BALANCED MODEL ORDER REDUCTION FOR LINEAR DYNAMIC SYSTEMS

A Dissertation

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in

SYSTEM AND CONTROL

Submitted by

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CANDIDATE'S DECLARATION

I hereby declare that the work which is presented here, entitled **"Balanced model order reduction for linear dynamic systems"** submitted in partial fulfilment of the requirement for the award of the degree of **Master of Technology** in **System And Control** at **Department of Electrical Engineering**, **Indian Institute of Technology Roorkee**, is an authentic record of my own work carried out during the period from June 2017 to May 2019 under the supervision and guidance of **Dr. Rajendra Prasad**, Professor, Department of Electrical Engineering, Indian Institute of Techonology Roorkee, Roorkee (India).

I also declare that I have not submitted the matter embodied in this report for award of any other degree.

Date:

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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my Knowledge.

(**Dr. Rajendra Prasad**)
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Abstract

Fractional calculus is widely regarded as the calculus of the 21st century. It generalises the order of differential and integral operators to non-integer orders. Model order reduction and controller design are an integral part of systems and control engineering. This thesis deals with the formulation of modified balanced truncation approach and its application in the design of a fractional order two degree of freedom internal model controller (FO-TDF-IMC). A generalized FO-TDF-IMC technique is mathematically formulated in this thesis, in which the set-point tracking controller is an integer order and the disturbance rejection controller is of fractional order type. Further, the fractional order TDF-IMC controller is converted into classical feedback form, where the controller is expressed as PID controller in cascade with fractional order low pass filter. To validate the efficacy of the proposed FO-TDF-IMC scheme, an example of a boiler system is taken. An extensive comparative analysis is undertaken with existing internal model control based techniques in literature such as one and two degree of freedom integer order internal model control technique. Further, the robustness of the proposed scheme is validated via introduction of input, output step disturbance and random disturbance respectively. The performance of the proposed approach is also scrutinized with respect to the key performance indices. The simulation results are a testimony to the effectiveness and superiority of the proposed technique.

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CHAPTER-1

INTRODUCTION

1.1 GENERAL

Deriving reduced-order models for large-scale linear systems has been an active area of research in the control systems literature because the analysis and design of algorithms for small systems is easy. The use of a reduced order model makes it easier to implement analysis, simulations and control system designs. Designing controller and observer is easy for small systems. Power system, as one of the most complicated artificial system, consists of numerous dynamic components (such as generators), which causes that the order of the system model becomes very high. The model with high order consumes abundant time and computer memory during power system dynamic analysis and simulation tests, and brings much difficulty to the global controller design. Therefore, it is quite necessary to reduce the power system model for simplifying the simulation and controller design.

Some of the important reasons for using low-order models over high order linear systems are listed as the following:

(i) To have a better understanding of the system.
(ii) To achieve feasible controller design.
(iii) To reduce hardware complexity.
(iv) To reduce computational complexity.

1.2 MOTIVATION AND LITERATURE SURVEY

The balanced truncation method (BTM) has been studied a lot since Moore [1] proposed the balanced realization theory in 1981. The model reduction based on the BTM can preserve the controllability, observability, and stability of the original system, and provide the upper bound of the error between the reduced model and original system [2]-[4].

Power system, as one of the most complicated artificial system, consists of numerous dynamic components (such as generators), which causes that the order of the system model becomes very high. The model with high order consumes abundant time and computer memory during power system dynamic analysis and simulation tests, and brings much difficulty to the global controller design [5]. Therefore, it is quite necessary to reduce the power system model for simplifying the simulation and controller design. The BTM, as a good linear model reduction method, has been applied to model reduction of power systems. In [6], the BTM is used to estimate the feasible order reduction of dynamic model in power system analysis. In [7] the order of the excitation model is reduced by adopting the BTM, and the robust PSS is designed based on the reduced model. The method is used to reduce the order of the multi-machine system model for the global PSS design in [8].

The BTM can keep the dynamic behavior of the original system well, but may not gain the satisfied steady-state approximation. For this reason, the application of the BTM may face the limitation under some situations, such as the situation that the reduced model is needed to match the original system well in steady state.

Here we modifies the BTM to narrow the steady-state deviations between the reduced model and original system by introducing a gain factor into the reduced model, on the premise that the reduced model can match the original system in the dynamic state. The testing results indicate that the modified method can decrease the deviations, lower the order of the system, and match dynamic behaviors of the original model.

Chapter-2

BALANCED TRUCATION METHOD

Balanced realization theory was initially proposed by Moore in 1981, on which balanced truncation method is based. In BTM we basically retain the characteristics of original system like controllability, observability and stability in reduced order model.

2.1 CONTROLLABILITY

As we know that system is described by its states, when it is possible to get a desired state of the system from an initial state in particular time period then system is called controllable, means its states are controllable. Controllability depends upon matrix [A] and matrix [B].

2.2 OBSERVABILITY

As we know that system is described by its states, when it is possible to get a desired state of the system from the output in particular time period then system is called observable, means its states are observable because by knowing its output we can get any desired state. Observability depends upon matrix [A] and matrix [C].

2.3 SINGULAR VALUE DECOMPOSITION

SVD can be defined, it is a transformation of correlated variables into a new set of uncorrelated variables that express various relations between the variables better than the previous set of variables.

SVD can be seen as a method for data reduction.

It is based on a theorem that says a rectangular matrix A can be written as a product of three matrices- an orthogonal matrix U, a diagonal matrix S and a transpose of an orthogonal matrix V.

$$A_{mn} = U_{mn} S_{mn} V_{mn}^T$$

Where $U^T U = I,\ V^T V = I$ and column of U are orthogonal eigenvectors of AA^T and column of V are orthogonal eigenvectors of $A^T A$ and S is a diagonal matrix containing the square roots of eigenvalues from U or V in descending order.

It is seen that BTM is very good in retaining the dynamic behavior of original system but it gives the poor results in the case of steady-state. So when the BTM is not a good choice when our main priority is to preserve the steady-state behavior. To overcome this problem here we have used the gain factor that helps to get better result. This gain is obtained by comparing original and reduced system which provide very satisfactory result in steady-state behavior as well as dynamic behavior. Sometimes it fails to retain the dynamic behavior of the original system but as we know that one method is not perfect in all scenarios so its output depends system to system.

2.4 CONVENTIONAL BALANCED TRUNCATION METHOD

For a stable linear time-invariant system, its mathematical model is

$$\dot{x} = Ax + Bx$$

$$y = Cx + Du \qquad 2.1$$

Where $x\epsilon\ R^n$ are the state variables; $u\epsilon\ R^m$ are the input variables; $y\epsilon\ R^p$ are output variables; $A\epsilon\ R^{m\times n}, B\epsilon\ R^{p\times n}, C\epsilon\ R^{p\times m}$ and $D\epsilon\ R^{p\times m}$ are constant matrices.

It is considered that system is controllable and observable. So with the help of Lyapunov equation, we can get the controllability gramian P and observability gramian Q as follow:

$$P = \int_0^\infty e^{At} BB^T e^{A^T t}\, dt \qquad 2.2$$

$$Q = \int_0^\infty e^{A^T t} C^T C e^{At}\, dt \qquad 2.3$$

are positive definite, and meet Lyapunov equations:

$$AP + PA^T + BB^T = 0 \qquad 2.4$$

$$A^T Q + QA + CC^T = 0 \qquad 2.5$$

If [P] = [Q] then we can write with the help of singular value decomposition

$$P = Q = \Lambda = diag(\sigma_1, \sigma_2, \sigma_3, \dots \dots \dots \dots ., \sigma_n) \qquad 2.6$$

If above conditions are met, then our system is said to be balanced.

Where $\sigma_1 \geq \sigma_2 \geq \sigma_3 \dots \dots \dots \dots \dots \geq \sigma_n \geq 0;\ \sigma_i\ is\ Hankel\ Singular\ Value.$

Normally for a generalized system, above condition rarely met so we use a transformation to transform our generalized system into balanced system by using a nonsingular matrix T.

$$\dot{\overline{x}} = \overline{A}\overline{x} + \overline{B}u$$
$$y = \overline{C}\overline{x} + \overline{D}u \qquad 2.7$$

Where $\overline{A} = TAT^{-1}$, $\overline{B} = TB, \overline{C} = CT^{-1}$, are the system, input and output matrices for the balanced system and the controllability grammian is given by $\overline{P} = TPT^{-1}$and observability grammian is given by $\overline{Q} = {T^{-1}}^T AT^{-1}$.

The Hankel singular values of a balanced system are arranged in high to low order. Higher the value means stronger the controllability and observability energy corresponding to that state. Basically it means that it will affect input and output response more dominantly than others whose values are lesser. Based on this we can neglect the lower values because they do not affect the input and output response that much. It is the basic idea behind the balanced truncation method. By neglecting the lower value stated the dynamic and steady-state response remain almost same as the original system.

For a balanced system, it is divided into two parts. One part that contains r main sates and second part contains n-r less important states. Above system model that is divided into two part is written as

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} \overline{A}_{11} & \overline{A}_{12} \\ \overline{A}_{21} & \overline{A}_{22} \end{bmatrix} \begin{bmatrix} \overline{x}_1 \\ \overline{x}_2 \end{bmatrix} + \begin{bmatrix} \overline{B}_1 \\ \overline{B}_2 \end{bmatrix} U$$

$$y = \begin{bmatrix} \overline{C}_1 & \overline{C}_2 \end{bmatrix} \begin{bmatrix} \overline{x}_1 \\ \overline{x}_2 \end{bmatrix} + \overline{D}u \qquad 2.8$$

where $\overline{x}_1 \epsilon R^n$, $\overline{x}_2 \epsilon R^{n-r}$

By truncating the less important states (let $\overline{x}_2 = 0$), the reduced model of system can be written as

$$\dot{x_1} = \overline{A}_{11}x_1 + \overline{B}_1 u$$
$$y = \overline{C}_1 x_1 + \overline{D}u \qquad 2.9$$

Let G(s) be the transfer function of matrices (A,B,C,D) and $G_r(s)$ be the transfer function of matrices ($\overline{A}_{11}, \overline{B}_1, \overline{C}_1$,D), then the upper bound of deviation between G(s) and $G_r(s)$) meets

$$\|G(s) - G_r(s)\|_{H\infty} \leq 2(\sigma_{r+1} + \cdots \ldots + \sigma_n) \qquad 2.10$$

2.5 THE MODIFIED BALANCED TRUNCATION METHOD

As we know that our reduced order model using conventional BTM can match dynamic behavior with original system but unable to produce the steady-state response, so in this section we will eliminate this problem by introducing a gain factor 'K' that will help the reduced order model to match the both the behavior.

For the SISO LTI system, Let (s) and Gr(s) be the transfer function of the original system and reduced order model as follows

$$G(s) = \frac{b_n s^n + b_{n-1}s^{n-1} + \cdots \ldots\ldots\ldots + b_0}{s^n + a_{n-1}s^{n-1} + \cdots \ldots\ldots\ldots + a_0} \qquad 2.11$$

$$G_r(s) = \frac{\overline{b}_r s^r + \overline{b}_{r-1}s^{r-1} + \cdots \ldots\ldots\ldots + \overline{b}_0}{s^r + \overline{a}_{r-1}s^{r-1} + \cdots \ldots\ldots\ldots + \overline{a}_0} \qquad 2.12$$

For matching the steady-state response, gain factor is given by

$$K = \left.\frac{G(s)}{G_r(s)}\right|_{s=0} = \frac{b_0}{a_0}\frac{\overline{a}_0}{\overline{b}_0} \qquad 2.13$$

Where a_0 and $\overline{a}_0$ positive, b_0 and $\overline{b}_0$ are non-zero, because the system is considered to be controllable, observable, and stable. Now the transfer function of the reduced order model can be written as $G_r'(s) = KG_r(s)$.

As final value theorem, if input is unit step the output of reduced order model is given by

$$\lim_{t\to\infty} y(t) = \lim_{s\to 0}(sG_r(s)\frac{1}{s}) = \frac{\overline{b}_0}{\overline{a}_0} \qquad 2.14$$

From above equation it can be seen that steady-state value of y only depends on the constant term of numerator and denominator. For stability of the reduced order model the constant term $\overline{a}_0$ of the denominator must not be changed. So we propose that the gain factor 'K' should be inserted in the front of the constant term $\overline{b}_0$ of the numerator. By performing this, the transfer function of the reduced order model changes as

$$G_r(s) = \frac{\overline{b}_{r-1}s^{r-1}+\overline{b}_{r-2}s^{r-2}+\cdots\text{.........}+K\overline{b}_0}{s^r+\overline{a}_{r-1}s^{r-1}+\cdots\text{.........}+\overline{a}_0} \qquad 2.15$$

From above equation we can find the final output of the reduced order model $G_r'(s)$ as

$$\lim_{t\to\infty} y(t) = \lim_{s\to 0}(sG_r(s)\frac{1}{s}) = \frac{\overline{Kb_0}}{\overline{a}_0} = \frac{b_0}{a_0} \qquad 2.16$$

It can be seen that steady-state response of reduced order model and original system is same.

Now for a multi-input multi-output system, considering the same dimensions of input and output.

G(s) and $G_r(s)$ are the transfer function of original system and reduced order model as follows

$$G(s) = \frac{1}{f(s)}\begin{bmatrix} g_{11}(s) \ldots \ldots .. g_{1p}(s) \\ g_{p1}(s) \ldots \ldots .. g_{2p}(s) \end{bmatrix} \qquad 2.17$$

$$G_r(s) = \frac{1}{f_r(s)}\begin{bmatrix} \overline{g}_{11}(s) \ldots \ldots .. \overline{g}_{1p}(s) \\ \overline{g}_{p1}(s) \ldots \ldots .. \overline{g}_{2p}(s) \end{bmatrix} \qquad 2.18$$

Where

$$f(s) = s^n + a_{n-1}s^{n-1} + \cdots \ldots \ldots \ldots . + a_0$$

$$g_{ij}(s) = \beta_n^{ij} s^n + \beta_{n-1}^{ij} s^{n-1} + \cdots \ldots \ldots \ldots . + \beta_0^{ij}$$

$$f_r(s) = s^r + \overline{a}_{r-1}s^{r-1} + \cdots \ldots \ldots \ldots . + \overline{a}_0$$

$$\overline{g_{ij}}(s) = \overline{\beta}_n^{ij} s^n + \overline{\beta}_{n-1}^{ij} s^{n-1} + \cdots \ldots \ldots \ldots . + \overline{\beta}_0^{ij}$$

The introduced gain factor K is defined as

$$K = G(s)G_r^{-1}(s)|_{s=0} = \frac{\overline{a}_0}{a_0} M\overline{M}^{-1} \qquad 2.19$$

Where, $M_{ij} = \beta_0^{ij}, \overline{M}_{ij} = \overline{\beta}_0^{ij}$ are the ith row and jth column componant of M and $\overline{M}$.

Now let $\overline{E} = K\overline{M}$, replace every constant term $\overline{\beta}_0^{ij}$ with $\overline{E}_{ij}$, then the transfer function matrix $G_r(s)$ is changed as

$$G_r'(s) = \frac{1}{f_r(s)}\begin{bmatrix} \overline{g}_{11}'(s) \ldots \ldots .. \overline{g}_{1p}'(s) \\ \overline{g}_{p1}'(s) \ldots \ldots .. \overline{g}_{2p}'(s) \end{bmatrix} \qquad 2.20$$

where

$$\overline{g}_{ij}'(s) = \overline{\beta}_n^{ij} s^n + \overline{\beta}_{n-1}^{ij} s^{n-1} + \cdots \ldots \ldots \ldots . + \overline{E}_{ij}$$

After getting the modified transfer function matrix $G_r'(s)$, we can obtain the reduced model (A_r', B_r', C_r', D_r') by performing the minimal state-space realization for $G_r'(s)$. It can be noted that the order of modified model (A_r', B_r', C_r', D_r')may be higher than the one of the model $(\overline{A}_{11}, \overline{B}_1, \overline{C}_1$,D), because the zeros of $G_r'(s)$ are a little different from the ones of $Gr(s)$. If this case occurs, the conventional BTM can be used to reduce the order of (A_r', B_r', C_r', D_r') to make the order of final reduced model (A_r, B_r, C_r, D_r) equal to the one of $(\overline{A}_{11}, \overline{B}_1, \overline{C}_1$,D).

2.6 MATLAB SIMULATION AND RESULTS

Proposed system

$$A = \begin{bmatrix} -1 & 0.545 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -3.27 & -0.05 & -5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3.333 & -3.333 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & -5.208 & 0 & -12.5 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -6 & 0 & -3.27 & -0.05 & 6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -3.333 & 3.333 \\ 0 & 0 & 0 & 0 & 0 & 0 & -5.283 & 0 & -12.5 \end{bmatrix}$$

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}^T$$

$$C = \begin{bmatrix} 1 & 0 & 1 & 1 & 1 & -1 & 1 & 1 & 1 \\ 1 & 0 & 1 & -1 & 1 & 1 & 0 & 1 & 1 \end{bmatrix}$$

Given that system is controllable, observable and stable. By the BTM we obtain these results

And the Hankel singular values are

Δ = diag(2.0017,0.9293,0.8311,0.3508,0.0989,0.0925,0.0140,0.0005)

From the matrix Δ, it can be seen that $\sigma_4 > \sigma_5$. So the states of the balanced system $(\overline{A}, \overline{B}, \overline{C})$ corresponding to the singular values $\sigma_4 \ldots \ldots \ldots .. \sigma_9$ are truncated, and the reduced model ($\overline{A}_{11}, \overline{B}_1, \overline{C}_1$,D) is obtained as

$$\dot{x}_1 = \begin{bmatrix} -0.6007 & -1.0826 & -0.0747 & 0.6526 \\ 0.9337 & -0.3948 & -3.0295 & 1.5630 \\ -1.1699 & 3.0092 & -1.9299 & -0.6306 \\ 0.5474 & -1.5763 & 1.1289 & -1.6936 \end{bmatrix} \overline{x}_1 + \begin{bmatrix} -0.1020 & -1.5473 \\ -0.6132 & 0.5982 \\ -0.9971 & -1.4878 \\ -0.6195 & 0.8970 \end{bmatrix} u$$

$$y = \begin{bmatrix} 0.0809 & 0.2216 & -1.5985 & -0.5545 \\ -1.5486 & -0.8275 & -0.8079 & 0.9389 \end{bmatrix} \overline{x}_1$$

Controllability Grammian matrix P and observability Grammian matrix Q is obtained as

$$P = \begin{bmatrix} 1.2205 & 0.0978 & 0.1672 & 0.1526 & -0.1452 & 0.5974 & -0.5105 & 0.0462 & 0.3478 \\ 0.0978 & 0.0183 & 0.0183 & 0.0338 & -0.0131 & 0.0766 & -0.1318 & -0.0167 & 0.0495 \\ 0.1672 & 0.0183 & 0.2483 & 0.0855 & -0.0816 & 0.1531 & 0.2122 & -0.0343 & -0.0281 \\ 0.1526 & 0.0338 & 0.0855 & 0.0855 & -0.0453 & 0.1178 & -0.0594 & -0.0872 & 0.0139 \\ -0.1452 & -0.0131 & -0.0816 & -0.0453 & 0.0740 & -0.0591 & -0.1392 & 0.0275 & -0.0047 \\ 0.5974 & 0.0766 & 0.1531 & 0.1178 & -0.0591 & 0.5000 & -0.7954 & 0.1333 & 0.3853 \\ -0.5105 & -0.1318 & 0.2122 & -0.0594 & -0.1392 & -0.7954 & 3.3049 & -0.4893 & -1.2742 \\ 0.0462 & -0.0167 & -0.0343 & -0.0872 & 0.0275 & 0.1333 & -0.4893 & 0.4452 & 0.2882 \\ 0.3478 & 0.0495 & -0.0281 & 0.0139 & -0.0047 & 0.3853 & -1.2742 & 0.2882 & 0.6185 \end{bmatrix}$$

$$Q = \begin{bmatrix} 1.0000 & -0.0358 & 0.1886 & -0.5985 & 0.1481 & 0.2202 & -0.1347 & 0.2751 & 0.2161 \\ -0.0358 & 1.3094 & -0.4064 & 0.8354 & -0.0213 & -0.3541 & -0.2832 & -0.2988 & -0.0719 \\ 0.1886 & -0.4064 & 1.4369 & -0.0371 & 0.1127 & 0.5365 & 0.1846 & -0.0778 & 0.0283 \\ -0.5985 & 0.8354 & -0.0371 & 1.7677 & -0.0889 & 0.3759 & -0.0647 & -0.7844 & -0.3046 \\ 0.1481 & -0.0213 & 0.1127 & -0.0889 & 0.0800 & -0.0092 & 0.0381 & 0.1408 & 0.0988 \\ 0.2202 & -0.3541 & 0.5365 & 0.3759 & -0.0092 & 2.8348 & -0.5611 & -1.0166 & -0.2732 \\ -0.1347 & -0.2832 & 0.1846 & -0.0647 & 0.0381 & -0.5611 & 0.3157 & 0.3175 & 0.0917 \\ 0.2751 & -0.2988 & -0.0778 & -0.7844 & 0.1408 & -1.0166 & 0.3175 & 0.8716 & 0.3445 \\ 0.2161 & -0.0719 & 0.0283 & -0.3046 & 0.0988 & -0.2732 & 0.0917 & 0.3445 & 0.1719 \end{bmatrix}$$

By the modified BTM, we can calculate the gain factor K as

$$K = \begin{bmatrix} 1.02728 & 0.553385 \\ 1.10608 & 1.00925 \end{bmatrix}$$

After introducing K into the transfer function (s) of $(\overline{A}_{11}, \overline{B}_1, \overline{C}_1, \text{D})$ to obtain $G_r(s)$, making the minimal state-space realization for $G_r'(s)$ to gain (A_r', B_r', C_r', D_r'), and reducing the order of (A_r', B_r', C_r', D_r'), we obtain the final reduced model (A_r, B_r, C_r, D_r) as follow:

$$\dot{x}_r = \begin{bmatrix} -0.5972 & -1.0737 & -0.0894 & -0.6638 \\ 0.9614 & -0.3988 & -2.9415 & -1.6672 \\ -1.1326 & 3.0409 & -1.9020 & 0.5120 \\ -0.5457 & 1.6691 & -1.0519 & -1.6394 \end{bmatrix} x_r + \begin{bmatrix} -0.1129 & -1.5506 \\ -0.5619 & 0.6522 \\ -1.0401 & -1.4507 \\ 0.6085 & -0.9139 \end{bmatrix} u$$

$$y = \begin{bmatrix} 0.0842 & 0.2968 & -1.5887 & 0.5214 \\ -1.5524 & -0.8081 & -0.8138 & 0.9662 \end{bmatrix} x_r$$

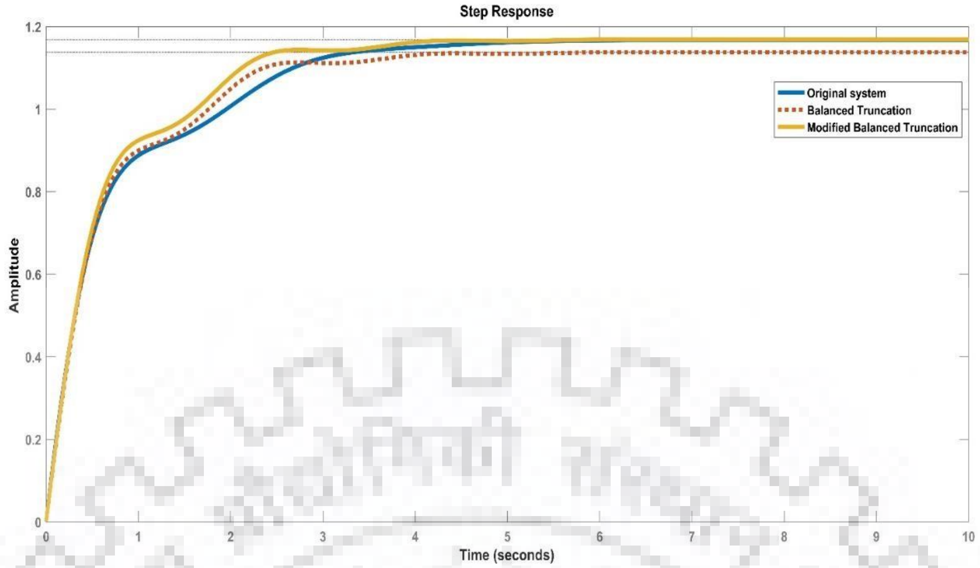

Figure 2.1: Step response of g_{11}

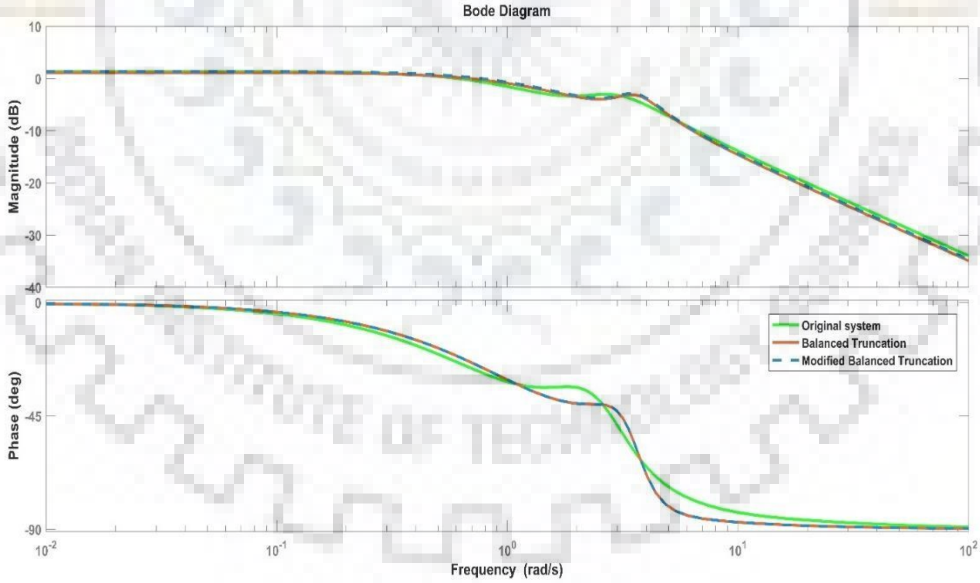

Figure 2.2: Bode plot of g_{11}

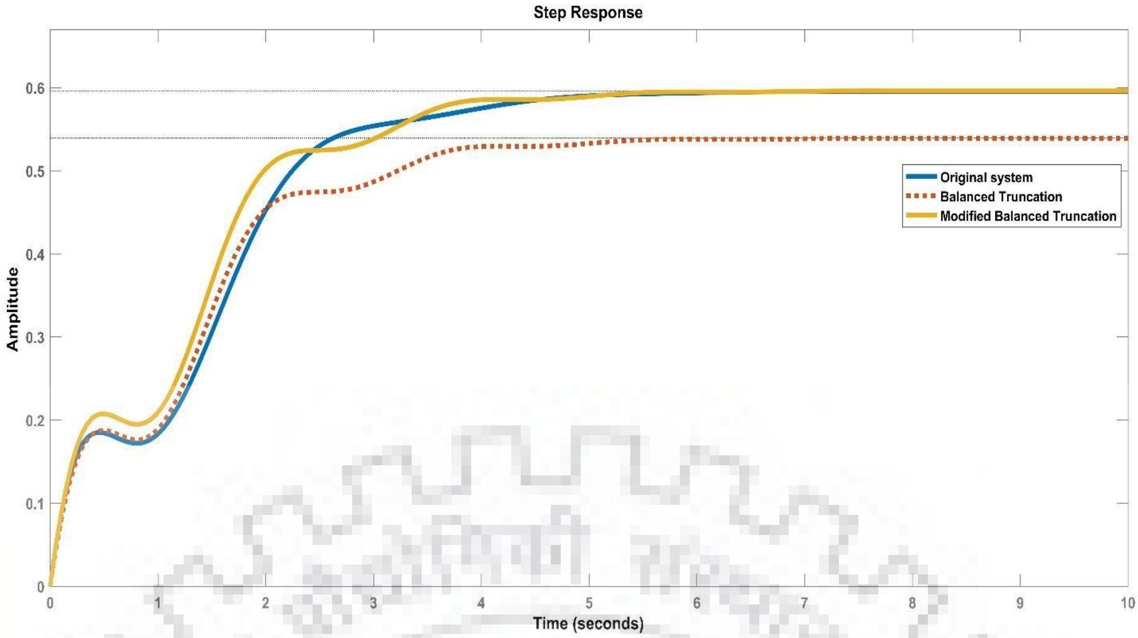

Figure 2.3: Step response of g_{21}

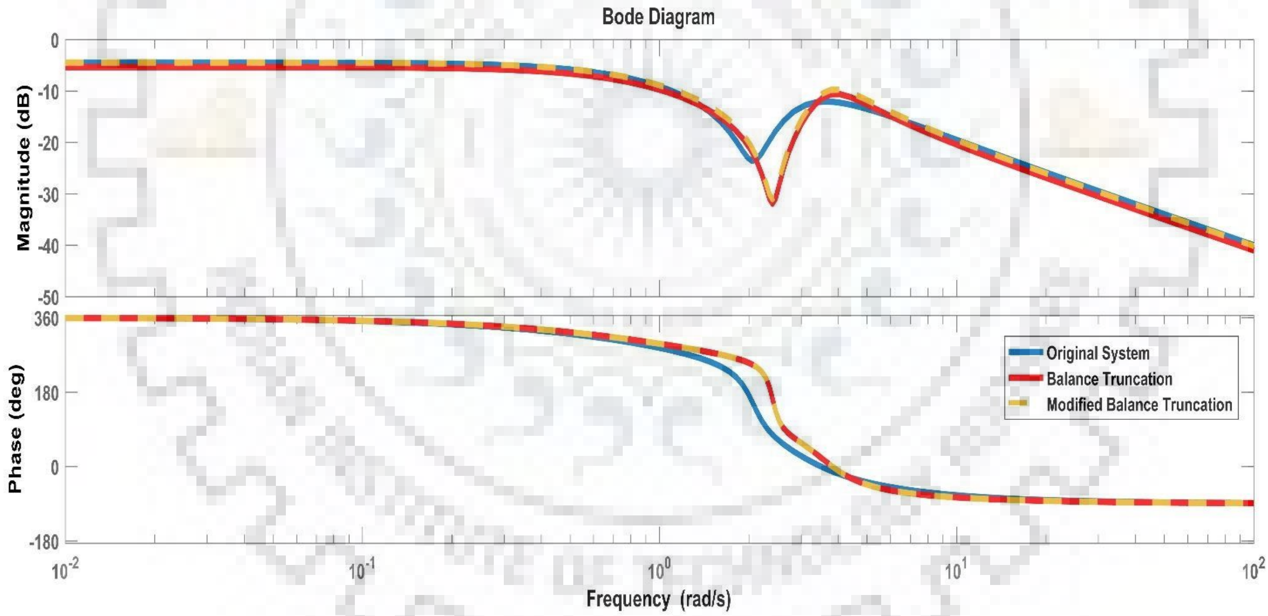

Figure 2.4: Bode plot of g_{21}

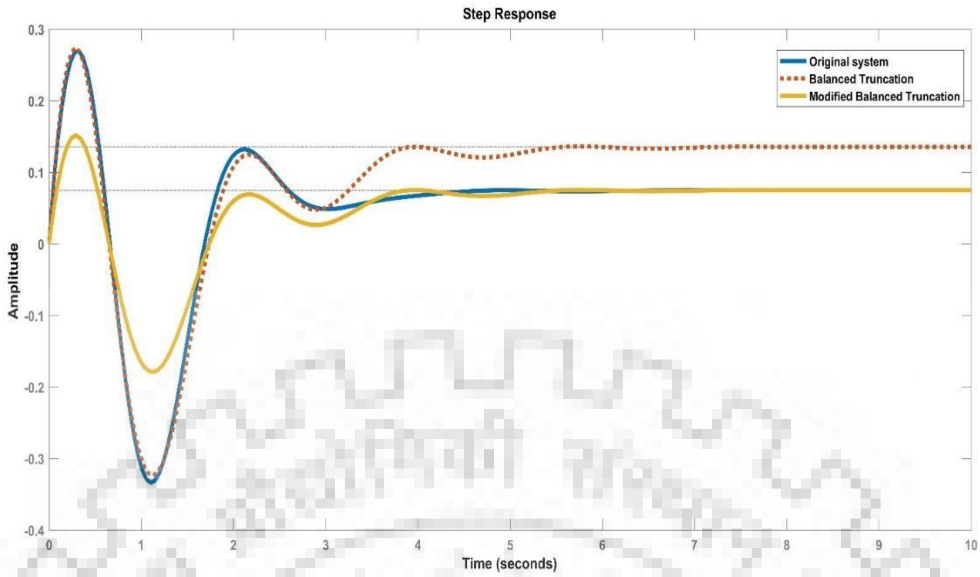

Figure 2.5: Step response of g_{12}

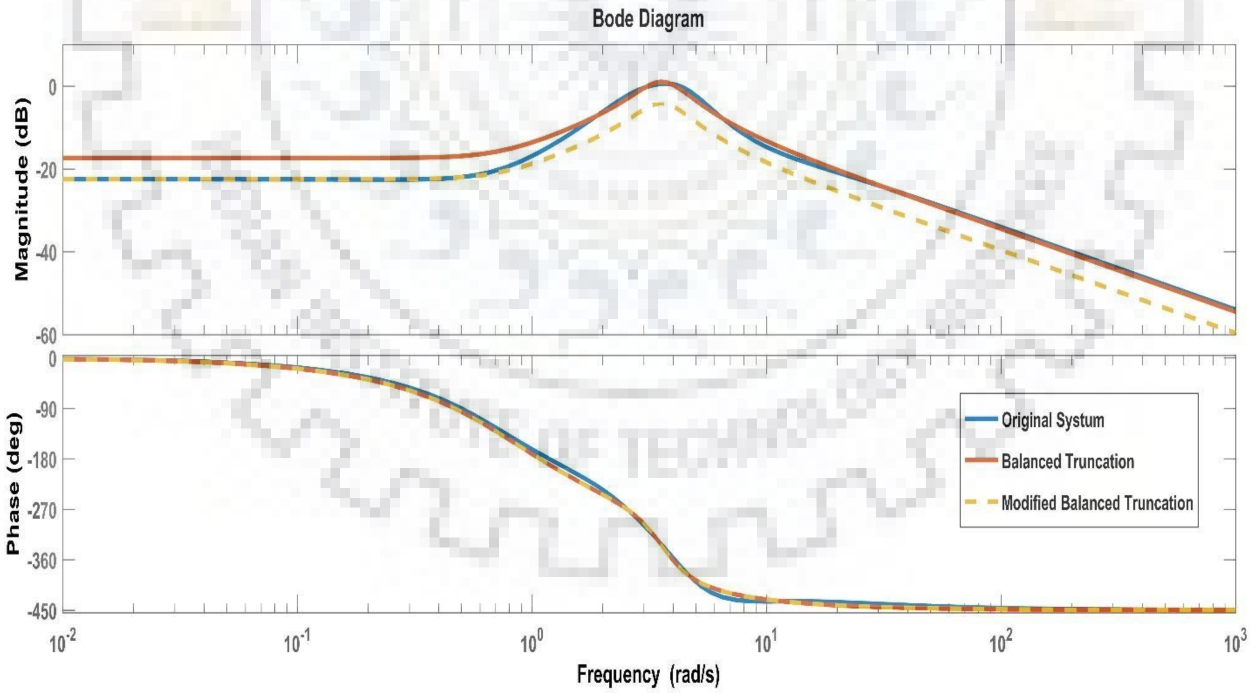

Figure 2.6: Bode plot of g_{12}

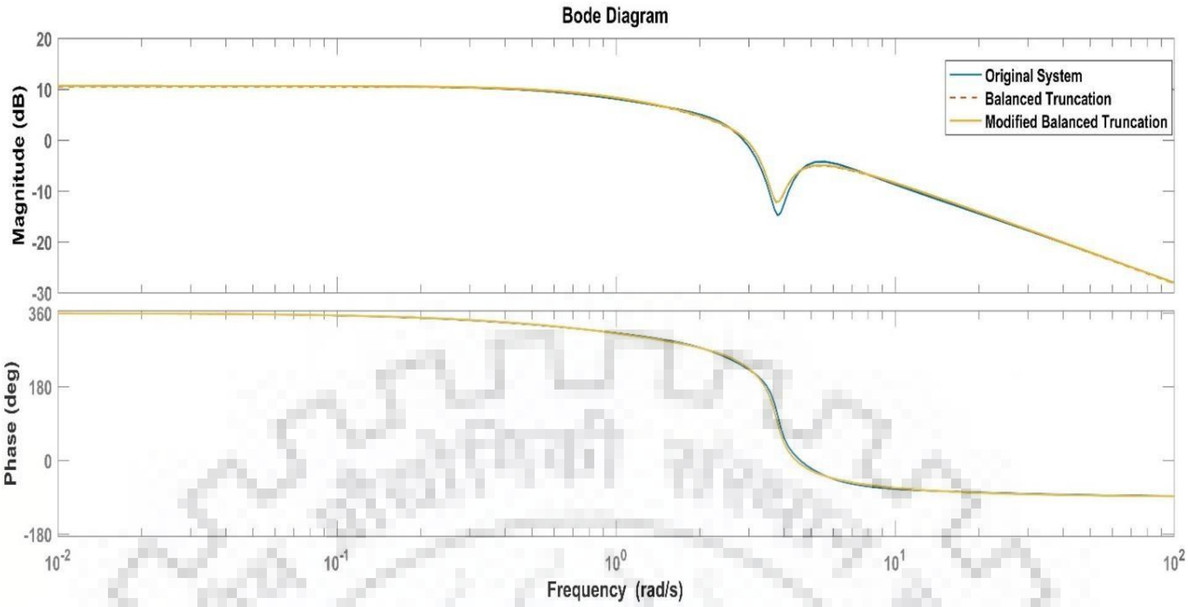

Figure 2.7: Bode plot of g_{22}

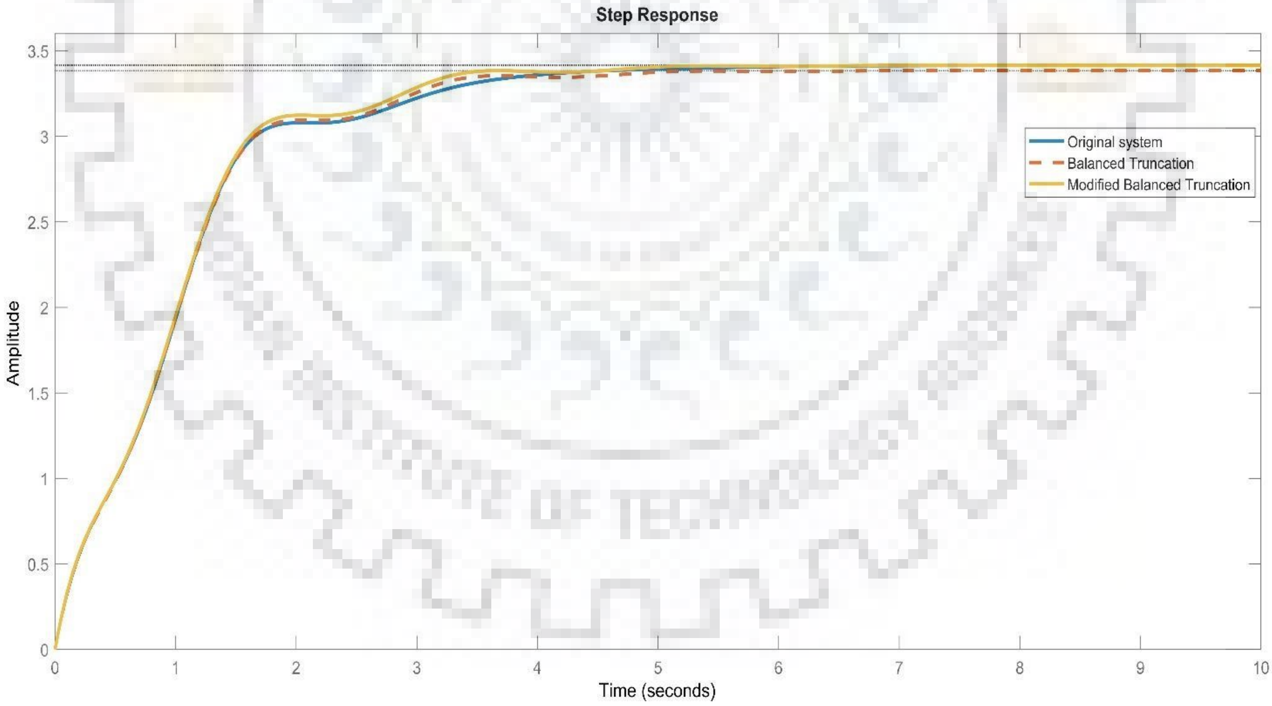

Figure 2.8: Step response of g_{22}

A comparison between various parameters of original system and reduced order system which is obtained using conventional balance truncation and modified balance truncation method:

Table 2.1: Comparison of various parameters of g_{11}

g_{11}	Original	BT	MBT
ISE	NA	7.13E-04	6.27E-04
SSE	NA	0.031037	0.3082
tr	2.2268	1.8102	1.8102
ts	3.6874	3.4059	3.4059
Mp	0	0	0
tp	6.2949	6.1839	6.1839

Table 2.2: Comparison of various parameters of g_{12}

g_{11}	Original	BT	MBT
ISE	NA	0.0024	0.0019
SSE	NA	-0.60549	0
tr	0.0345	0.0668	0.0668
ts	3.953	5.0889	5.0889
Mp	2.5974	1.0219	1.0219
tp	1.1052	1.1288	1.1288

Table 2.3: Comparison of various parameters of g_{21}

g_{11}	Original	BT	MBT
ISE	NA	0.0025	3.85e-04
SSE	NA	0.057181	0
tr	2.5194	2.9046	2.9046
ts	4.4642	3.9024	3.9024
Mp	0	0	0
tp	7.1259	7.6072	7.1259

Table 2.4: Comparison of various parameters of g_{22}

g_{11}	Original	BT	MBT
ISE	NA	6.13E-04	6.65E-04
SSE	NA	0.0313	0
tr	1.8011	1.6367	1.6367
ts	3.8334	3.2408	3.2408
Mp	0	0	0
tp	7.7827	7.1655	7.1655

Chapter-3

INTERNAL MODEL CONTROL TECHNIQUE

3.1 INTRODUCION

In control theory, the era before 1980 was limited to the performance of controllers for single-input, single-output (SISO) systems in view of stability considerations, and plant variations were almost never an issue. So, whenever industries uses complex processes such as higher order process or process with dead-time (e.g., transport dead-time on paper, mining, oil, food processing, resource allocation in computing etc), then model based control algorithms like dead-beat algorithm[9], Dahlin's algorithm[10], Kalman's approach[11], and Smith-predictor algorithm[12] were utilized to design controllers. These controllers provided an optimal response in absence of model uncertainties. However, Brosilow[13] developed a technique for tuning smith predictor controller, which failed to incorporate all the uncertainties in model parameter, and thereby creating robustness problems. The uncertainties are generally introduced due to process delays, high nonlinearity at different operating conditions, environmental variations (like temperature, pressure, relative humidity etc.), stochastic disturbances, and varying steady states. The disturbances could be eliminated using filters but the controller complexity increases. According to Garcia and Morari[14], the control system must be optimal in the sense that it maintains stability and robustness, alters the quantity of interest in a process to a desired set-point with fast and smooth tracking capacity, while rejecting environmental and process uncertainties, along with handling constraints on input and states. Besides, robust stability of the process is very necessary for high performance, safety, reduced manpower, and economic point of view for process industries.

In this backdrop, optimal controllers prove good dynamic compensator to deal with set-point tracking, and input and state constraints, at the same time bringing optimality of the required performance criterion (quadratic performance index, integral square error) but robustness investigation is implicit, and control policy fails to process with time delay[15]. To obtain robust control performance against the nonlinear design of plants subjected to uncertainty and disturbances, a variety of adaptive control techniques like programmed adaptation and on-line adaptive control strategies, and robust techniques were evolved. Apart from rigorous computational framework, this scheme can successfully tolerate parameter uncertainties, but the prerequisite to apply the adaptation algorithm is the complete knowledge of the reference trajectory or states to be tracked, and therefore, this kind of approach is unsuitable for the problem of tracking unknown trajectories[16]. While the robust control method based on H∞ demands the knowledge of limit of disturbance for asymptotic stability and disturbance rejection[17]. On the other hand, modern control techniques based on artificial techniques such as fuzzy logic and neural networks do not require knowledge of plant model, and these schemes provide robustness despite model discrepancies and noise disturbance. However, the computational expenses and the requirement of the expert's advice for system identification have seriously restricted their application in practice[18]. Alternatively, in widely used standard PID type controllers, the most popular tuning rules Ziegler Nichols and Cohen-Coon[19] have been a generic and efficient solution to real world control problems for more than three decades, and have the capability to achieve desired optimal performance only for specific inputs with little tolerance in plant variations. Thus, the inevitable mismatches between the assumed (nominal) models and the real-world processes destroyed the viability of many control schemes, thereby demanding certain novel approach in the field of robust control to increase the efficiency of the control system in the presence of plant uncertainties and disturbance. In this regard, internal model control (IMC) provides an advanced, effective, intuitive, generic, novel, powerful, and simple framework for the analysis and synthesis of control system performance, especially robust and optimal properties[20].

The purpose of this paper is to review and explain the different aspects, methodologies, progress, and future prospects in internal model control technique for single-input, single-output, linear time-invariant systems. No claim is made about developing anything novel. We just summarize what is available at different places in literature and present it in a tutorial prospect. Furthermore, valuable insight regarding the controller, its tuning techniques, modified structures, and future prospects are highlighted.

3.2 IMC Structure

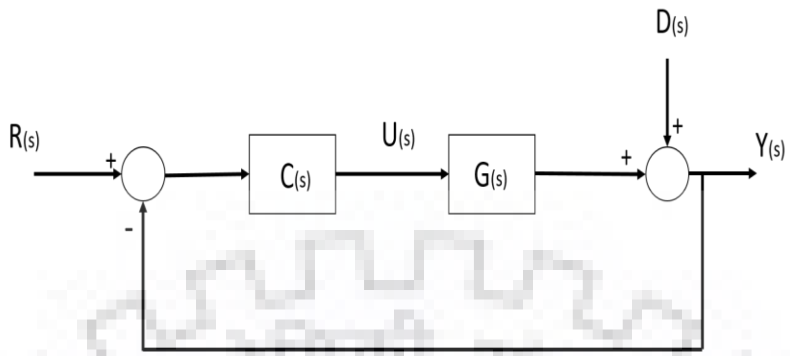

Figure: 3.1: Classical feedback structure

IMC is basically a classical feedback structure as shown above with plant G(s) and controller C(s). A plant model $G_M(s)$ is added and subtracted in feedback path of the controller C(s) as shown in Figure 3.2 to achieve IMC structure. The plant model fed back to the controller gives a new controller Q(s), and the internal model along with controller is obtained in Figure 3.3.

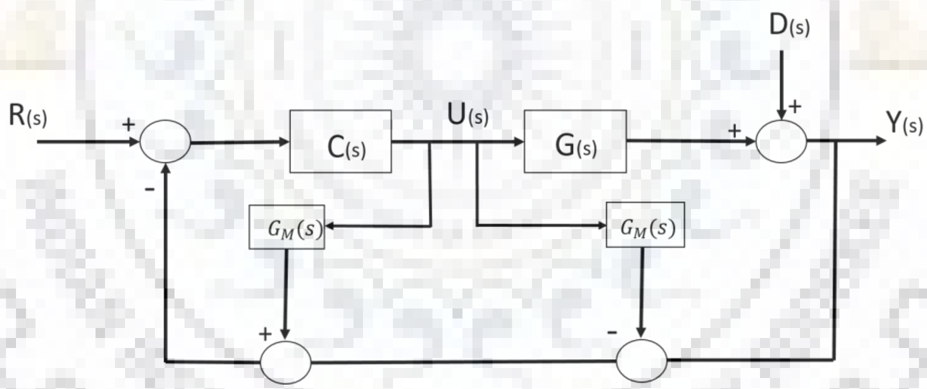

Figure: 3.2: Classical feedback structure with plant model

Relation between Q(s) and C(s) is given by these equations

$$Q(s) = \frac{C(s)}{1+G_M(s)C(s)} \quad 3.1$$

$$C(s) = \frac{Q(s)}{1-G_M(s)Q(s)} \quad 3.2$$

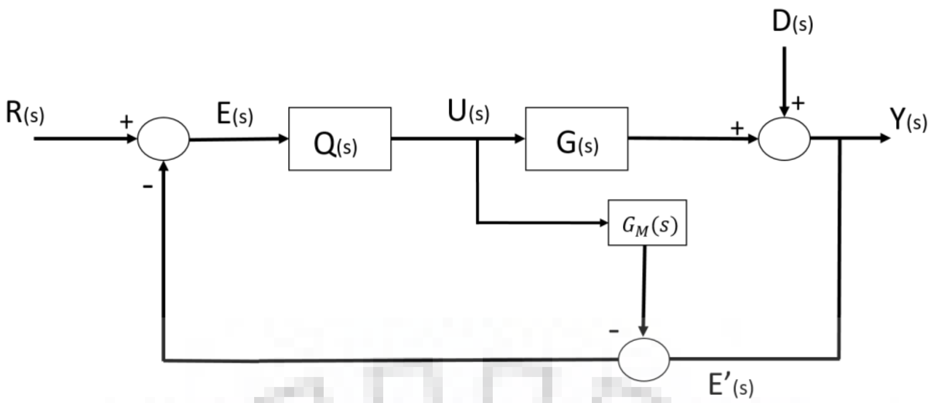

Figure: 3.3 IMC feedback structure

Thus internal model control system consist a controller named as Q(s) and a plant model $G_M(s)$. The difference between output of G(s) and $G_M(s)$ is represented by $E'(s)$ and it represents the mismatch between plant and plant model.

Different input-output relationships from block diagram of an IMC structure figure are given below

$$E'(s) = \frac{D(s)}{1+Q(s)\big(G(s)-G_M(s)\big)} \qquad 3.3$$

$$U(s) = \frac{Q(s)}{1+Q(s)\big(G(s)-G_M(s)\big)}\big(R(s)-D(s)\big) \qquad 3.4$$

$$E(s) = \frac{1}{1+Q(s)\big(G(s)-G_M(s)\big)}\big(R(s)-D(s)\big) \qquad 3.5$$

$$Y(s) = \frac{G(s)Q(s)R(s)}{1+Q(s)\big(G(s)-G_M(s)\big)} + \frac{\big(1-G_M(s)Q(s)\big)D(s)}{1+Q(s)\big(G(s)-G_M(s)\big)} \qquad 3.6$$

Equation can also be described as

$$Y(s) = \rho(s) + \varepsilon(s)D(s);\ \rho(s)+\varepsilon(s) = 1 \qquad 3.7$$

Where $\varepsilon(s)$ represents sensitivity and $\rho(s)$ is complementary sensitivity functions. And $\rho(s)$ determines performance of the system whereas $\varepsilon(s)$ is for robustness of the system.

3.3 PROPERTIES OF IMC STRUCTURE

- Dual Stability

If the plant model is chosen perfectly means $G_M(s)$ = G(s) and no disturbance is present then from the equations, the system becomes open-loop and closed-loop system will be stable too if we chose G(s) and Q(s) stable.

- Perfect Control:-

If perfect plant model is chosen as $G_M(s)$ = G(s) and controller Q(s) is equal to the inverse of model plant (Q(s) = $G_M^{-1}(s)$) with stable G(s) then system is perfectly controllable as Y(s) = R(s).

Basically IMC structure used open-loop controller to provide perfect closed-loop performance.

It is clear from above discussion that IMC structure has many advantage as compared to classical feedback controller but ideal IMC structure requires perfect plant model which is in practical world is not possible as all practical systems are non-linear in nature. And as controller Q(s) is chosen as inverse of plant model $G_M(s)$ which is not possible in all the cases and inverse of plant model can create instability in presence of plant mismatch which may produce undesirable oscillation in output.

To overcome this problem first plant model is factorised into two parts in which one part is invertible and minimum phase system (poles are on LHS of the s-plane) whereas other part is non-invertible and non-minimum phase system (poles are on RHS of the s-plane). Now the chosen controller is basically inverse of invertible part of plant model.

$$G_M(s) = G_{M+}(s)G_{M-}(s) \qquad 3.8$$

where

$G_{M+}(s) = is\ noninvertble\ and\ nonminimum\ phase$

$G_{M-}(s) = is\ invertible\ and\ minimum\ phase$

and

$$Q_1(s) = G_{M-}^{-1}(s) \tag{3.9}$$

But a problem arises as the controller $Q_1(s)$ is stable but it may not be proper. So to make controller proper and robust against the plant model mismatch, a low pas filter (LPF) is used with the inverted model $Q_1(s)$ to provide complete IMC controller.

The low pass filter is used in the form given below

$$F(s) = \frac{1}{(\lambda s+1)^n} \tag{3.10}$$

$$OR\ \ F(s) = \frac{n\lambda+1}{(\lambda s+1)^n} \tag{3.11}$$

where λ is adjustable parameter (tuning parameter) and the value of "n" is selected such that $Q_1(s)$ becomes proper or semi-proper.

Equation and are for type-1 (step input) and type-2 (ramp input) system respectively. Filter used other than above mentioned equations may improve performance of system but reduces the robustness of system. The filter makes the controller robust and also reduces the mismatch between pant and plant model at higher frequencies. A care must be taken whenever choosing the value of λ because high value of λ surely increase the robustness but tracking speed decreases.

Finally the IMC controller is now given by

$$Q(s) = Q_1(s)F(s) = G_{M-}^{-1}(s)F(s) \tag{3.12}$$

Now the output equation can be rewritten as

$$Y(s) = \frac{G_{M+}(s)F(s)R(s)}{1+Q(s)\big(G(s)-G_M\,(s)\big)} + \frac{\big(1-G_{M+}(s)F(s)\big)D(s)}{1+Q(s)\big(G(s)-G_M\,(s)\big)} \quad 3.13$$

3.4 Fractional Order Two Degree of Freedom IMC Controller

As mentioned above Internal Model Control (IMC) is a control technique based on Q parametrization which was initially proposed by Manfred Morari and co-workers[21]. It provides many advantage over the classical feedback approaches such as dual stability, perfect control and zero steady state error and some tuning parameters. In this technique a plant model is used for control purpose. In one degree of freedom IMC method the controller basically control the difference between output of plant and plant model which nothing but equivalent mismatch and disturbance. But in one degree of freedom IMC method we cannot track set point and disturbance rejection simultaneously. So a two degree of freedom internal model control technique is used here that has two different controller, one for set point tracking purpose and the other one is for disturbance rejection purpose.

However it is felt to improve the system performance even further with the use of fraction order calculus. An attempt was made to exploit the tools of fractional order calculus in control theory and applications [22]. Fractional order internal model control (FO-IMC) uses a fractional order filter in such a way that the overall closed-loop transfer function of the system mirrors the bode ideal closed loop transfer function which means that the system is able to retain the robustness in a desired range of frequency.

Using a separate fractional order controller for set point tracking puts an upper bound on the extent to which system performance can be improved. To improve the performance of the system even more a second fractional order controller can be used in the feedback path similar to the TDF-IMC structure. A fractional order controller shows better disturbance rejection, an improved robustness and excellent capability to handle uncertainty in system parameters. Therefore, it is proposed to add a fractional order controller in the feedback path, while keeping an integer order controller for set point tracking. This ensures computational simplicity as well as an improved disturbance handling capability for the system.

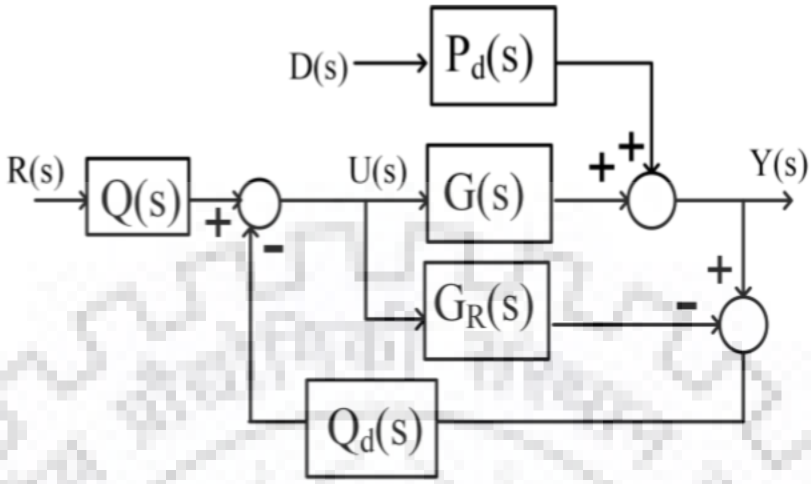

Figure: 3.4 FO-TDF IMC structure

Figure. 3.4 further can be simplified using transformations given in equations (3.14) and (3.15)

$$F(s) = \frac{Q(s)}{Q_d(s)} \tag{3.14}$$

$$C_f(s) = \frac{Q_d(s)}{1-G_R(s)Q_d(s)} \tag{3.15}$$

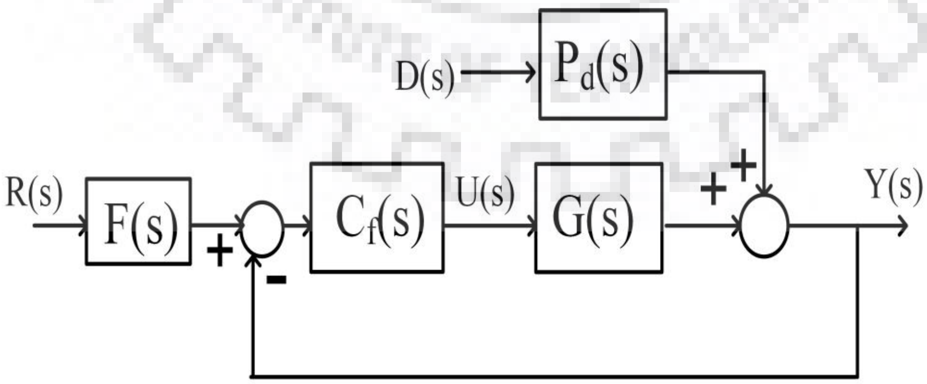

Figure: 3.5 FO-TDF IMC structure

Let us consider a higher order system having the following transfer function

$$G(s) = \frac{\sum_{i=0}^{m} p_i s^i}{\sum_{j=0}^{n} q_j s^j}; n \geq m \qquad 3.16$$

Now model order reduction is used to obtain a reduced order model for the above system in (3.14). Model order reduction (MOR) refers to a set of techniques used for reduction of computational complexity of higher order systems in such a manner that the input-output behaviour of the original system is retained to the maximum possible extent in the reduced order model. Several techniques are enlisted in literature for reduced order modelling such as Balanced truncation, Routh approximation, Pade approximation, Genetic algorithm, Big bang Big crunch optimization, Mihailov's criteria, etc.

Here balanced truncation method is used for model order reduction, the reduced order model for the system in (3.14) can be given by

$$G_R(s) = \frac{m_0 + m_1 s}{s^2 + n_1 s + n_0}; \;\; m_1 < 0 \qquad 3.17$$

Where $m_i, n_j \in \Re \forall i, j$ are the numerator and denominator coefficients of the reduced order model. It is assumed that $m_i < 0$, for stability purpose it can be proven that $n_j > 0 \forall j$.

Equation (3.17) can be re-written as

$$G_R(s) = \frac{m_0(1 + m_2 s)}{s^2 + n_1 s + n_0} \qquad 3.18$$

where $m_2 = \frac{m_1}{m_0}$.

For the application of the proposed internal model control method, the plant model is now divided into minimum ($G_{R-}(s)$) and non-minimum phase parts ($G_{R+}(s)$) such that

$$G_R(s) = G_{R+}(s) G_{R-}(s) \qquad 3.19$$

so

$$G_{R+}(s) = 1 + m_2 s, G_{R-}(s) = \frac{m_0}{s^2+n_1 s+n_0} \quad 3.20$$

Using the internal model control principle, the set point tracking controller can be formulated as

$$Q(s) = G_{R-}^{-1}(s)F_1(s) \quad 3.21$$

Here F(s) is chosen as a low pass filter to wean away the high frequency dynamics and to ensure that Q(s) is proper.

It is given as in equation (3.22)

$$F_1(s) = \frac{1}{(\lambda s+1)^2} \quad 3.22$$

where λ is the filter time coefficient which is an adjustable parameter (tuning parameter).

After simplification of (3.21) we get

$$Q(s) = \frac{s^2+n_1 s+n_0}{m_0(\lambda s+1)^2} \quad 3.23$$

On the other hand, the disturbance rejection filter is computed as

$$Q_d(s) = G_{R-}^{-1}(s)F_2(s) \quad 3.24$$

For an efficient disturbance rejection, we choose a fractional order filter $F_2(s)$, which can be expressed via following fraction order transfer function

$$F_2(s) = \frac{1}{1+\eta s^{\upsilon+1}} \tag{3.25}$$

where $\eta > 1$ & $\upsilon \epsilon$ (0,1).

On substitution of the filter transfer function from (3.25) in (3.24), the disturbance rejection controller is obtained as

$$Q_d(s) = \frac{s^2+n_1 s+n_0}{m_0(1+\eta s^{\upsilon+1})} \tag{3.26}$$

Using equations (3.18) and (3.26), the expressions for controller $C_f(s)$ is obtained as

$$C_f(s) = \frac{s^2+n_1 s+n_0}{m_0 s(\eta s^{\upsilon}-m_2)} \tag{3.27}$$

Further simplification of (3.27) yields the final expression of fractional order controller as

$$C_f(s) = \left(\frac{n_1}{m_0} + \frac{n_0}{m_0}\left(\frac{1}{s}\right) + \frac{1}{m_0} s\right)\left(\frac{1}{\eta s^{\upsilon}-m_2}\right) \tag{3.28}$$

Equation (3.28) indicates that the proposed disturbance rejection controller is a series combination of integral order PID controller and fractional order filter. The fractional order filter shows more accurate and precise control and the overall fractional order control aids in an improved disturbance rejection capability.

CHAPTER-4

MATLAB SIMULATIONS AND RESULTS

Proposed transfer function of a boiler is given as[24]

$$G(s) = \frac{s+1.5}{5s^4+40s^3+56.5s^2+58.5s+5} \tag{4.1}$$

Transfer function given in equation (4.1) can be reduced using modified balanced truncation method, after model order reduction we get

$$G_R(s) = \frac{-0.004s+0.0391}{s^2+1.2467s+0.1304} \tag{4.2}$$

Now rearranging reduced order transfer function as shown before by using equations (3.15) and (3.16)

$$G_R(s) = \frac{0.0391(1-0.1023s)}{s^2+1.2467s+0.1304} \tag{4.3}$$

Low pass filter $F_1(s)$ according to equation (3.20) is given as

$$F_1(s) = \frac{1}{(\lambda s+1)^2}$$

where $\lambda = 0.9$ is taken which gives us the LPF $F_1(s)$ as

$$F_1(s) = \frac{1}{(0.9s+1)^2} \tag{4.4}$$

For disturbance rejection here fraction order filter $F_2(s)$ is chosen which is given below

$$F_2(s) = \frac{1}{1 + \eta s^{\upsilon+1}}$$

where $\eta = 0.2$ and $\upsilon = 0.1$ is taken which gives us

$$F_2(s) = \frac{1}{1+0.2s^{1.1}} \tag{4.5}$$

After substituting the equations (4.3), (4.4) and (4.5) into equation (3.28), we get transfer function of fractional order controller

$$C_f(s) = \left(\frac{n_1}{m_0} + \frac{n_0}{m_0}\left(\frac{1}{s}\right) + \frac{1}{m_0}s\right)\left(\frac{1}{\eta s^{\upsilon} - m_2}\right)$$

$$C_f(s) = \left(\frac{1.2467}{0.0391} + \frac{0.1303}{0.0391}\left(\frac{1}{s}\right) + \frac{1}{0.0391}s\right)\left(\frac{1}{0.2s^{0.1}+0.102}\right) \tag{4.6}$$

Transfer function of fractional order controller in equation (4.6) is basically series combination of PID controller and fractional order filter.

A comparison between step response of original system and reduced order model is given in Figure: 4.1

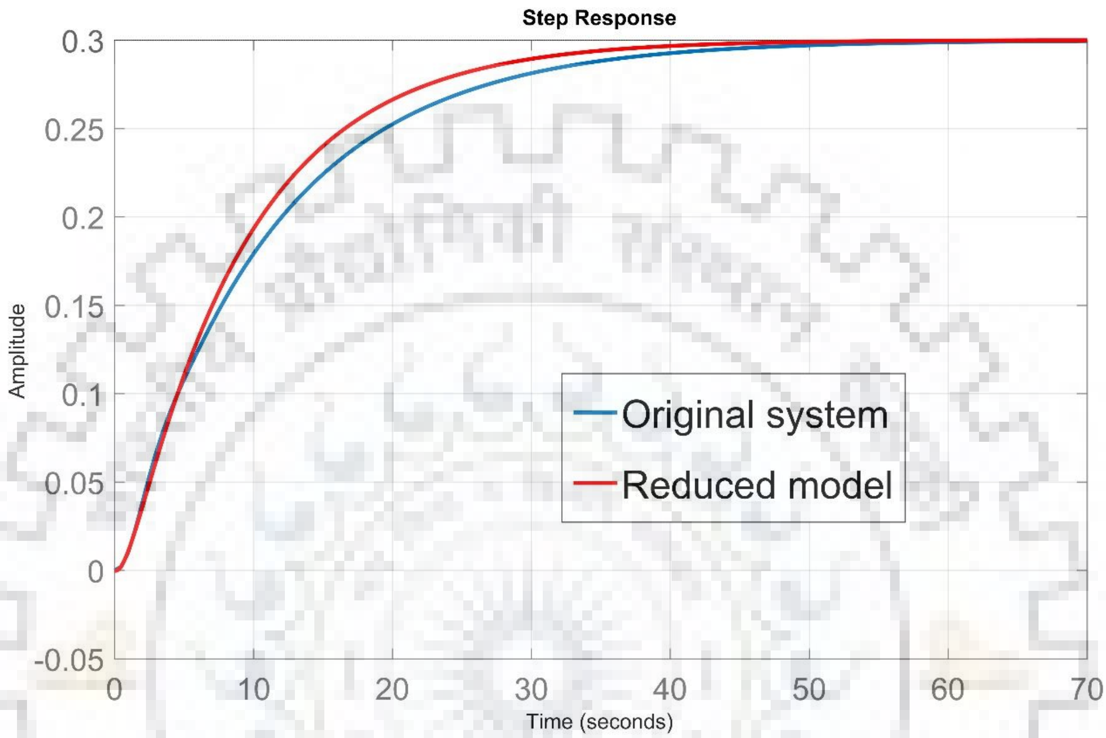

Figure 4.1: step response of original system and reduced order model

A Comparison of step input tracking and input disturbance rejection of proposed technique versus various existing techniques shown in Figure 4.2 and Figure 4.3 shows the Comparison of step input tracking and output disturbance rejection of proposed technique versus various existing techniques whereas in figure: 4.4 simulation result is shown when random error or disturbance is present.

As it can be seen that proposed FO-TDF-IMC technique produces better results than the other existing techniques in both the case when disturbance is present in input (Figure: 4.2) as well as when disturbance is present in output (Figure: 4.3).

In the case of random disturbance or error proposed FO-TDF-IMC technique performs better than other IMC techniques.

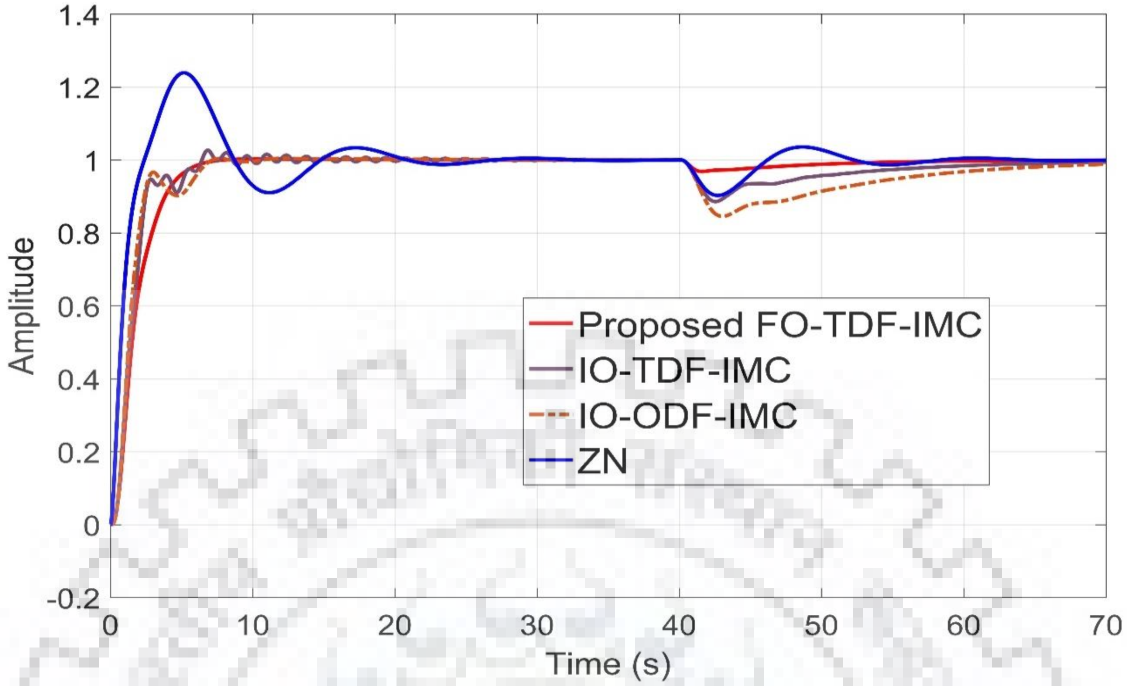

Figure 4.2: Comparison of step input tracking and input disturbance rejection of proposed technique versus various existing techniques

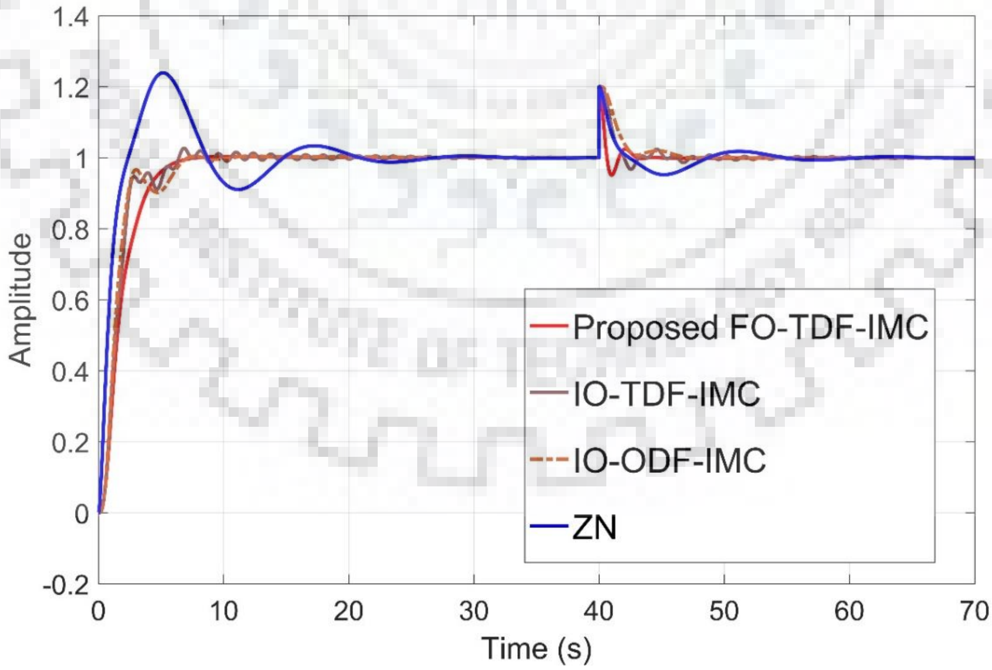

Figure: 4.3: Comparison of step input tracking and output disturbance rejection of proposed technique versus various existing techniques

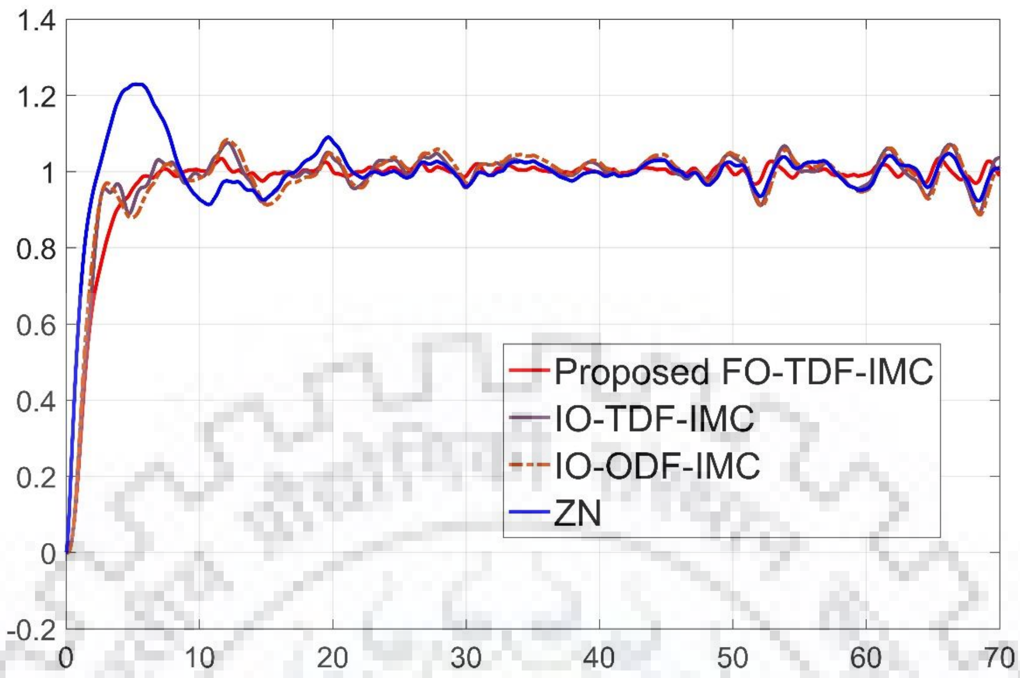

Figure: 4.4: Comparison of step input tracking and random input disturbance rejection of proposed technique versus various existing techniques

A comparison of performance indices of proposed FO-TDF-IMC technique and other IMC techniques are shown in Table: 4.1 and Table: 4.2.

Table 4.1: Comparison of performance indices when disturbance is present in input

CONTROLLER	ISE	IAE	ITAE
Proposed FO-TDF-IMC	0.02727	0.6237	14.49
IO-TDF-IMC	1.142	2.819	55.91
IO-ODF-IMC	1.206	3.552	96.97
ZN	0.7669	2.839	38.84

Table 4.2: Comparison of performance indices when disturbance is present in output

CONTROLLER	ISE	IAE	ITAE
Proposed FO-TDF-IMC	0.03434	0.4813	6.927
IO-TDF-IMC	1.115	2.073	17.07
IO-ODF-IMC	1.085	2.045	17.68
ZN	0.7676	2.752	34.37

CHAPTER-5

CONCLUSIONS AND FUTURE SCOPE

Model order diminution and controller design are integral concepts in control of real systems. This thesis has twin-fold objectives: formulation of modified balanced truncation technique to ameliorate the problem of steady state error and articulation of fractional order two degree of freedom internal model control principle for controller design of boiler system. Fractional order control offers several advantages over integral order control schemes such as greater degree of freedom and an enhancement in system response over the integral order control techniques. Keeping this in mind, the IMC scheme is extended to fractional order case, where the set point tracking controller and disturbance rejection controller are of integer order and fractional order respectively. An example of a boiler system is taken to demonstrate the effectiveness of the proposed scheme. An extensive comparative analysis is undertaken with respect to integer order single degree and two degree of freedom techniques in literature. It can be seen that the proposed scheme exhibits good set point tracking and excellent capability of disturbance rejection over the existing schemes in literature. The values of the performance indices, namely integral square error, integral absolute error and integral time absolute error are the least for the proposed scheme, thus authenticating the efficacy of the proposed technique. Further, even when a disturbance is introduced into the system at the input and the output, the FO-TDF-IMC technique rejects it effectively and swiftly, thus establishing the robustness of proposed approach.

A cursory glance at the existing fractional order literature indicates that the fractional order control theory is wide open for upcoming research. The hardware implementation of fractional order controllers is a principal stumbling block in its adoption in industrial applications. Sometimes, the control energy required for implementation of fractional order controller is high, which may limit its practicality. Therefore, the future work must revolve around these issues and making it more suitable for seamless integration into industries.

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