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A new robust LMI-based model predictive control for continuous-time uncertain nonlinear systems

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ABSTRACT

This paper presents a new robust predictive controller for a special class of continuous-time non-linear systems with uncertainty. These systems have bounded disturbances with unknown upper bound as well as constraints on input states. The controller is designed in the form of an optimization problem of the 'worst-case' objective function over an infinite moving horizon. Through this objective function, constraints and uncertainties can be applied explicitly on the controller design, which guarantees the system stability. Next, LMI tool is used to improve the calculation time and complexity. To do this, in order to find the optimum gain for state-feedback, the optimization problem is solved using LMI method in each time step. Finally, to show the efficiency and effectiveness of the proposed algorithm, a surge phenomenon avoidance problem in centrifugal compressors is solved.

1. Introduction

In recent years, attention to robust approaches to controller design has increased strictly [1–6]. Meanwhile, model predictive controller is widely used to control industrial systems [4–8] due to its unique features. Given the fact that most operational systems are non-linear and bounded systems, the predictive controllers are used on the basis of linear or non-linear models with uncertainty [9–14]. One reason for this is that non-linear predictive control algorithms lead to non-convex, non-linear optimization problems, the solution requires reiterative methods along with extended calculation times [8]. In addition, the convergence region of these kinds of algorithms is qualitative which increases online calculation time. On the other hand, using linear model and square cost function lead to a convex square optimization problem that can be solved easily for predictive control algorithms. However, in many systems, the non-linear effects cannot be ignored. In these conditions, the system can be approximated by a linear model and considered on the scope approximation error [12–14]. Predictive control has a strong advantage: it can consider constraints explicitly in the problem, but it cannot calculate the model uncertainty explicitly in the formulation. Using robust predictive control methods, uncertainty in the process model can be combined explicitly with the problem [15–18].

Modelling the system is a major prerequisite in predictive control design. Also, the model accuracy plays an important role in controller good performance.

Practically, systems have uncertainty in models, which should be considered in designing robust controller in order to guarantee the stability of closed-loop system throughout the uncertainty scope. Various algorithms have been presented for robust predictive controller design. These algorithms should have three important characteristics. First, the time required for calculation should be functional and appropriate. Second, it should provide a vast stability region for the system. Third, the controller performance given the system uncertainties should be in an appropriate condition. There are different methods that cope with these conditions.

In first method, the non-linear system is presented along with a linear model and a non-linear term which is Lipchitz. Then, in robust stability, sentences including this non-linear term are substituted by its upper bound and turn into a linear matrix inequality. In this method, the robust predictive controller problem turns into a state physic design, obtained by solving a linear matrix inequality (LMI). Therefore, in each moment an optimization problem is solved in the format of LMI which compared to an online, non-linear, convex optimization problem, can have a smaller calculation time and complexity [12–14,19].

In another algorithm for robust predictive controller, an offline predictive control method has been used to reduce the calculation time and complexity. In this method, state-feedback has been calculated for pre-specified regions of the state space in an offline manner and the results are stored in a table. Then, for online

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implementation, the calculation time is only assigned to search for corresponding physic with the existing state [20]. In this method, if the working area of a non-linear system is big, stating it with only one single linearized model around the desired working point is not an exact specification for the non-linear system. Therefore, in [21,22] a tabulated predictive controller or a multi-point predictive controller has been used for limited, non-linear systems with extensive working range. In this method, the working area is divided into smaller parts according to the algorithm which include a set of approximate stability regions around different equilibrium points on the surface of the equilibrium system. Then, for each region, a local controller is calculated. These regions are chosen in a way that have overlap and the system stability is guaranteed by this algorithm. However, since this algorithm states the non-linear model in each region with a time-variable linear model along with multi-dimensional structural uncertainty, it needs a huge calculation time.

In order to calculate the predictive controller problems in an online manner, one of the appropriate tools is LMIs that have small calculation time and complexity. In this paper, for a special class of non-linear systems, some LMI-based robust predictive controllers are presented. As it was mentioned, in first controlling method, the non-linear system is presented along with a linear model and a non-linear term which is Lipchitz. In the design of an LMI-based robust MPC, the Lipchitz condition is an essential requirement in the design process [23–25] and somehow leads to the linearization of the controller design while in the paper, it has been tried to present a method that removes the Lipchitz condition and includes a greater class of non-linear system in the model. The most important innovation of this paper is to provide an LMI-based predictive control method for a class of continuous non-linear systems in the presence of disturbance and uncertainty, while ensuring simplicity and less time for computation, confirms the optimal control signal and in addition to compliance with constraints of variables and states, it is not necessary to have the Lipchitz condition on the non-linear part.

This paper is composed of the following sections: Section two presents the new robust MPC. Section three designs a robust MPC controller to stabilize the compressor system. Section four, by presenting a simulation, proves the efficiency of the controller. Finally, section five concludes the paper.

2. Robust LMI-based MPC

Consider the following continuous-time non-linear system

$$\dot{x}(t) = Ax(t) + Bu(t) + w(t, x) \qquad (1)$$

where $x(t) \in R^{n_x}$ shows the system states, $u(t) \in R^{n_u}$ the control input, $w(t, x) : R^{n_x} \rightarrow R^{n_w}$ continuous non-linear uncertainty function. The $w(t, x)$ is considered in the following set

$$W = \{w(t, x) \in R^{n_w} |\, ||w|| \leq w_{max}\} \qquad (2)$$

The system has the following limitations $x(t) \in \bar{X}, u(t) \in \bar{U}, \forall t > 0$. Where $\bar{X} \subset R^{n_x}$ is bounded and $\bar{U} \subset R^{n_u}$ is compact.

Lemma 1: ([26]). *Let $S : R^{n_x} \rightarrow [0, \infty)$ be a continuously differentiable function and $\alpha_1(||x||) < S(x) < \alpha_2(||x||)$, where α_1, α_2 are K_∞ class functions. Suppose $u : R \rightarrow R^{n_u}$ is chosen, and there exit $\lambda > 0$ and $\mu > 0$ such that*

$$\dot{S}(x) + \lambda S(x) - \mu w^T(t, x)w(t, x) \leq 0 \qquad (3)$$

with $x \in X, w \in W$. Then, the system trajectory starting from $x(t_0) \in \Omega \subseteq X$, will remain in the set Ω, where

$$\Omega = \left\{ x \in R^{n_x} | S(x) \leq \frac{\mu w_{max}^2}{\lambda} \right\} \qquad (4)$$

Lemma 2: ([12]). *Let M, N be real constant matrices and P be a positive matrix of compatible dimensions. Then*

$$M^T PN + N^T PM \leq \varepsilon M^T PM + \varepsilon^{-1} N^T PN \qquad (5)$$

Holds for any $\varepsilon > 0$.

Lemma 3: *(Schur complements [27]). The LMI*

$$\begin{bmatrix} Q(x) & S(x) \\ S^T(x) & R(x) \end{bmatrix} > 0 \qquad (6)$$

In which, $Q(x) = Q^T(x), R(x) = R^T(x)$ and $S(x)$ are affine functions of x, and are equivalent to

$$\begin{array}{ll} R(x) > 0 & Q(x) - S(x)R^{-1}(x)S^T(x) > 0 \\ Q(x) > 0 & R(x) - S(x)Q^{-1}(x)S^T(x) > 0 \end{array} \qquad (7)$$

The state-feedback control law for system (1) in kT time is chosen as

$$u(kT + \tau, kT) = Kx(kT + \tau, kT)(\tau \geq 0) \qquad (8)$$

This control signal is true for the following constraint

$$||u(kT + \tau, kT)||_2 \leq u_{max} \qquad (9)$$

Finally, the chosen infinite horizon quadratic cost function is specified as

$$J = \int_0^\infty (x(kT + \tau, kT)^T Qx(kT + \tau, kT)$$
$$+ u(kT + \tau, kT)^T Ru(kT + \tau, kT)$$
$$- \mu w(kT + \tau, kT)^T w(kT + \tau, kT))d\tau, \mu > 0 \qquad (10)$$

where Q and R are positive definite weight matrices. In the objective function (4), the uncertain but negative

effect with weight μ is introduced, where μ is positive constant [28].

Theorem 1: *Consider system* (1), $x(kT)$ *is the measure value in sampling time of* kT. *There is a state-feedback control law* (8) *that is true in stability condition and in input constraint* (9) *in every moment. If the optimization problem with LMI constraints can be feasible.*

$$
\begin{array}{c}
\min \gamma \\
\gamma, X \\
\begin{bmatrix} I & x(kT)^T \\ x(kT) & X \end{bmatrix} \geq 0 \\
(AX + BY)^T + AX + BY + (\alpha + \lambda)X \leq 0 \\
-X + \gamma \varepsilon^{-1} I \leq 0 \\
\begin{bmatrix} -u_{max}^2 I & Y^T \\ Y & -X \end{bmatrix} \leq 0
\end{array}
\tag{11}
$$

where $X > 0$ *and* Y *are matrixes obtained from the above-mentioned optimization problem. As such, state-feedback matrix in every moment is obtained as* $K = YX^{-1}$.

Proof: Considering a quadratic Lyapunov function, we have

$$
V(x(t)) = x(t)^T P x(t), P > 0
\tag{12}
$$

In sampling time for kT assume that $V(x(t))$ is true in the following condition

$$
x(t)^T P x(t) < \gamma
\tag{13}
$$

$$
\begin{aligned}
\frac{dV(x(kT + \tau, kT))}{dt} \\
\leq -(x(kT + \tau, kT)^T Q x(kT + \tau, kT) \\
+ u(kT + \tau, kT)^T R u(kT + \tau, kT) \\
- \mu w(kT + \tau, kT)^T w(kT + \tau, kT))
\end{aligned}
\tag{14}
$$

In order to obtain the robust efficiency, we should have $x(\infty, kT) = 0$ which results in $V(x(\infty, kT)) = 0$. By integrating both sides of the Equation (14), we have

$$
J \leq V(x(kT))
\tag{15}
$$

where γ is a positive scalar (the upper bound of the objective (10)). ∎

In order to obtain an MPC robust algorithm, the Lyapunov function should be minimized considering the upper bound [29]. So

$$
\begin{array}{c}
\min \gamma \\
\gamma, P \\
\text{subject to} \\
x(t)^T P x(t) \leq \gamma
\end{array}
\tag{16}
$$

By defining $X = \gamma P^{-1}$ and using Schur Complements, we have

$$
\begin{array}{c}
\min \gamma \\
\gamma, X \\
\begin{bmatrix} I & x(kT)^T \\ x(kT) & X \end{bmatrix} \geq 0
\end{array}
\tag{17}
$$

In the following, according to Lemma 1, for system (1) we have

$$
\dot{S}(x(t)) + \lambda S(x(t)) - \mu w(t, x)^T w(t, x) \leq 0
\tag{18}
$$

Then, according to (12) we have

$$
\begin{aligned}
\dot{x}(t)^T P x(t) + x(t)^T P \dot{x}(t) + \lambda x(t)^T P x(t) \\
- \mu w(t, x)^T w(t, x) \leq 0
\end{aligned}
\tag{19}
$$

$$
\begin{aligned}
x(t)^T((A + BK)^T P + P(A + BK) + \lambda P)x(t) \\
+ w(v)^T P x(t) + x(t)^T P w(t, x) \\
- \mu w(t, x)^T w(t, x) \leq 0
\end{aligned}
\tag{20}
$$

According to Lemma 2, we have

$$
\begin{aligned}
w(t, x)^T P x(t) + x(t)^T P w(t, x) \\
\leq \alpha x(t)^T P x(t) + \alpha^{-1} w(t, x)^T P w(t, x)
\end{aligned}
\tag{21}
$$

By substituting (21) in (20), it is obtained that

$$
\begin{aligned}
x(t)^T((A + BK)^T P + P(A + BK) + (\alpha + \lambda)P)x(t) \\
+ \alpha^{-1} w(t, x)^T P w(t, x) - \mu w(t, x)^T w(t, x) \leq 0
\end{aligned}
\tag{22}
$$

Consider

$$
P \leq \lambda_{max} I \leq \varepsilon I
\tag{23}
$$

where λ_{max} is the maximum eigenvalue of P and εI is the corresponding upper bound [12], then

$$
\begin{aligned}
x(t)^T((A + BK)^T P + P(A + BK) + (\alpha + \lambda)P)x(t) \\
+ (\alpha^{-1}\varepsilon - \mu)w(t, x)^T w(t, x) \leq 0
\end{aligned}
\tag{24}
$$

By choosing

$$
\mu = \frac{\varepsilon}{\alpha}
\tag{25}
$$

Equation (24) is reduced to

$$
\begin{aligned}
x(t)^T((A + BK)^T P + P(A + BK) \\
+ (\alpha + \lambda)P)x(t) \leq 0
\end{aligned}
\tag{26}
$$

Substituting $P = \gamma X^{-1}$, $X > 0$ and $K = YX^{-1}$,

$$
\begin{aligned}
((A + BYX^{-1})^T X^{-1} + X^{-1}(A + BYX^{-1}) \\
+ (\alpha + \lambda)X^{-1})\gamma \leq 0
\end{aligned}
\tag{27}
$$

Pre and post multiplying by X,

$$(AX + BY)^T + AX + BY + (\alpha + \lambda)X \leq 0 \quad (28)$$

Given (23), we have

$$P \leq \varepsilon I \quad (29)$$

Substituting $P = \gamma X^{-1}$ and pre multiplying by X, we have

$$-X + \gamma \varepsilon^{-1} I \leq 0 \quad (30)$$

Finally, the input constraint is investigated [12]. According to (9), we have

$$||u(kT + \tau, kT)||_2 \leq u_{\max} \quad (31)$$

Given (13) and (15), it is known that the states $x(kT + \tau, kT)$ determine and ellipsoid invariant set

$$S = \{x | x^T X x \leq 1\} \quad (32)$$

Therefore

$$\begin{aligned} &||u(kT + \tau, kT)||_2^2 \\ &= ||Kx(kT + \tau, kT)||_2^2 \\ &= \left| \left| YX^{\frac{-1}{2}} \left(X^{\frac{-1}{2}} x(kT + \tau, kT) \right) \right| \right|_2^2 \leq \left| \left| YX^{\frac{-1}{2}} \right| \right|_2^2 \end{aligned} \quad (33)$$

From (31) and (32), we can rewrite the input two-norm constraint in (31) as

$$Y^T X^{-1} Y - u_{\max}^2 I \leq 0 \quad (34)$$

By applying Schur complement. (34) is equivalent to

$$\begin{bmatrix} -u_{\max}^2 I & Y^T \\ Y & -X \end{bmatrix} \leq 0 \quad (35)$$

So, the proof is completed.

3. Robust model predictive control on surge

Surge is a condition that occurs on compressors when the amount of gas is insufficient to compress and the turbine blades lose their forward thrust, causing a reverse movement in the shaft. It can cause extensive structural damage in the machine because of the violent vibration and high thermal loads that generally accompany the instability. For this reason, compressor system control as one of the most practical systems is considered in this section.

3.1. Compressor model

Pure surge model of Moore and Greitzer [30] for the centrifugal compressor are as the followings

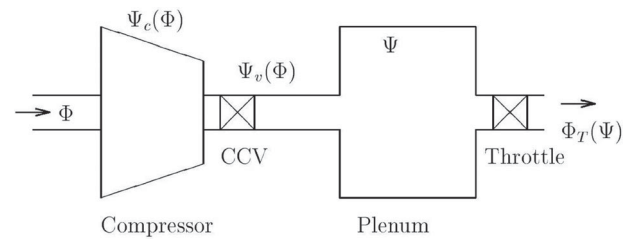$$\dot{\psi} = \frac{1}{4B^2 l_c} (\phi - \phi_T(\psi) - d_\phi(t))$$

Figure 1. The compressor system with CCV [32].

$$\dot{\phi} = \frac{1}{l_c} (\psi_c(\phi) - \psi + d_\psi(t)) \quad (36)$$

where ψ is the coefficient of increase in compressor pressure, ϕ is the coefficient of compressor's mass flow, $d_\phi(t)$ and $d_\psi(t)$ are the disturbances of flow and pressure. Also, $\phi_T(\psi)$ is the characteristic of throttle valve and $\psi_c(\phi)$ is the characteristic of the compressor. B is the Greitzer's parameter and l_c shows the length of channels (ducts). Moor and Greitzer's [30] compressor characteristic is defined as

$$\begin{aligned} \psi_c(\phi) = \psi_{c0} + H \left(1 + \frac{3}{2} \left(\frac{\phi}{W} - 1 \right) \right. \\ \left. - \frac{1}{2} \left(\frac{\phi}{W} - 1 \right)^3 \right) \end{aligned} \quad (37)$$

where ψ_{c0} is the value of characteristic curve in $0db$, H is half of the height of the characteristic curve, and W is the half of the width of the characteristic curve. The equation for throttle valve characteristic is also derived from [31] as follows

$$\phi_T(\psi) = \gamma_T \sqrt{\psi} \quad (38)$$

Figure 1 is the diagram of compression system with Close Couple Valve (CCV).

The system model equations, considering a CCV, are

$$\dot{\psi} = \frac{1}{4B^2 l_c} (\phi - \phi_T(\psi) - d_\phi(t))$$

$$\dot{\phi} = \frac{1}{l_c} (\psi_c(\phi) - \psi - \psi_V(\phi) + d_\psi(t)) \quad (39)$$

Considering $\psi_V(\phi)$ as the input for system control and $x_1 = \psi, x_2 = \phi$, the equations of compressor state space are

$$\dot{x}_1 = \frac{1}{4B^2 l_c} (x_2 - \phi_T(x_1) - d_\phi(t))$$

$$\dot{x}_2 = \frac{1}{l_c} (\psi_c(x_2) - x_1 - u + d_\psi(t)) \quad (40)$$

3.2. Controller design

In designing a surge controller in the compressor system (40), it is assumed that the values of throttle valve, as well as the compressor characteristic are unknown.

So, rewriting the compressor equation in the form of Equation (1) yields:

$$A = \begin{bmatrix} 0 & \dfrac{1}{4B^2 l_c} \\ -\dfrac{1}{l_c} & 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ -\dfrac{1}{l_c} \end{bmatrix} \quad (41)$$

$$w(t, x) = \begin{bmatrix} \dfrac{1}{4B^2 l_c}(\phi_T(x_1) + d_\phi(t)) \\ \dfrac{1}{l_c}(\psi_c(x_2) + d_\psi(t)) \end{bmatrix} \quad (42)$$

According to the compressor model, n_x, n_u and n_w are 2, 1 and 2, respectively. Since the controlling signal has a CCV output, so we have

$$u(t) > 0 \quad (43)$$

The next constraint and limitation is that the flow has some maximum and minimum values. This constraint should also be considered.

$$-\phi_m \le \phi(t) \le \phi_{\text{Choke}} \quad (44)$$

The LMI parameters are selected

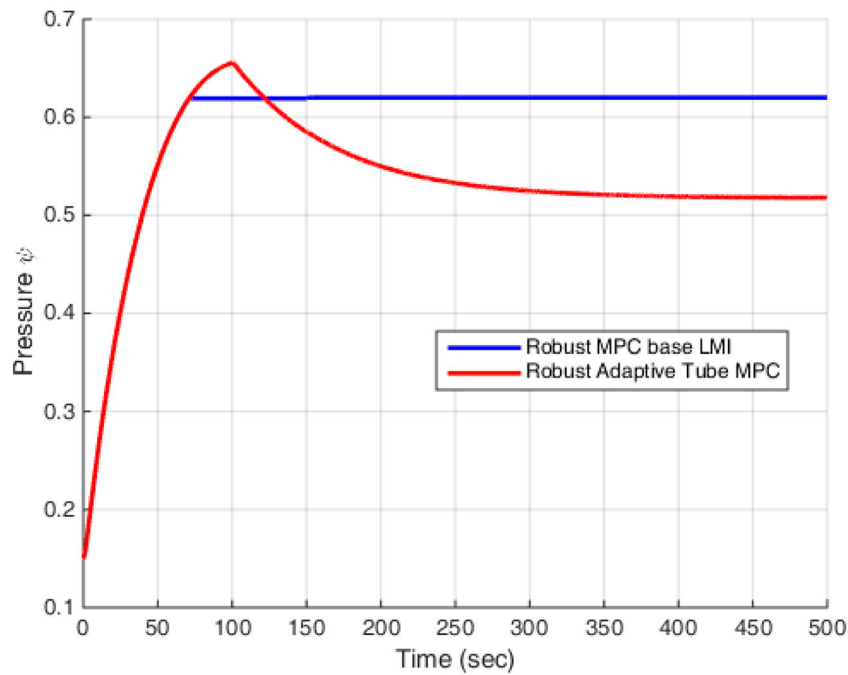$$\alpha = 10^{-3}, \ \lambda = 10^{-3}, \ \mu = 10, \ \varepsilon = 10^{-2} \quad (45)$$
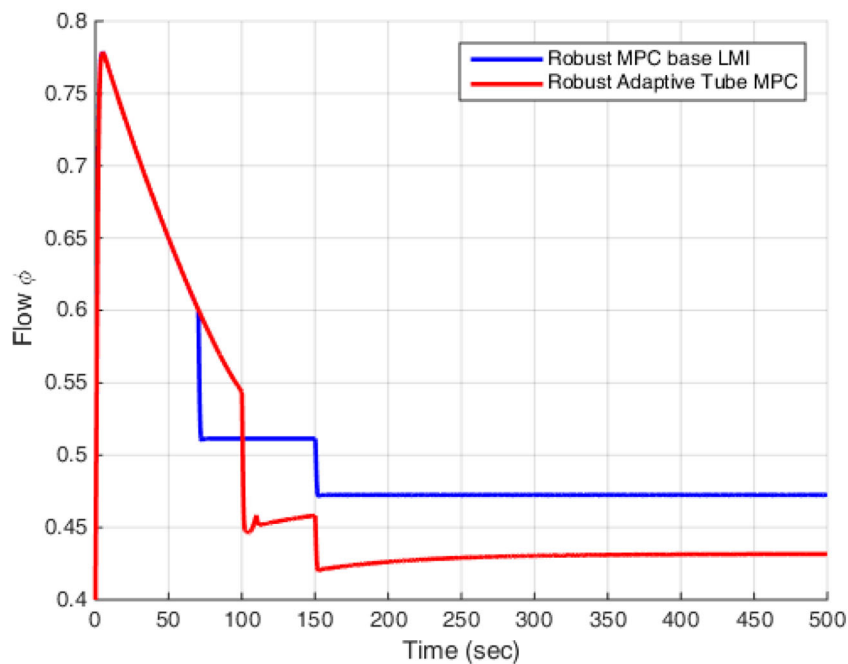

Figure 2. Pressure of compressor.

Figure 3. Flow of compressor.

4. Simulation

This section includes a simulation to prove the robustness and effectiveness of the presented controller. Several studies have recently been conducted on optimal and robust control for surge instability in the compressor system [33–38]. In this paper, reference [33] is used to perform a comparison as well as to examine the capability of the proposed method. To do this, the system is simulated in three different modes. In all three modes, the scenario is that until the time 150 s the value of throttle valve is $\gamma_T = 0.65$, which is the compressor working point on the right side of the surge line. After 150 s, the value of throttle valve is reduced to $\gamma_T = 0.6$ which causes the compressor working point to go to the left side of the surge line and the system suffers from limit cycling. Values of compressor parameters used in simulation are according to [39].

$$B = 1.8, \ l_c = 3, \ H = 0.18, \ W = 0.25, \ \psi_{c0} = 0.3$$
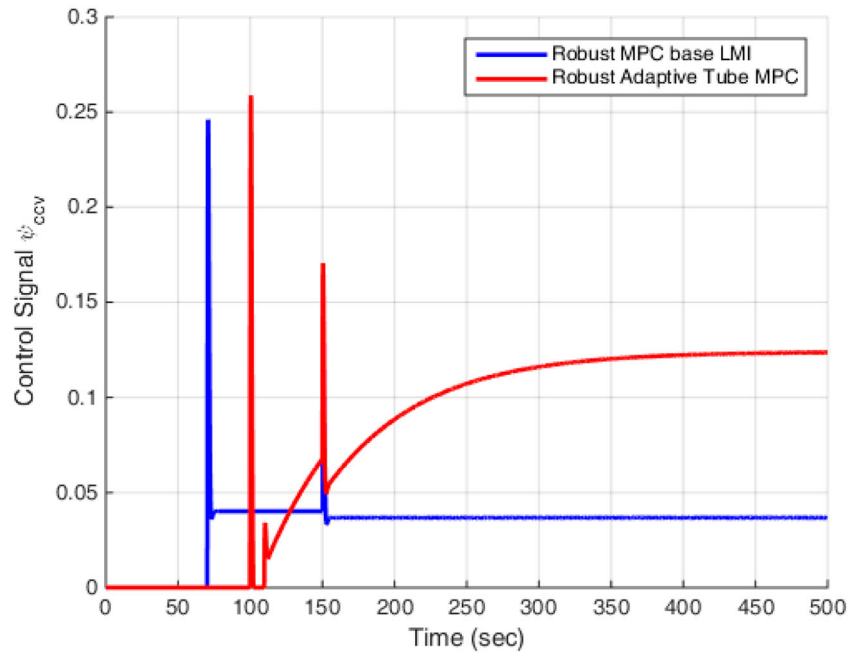$$(46)$$

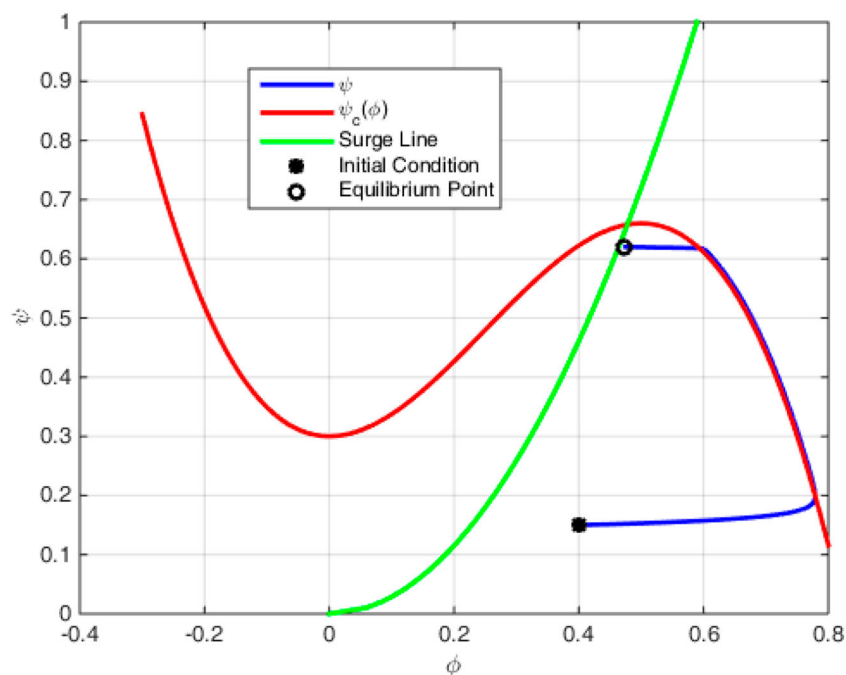**Figure 4.** Control signal.

Figure 5. Compression system trajectories.

The initial points of process were $(x_1(0), x_2(0)) = (0.15, 0.4)$.

In the first mode, it is assumed that there is no external disturbance on the compressor system.

$$d_\phi(t) = 0 \\ d_\psi(t) = 0 \tag{47}$$

The states and control signal for compression system using proposed method are shown in Figures 2–4. Also, it is compared with robust adaptive tube MPC [33] to demonstrate the effectiveness of the proposed controller. As it can be seen, simulation results illustrate the robustness of the proposed controller to steer the centrifugal compressor against change in throttle valve opening percentage. As shown in Figures 2 and 3, using the proposed controller, the compressor operates at high pressure away from the surge condition. Figure 4 presents the controlling signal. Since CCV is considered as the controller operator, its output must be positive. According to Figure 4, the control signal has lower amplitude than the robust adaptive tube MPC which indicates better optimization in the proposed controller.

Figure 5 shows the trajectory of compressor in a performance curve. It shows how the controller prevents the compressor from entering to the surge area.
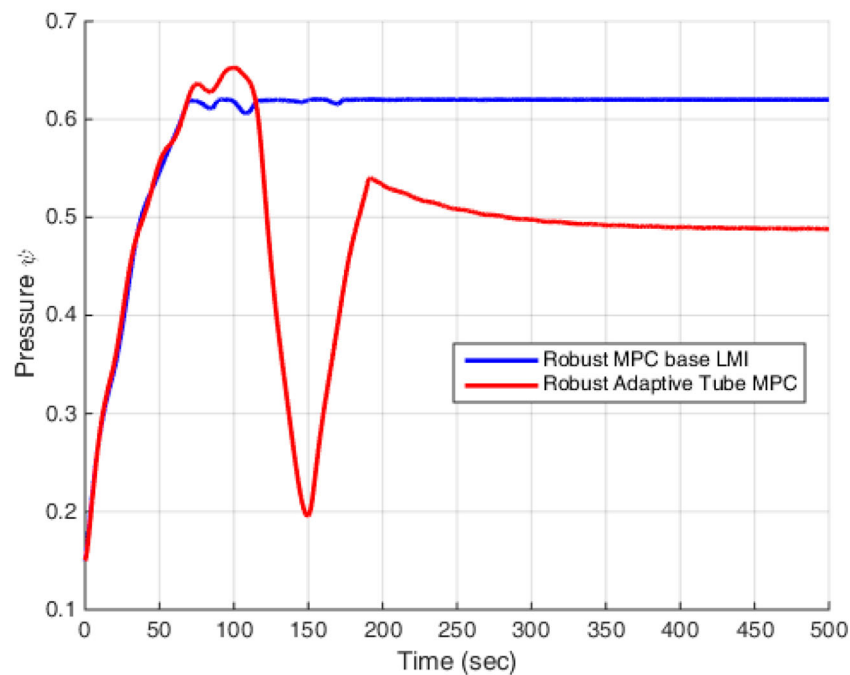

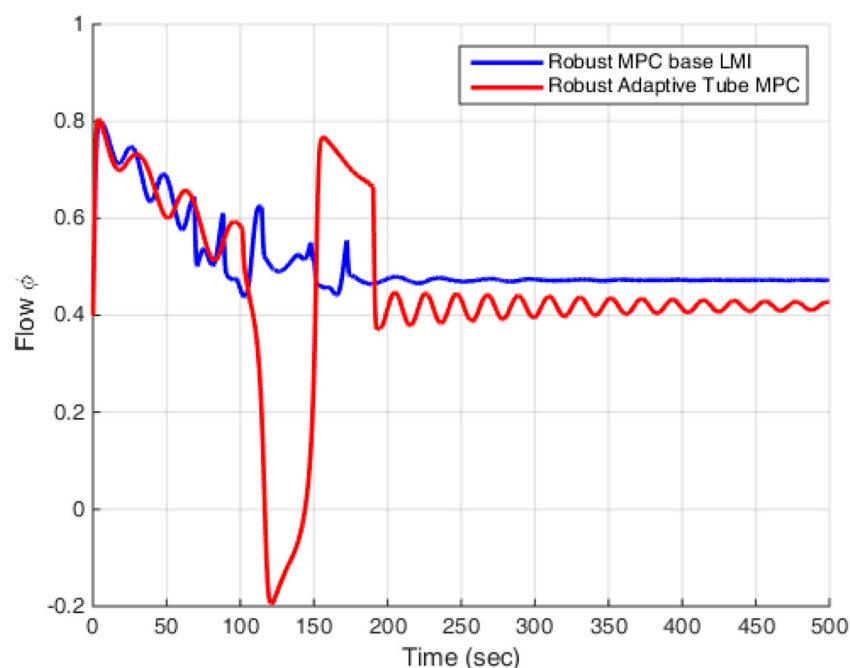**Figure 6.** Pressure of compressor.

Figure 7. Flow of compressor.

In the second scenario, it is assumed that some transitory disturbances are applied to the system. These disturbances are modeled as

$$d_\phi(t) = 0.15e^{-0.015t}\cos(0.2t)$$

$$d_\psi(t) = 0.1e^{-0.005t}\sin(0.3t) \tag{48}$$

Figures 6 and 7 present compressor pressure and flow, respectively. As it can be seen, simulation results illustrate the robustness of the proposed controller to steer the centrifugal compressor against disturbance and change in throttle valve opening percentage. It is clear from Figure 6, the proposed method yields higher pressure rate. It is also seen from Figure 7 that the compressor operates at steady state oscillations less than robust adaptive tube MPC [33]. Limited states oscillations and higher pressure rate away from the surge condition should be considered as advantages of the proposed controller.

The control signal is also presented in Figure 8. According to Figure 8, the control signal from proposed method has lower amplitude and changes in comparison with the robust adaptive tube MPC.
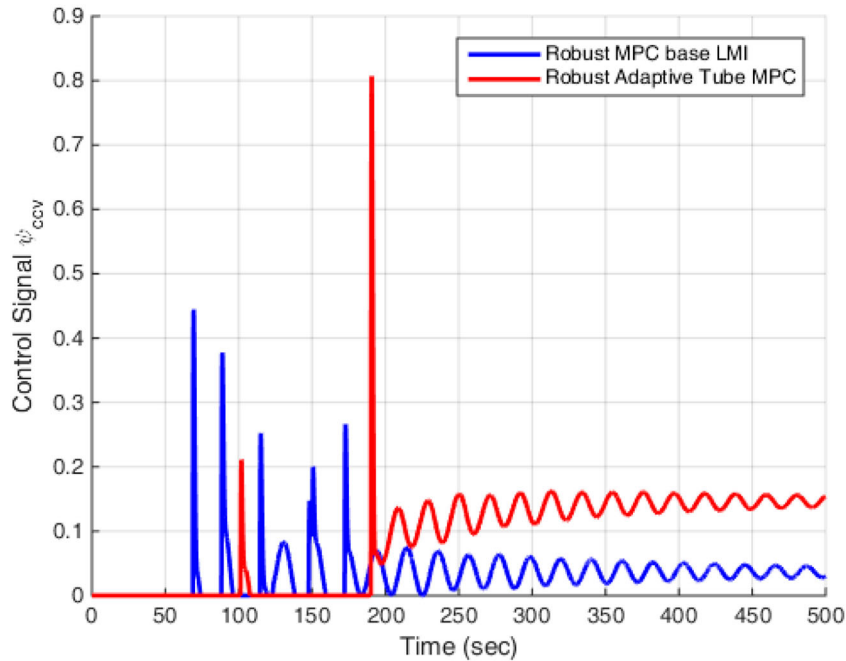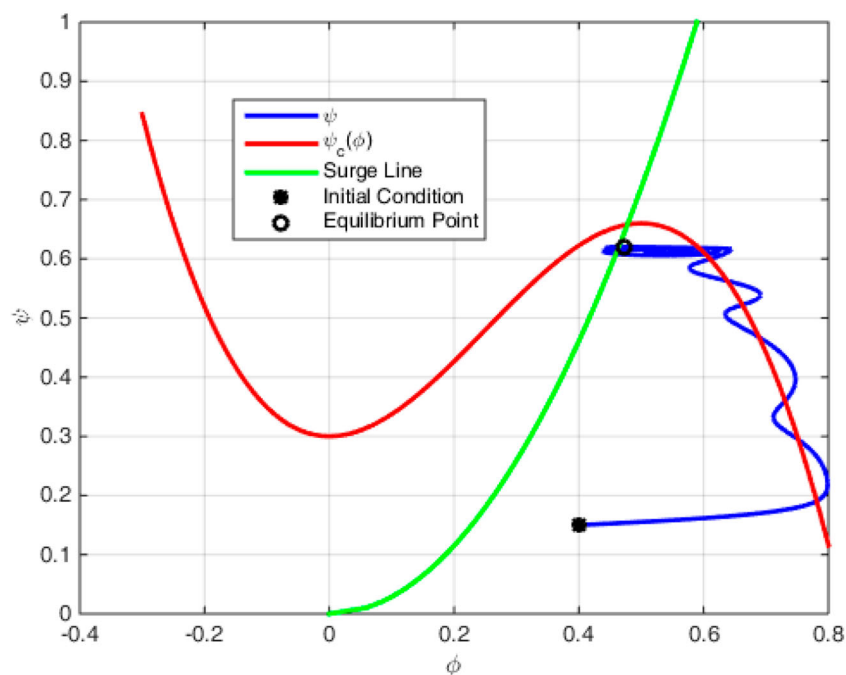

Figure 8. Control signal.

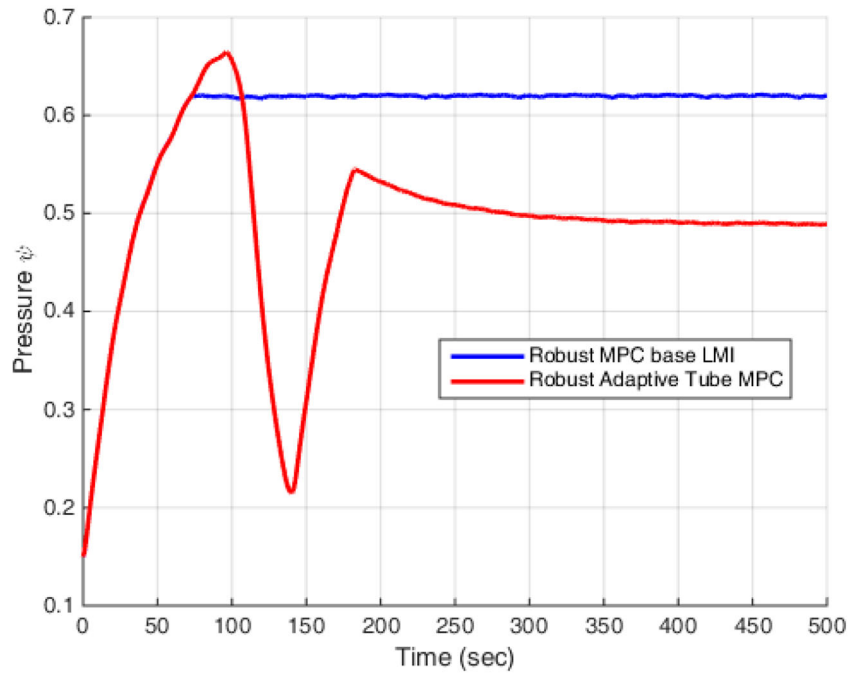**Figure 9.** Compression system trajectories.
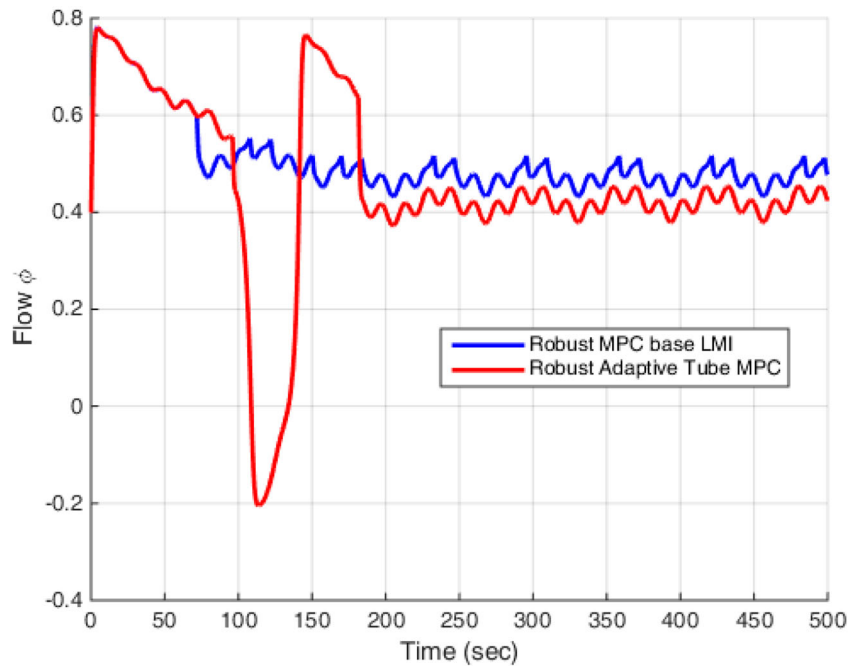
Figure 10. Pressure of compressor.

Figure 11. Flow of compressor.

The trajectory of the compressor is also shown in Figure 9 and it conveys the ability of the controller for disturbance rejection.

In the third scenario, it is assumed that some stable disturbances are applied to the system. These disturbances are modeled as follows

$$d_\phi(t) = 0.02 \sin(0.1t) + 0.02 \cos(0.4t)$$
$$d_\psi(t) = 0.02 \sin(0.1t) + 0.02 \cos(0.4t)$$
(49)

As it can be seen in Figures 10 and 11, simulation results illustrate the robustness of the proposed controller to steer the centrifugal compressor against stable disturbance and change in throttle valve opening percentage.

By using the proposed controller, the compressor operates at higher pressure rate away from the surge condition, however, the flow rate is higher than the robust adaptive tube MPC.

The CCV output is also presented in Figure 12 that satisfies the (43) and (44) constraints.

The performance curve for the compressor is also shown in Figure 13. It can be seen that, in spite of the existence of disturbance, the controller has been able to prevent the surge.

From the simulation results for these scenarios, it can be concluded the proposed controller provides higher pressure rate than robust adaptive tube MPC [33]. Also,
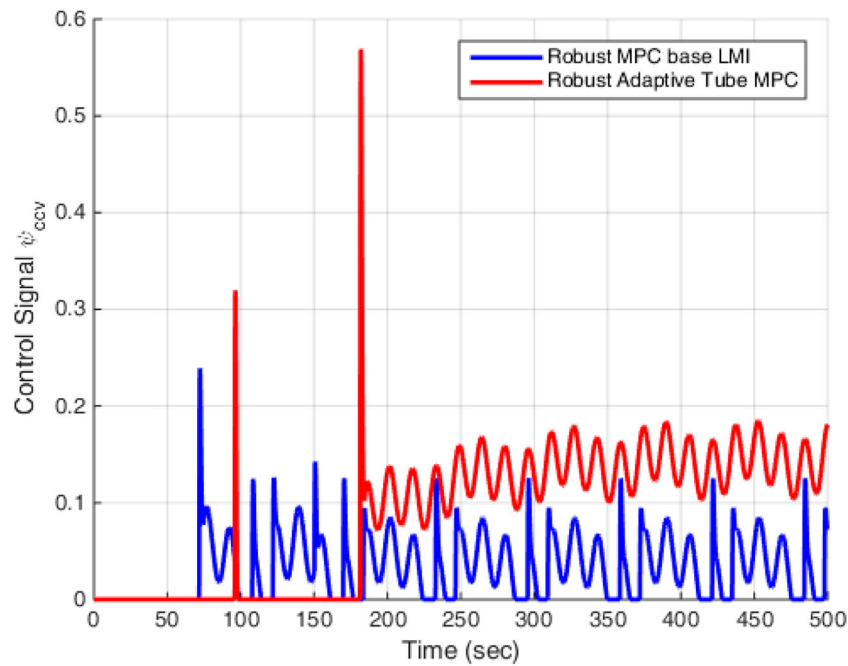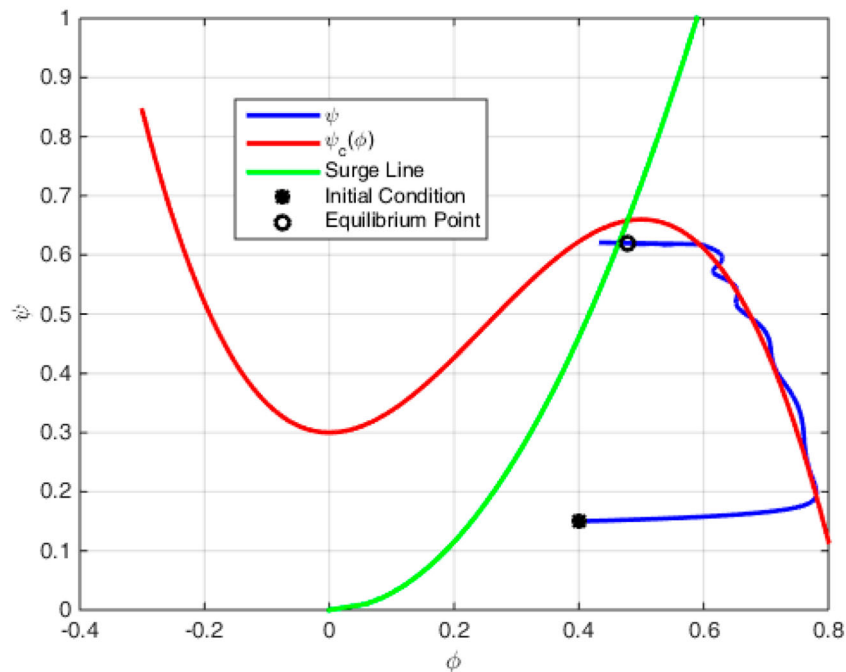
Figure 12. Control signal.

Figure 13. Compression system trajectories.

Table 1. The computational time required for proposed method (RMPC) and RAMPC [33].

RMPC		RAMPC	
Self-time of cost function	5.711 s	Self-time of cost function	11.592 s
Self-time of LMI	3.428 s	Self-time of estimator	43.896 s
Total time	161.789 s	Total time	1189.919 s

the flow has less fluctuating than the reference [33], of course, the control signals obtained from the proposed method have less amplitude and smoother behaviour. In addition, the computational time required for these two methods is given in Table 1.

In the RAMPC method [33], for solving the objective function and obtaining the control signal, an estimation is made on each prediction horizon which makes the problem complexity and time-consuming. But in the proposed LMI-based method, in spite of the infinite prediction horizon, this complexity is reduced and less computation time is achieved because of nonexistence of an estimator.

5. Conclusion

A new robust predictive controller for a special class of continuous-time non-linear systems with uncertainty

and unknown bounded disturbances has been presented in this paper. The controller system is trying to designate a state-feedback control law in order to minimize the upper bound of LMI-based infinite horizon cost function in the framework of linear matrix inequalities. The proposed method offers advantages such as robustness to uncertainty and boundary disturbance, lower computational complexity and thus lower computation time. Finally, the proposed controller is used to solve a surge problem in centrifugal compressors. The results obtained from simulation show the efficiency and resistance of this controller.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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