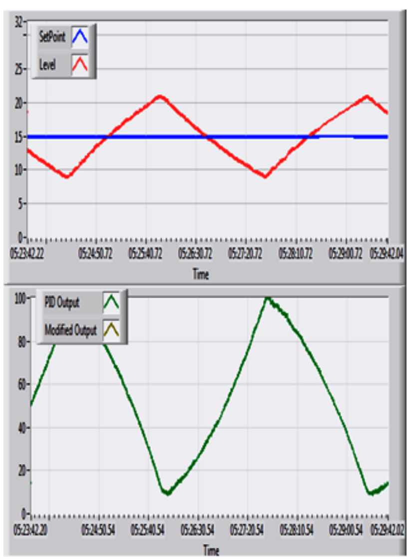
(a) He model "Table 6.2"



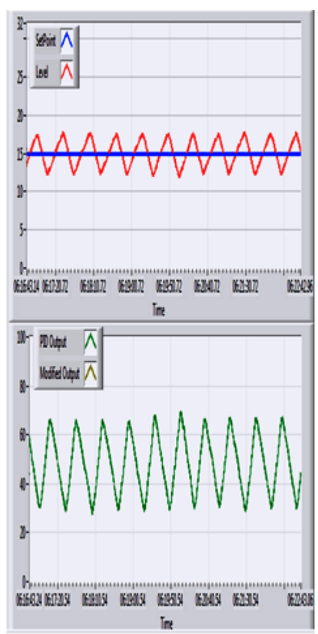
(b) Kano model "Table 6.2"



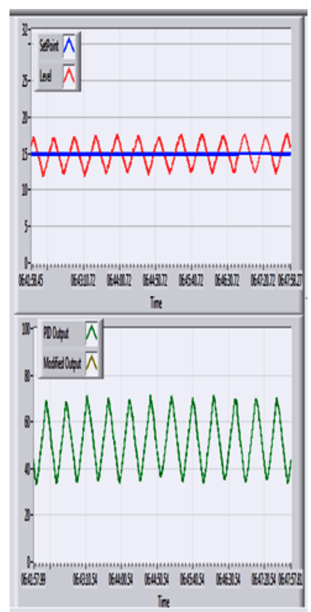
(c) He model "Table 6.2"



(d) Kano model "Table 6.2"

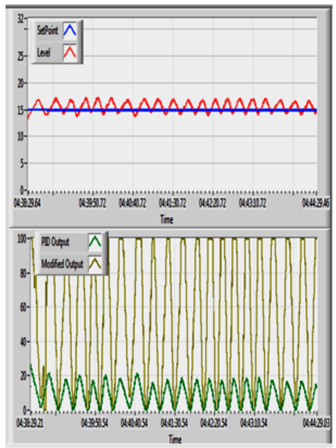


(e) He model "Table 6.2"

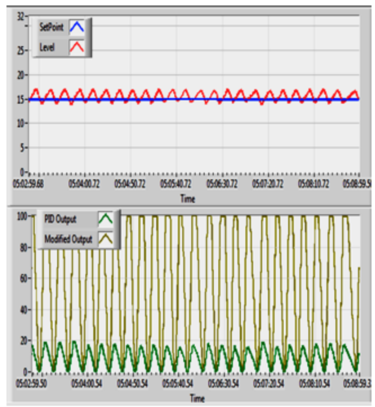


(f) Kano model "Table 6.2"

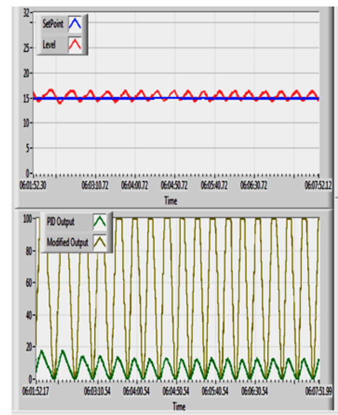
Figure 6.4: Plant response for both He and Kano model using PI controller .



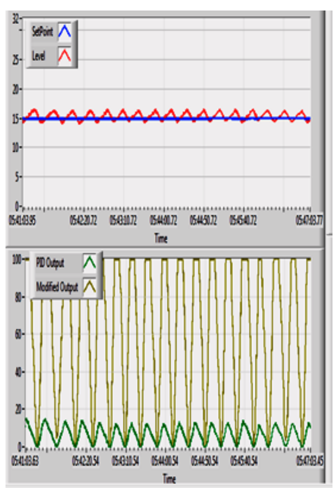
(a) Fs=40,Fd=15 with He model



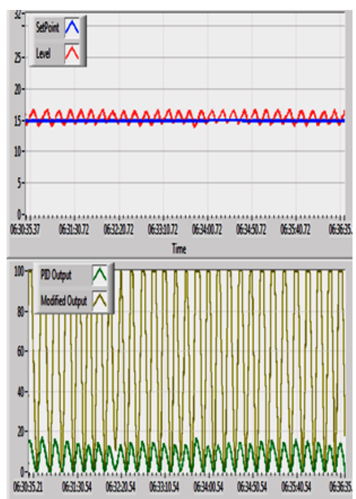
(b) Fs=40,Fd=15 with Kano model



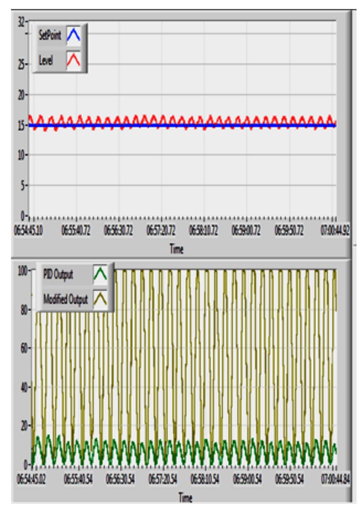
(c) Fs=40,Fd=40 with He model



(d) Fs=40,Fd=40 with Kano model



(e) Fs=30,Fd=0 with He model



(f) Fs=30,Fd=0 with Kano model

Figure 6.5: Plant responses for both He and Kano model using the proposed compensator.

CHAPTER 7

SUMMARY, CONCLUSION AND RECOMMENDATION

7.1 Summary

In this research work, a constrained Kalman filter (CKF) weights computation is proposed for multi-model design for nonlinear system identification and fault detection. This overcomes some of the drawback of commonly used weights computation methods for output blended multi-model such as lack of precision, sensitivity to parameter selection, and restriction to partition strategy. The two implemented constrained Kalman filter (CKFP and CKFI) in this work are tested for multi-model systems identification using clustering partition with linear local models and fault diagnosis. Experimental results show that CKF method is of good performance in both cases and better than other commonly used validity such as simple residue, reinforcement residue, quadratic criterion, and Bayesian validity computations. Particularly for fault detection and isolation, CKF is shown to have good robustness to noise.

Furthermore, MMCKF has been implemented to detect and isolate fault which is stiction in a closed loop liquid level control process. Series of cases are considered to validate the efficiency of the scheme. Besides, based on the ability of the proposed CKF to detect and isolate fault correctly a new stiction compensation method based on heuristic optimization is proposed. This is based on gravitation search algorithm (GSA) method which works by utilizing Newton's law of gravity. In addition, the comparison between the existing stiction compensation method (LMS-FIR based approach) [10] and the proposed stiction compensation method are provided, the proposed method outperformed LMS-FIR based approach. Based on further investigations on LMS-FIR method, an improved version of it is proposed using GSA. This is named as GSA-LMS-FIR based stiction compensation method and its performance is tested under an experimental set-up.

7.2 Conclusion

In this thesis work, series of simulation and experiment are carried out on the previous, the improved, and the proposed stiction compensation methods including the multi-model based fault detection and isolation using constrained Kalman filter (MMCKF). Besides, an intelligent algorithm (Functional Network (FN)) has been used to model a process having a sticky valve.

The proposed stiction compensation methods in this research work are simpler in their implementation than the Knocker method [25] and others. For instance, Knocker based method requires three pulse parameters that must be tuned properly to have a reduced measurement oscillation. Besides, there is no design law and governing rules that can directly map the setting of these parameters with the severity of the stiction quantified or estimated. Moreover, the Knocker based methods compensate stiction in such a way that it lead to aggressive movement of the valve stem causing quick wearing of the valve stem or damage to the valve. In addition, in the case of LMS-FIR compensation [10], the method do trap in local optimum during the search for the global weights to eliminate stiction phenomenon whereas the proposed approaches remove all the drawbacks or have no such drawbacks.

Another advantage of the proposed techniques is that it greatly reduced the load on the controller, in the effect is immensely reducing the total non-linearity effects on the control loop and specifically controller.

Finally, the fault detection and isolation scheme (FDI) implemented in this research work and the proposed GSA based and GSA-LMS-FIR based stiction compensation can be used as a single system to detect, isolate and compensate a control valve non-linearity such as stiction and any other faults in a closed loop process when integrated together.

7.3 Implementation, Contribution and Recommendation

7.3.1 Implementation/Contribution

- An intelligent technique, Functional network (FN), is implemented to model a closed loop process, healthy and the one suffering from the stiction phenomenon in preparation to utilize MMCKF used as fault detection and isolation scheme.

- In this work, the proposed multi-model technique using constrained Kalman filter (MMCKF) is used to detect faults in a closed loop process and determine how severe the detected fault is and it is shown that it's useful for stiction diagnosis.

- It is also proposed to use multi-model technique using CKF to isolate one fault from the other ones so that right correction or compensation method will be applied to solve the fault occurring in the process under study.

- A heuristic optimization stiction compensation approach (GSA based method) is proposed in this research work to compact stiction phenomenon in a closed loop process with a valve non-linearity such a process suffering from stiction.

- LMS-FIR stiction compensation method is implemented to compensate stiction in a closed loop process suffering from the stiction phenomenon and comparison between this method and the proposed method are performed. This led to propose an improved or a new version of LMS-FIR compensation which is then named as GSA-LMS-FIR compensator.

7.3.2 Recommendation

This thesis or research work is ended with the following future work:

- The current work uses one of the available heuristic optimization methods (GSA) to tune linear adaptive filter to reduce the oscillation effect of stiction, other optimization techniques such as Particle swamp optimization(PSO), Tabu-search, Genetic algorithm, Evolutionary programming, Simulated annealing and others could as well be used to do that and possible comparisons could be done. Therefore, for future work it is recommended to try those mentioned approach.

- A linear adaptive filter is utilized, a non-linear adaptive filter can be used in place of the linear one to completely remove the oscillatory effect of stiction. This can be done by simply remove the linear filter used and put the non-linear one in its place. This will then be integrated with the gravitational search algorithm so that stiction effect would be completely removed.

- The approach employed in this research work uses both the simulation and experiment for validation. In the experiment part, soft stiction element coded into National instrument(NIC) compact processor is used to introduce stiction behavior into the real healthy valve. It is suggested to use a valve suffering from real stiction.

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