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Model predictive and fuzzy logic controllers for reactor power control at Reaktor TRIGA PUSPATI

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Abstract. The Reaktor TRIGA PUSPATI (RTP) rely extensively on a core power control system for control reactivity to fulfilment the fundamental safety function for a nuclear reactor. It is technically challenging to operate within tight multiple parameter constraints and keep the core power output stable. At present, the power tracking performance of the system could be considered unsatisfactory which produces a relatively long settling time and high control effort. Hence, a study of a model predictive control (MPC) strategy by integrating the current Power Change Rate Constraint (PCRC) using fuzzy logic which is part of the core power control design is conducted. In this paper, the MPC design based on mathematical models of the reactor core included point kinetics model, thermal-hydraulic model, reactivity model and dynamic rod position model help to enhance core power control. The power tracking performance of the proposed control method and previous Feedback Control Algorithm-Fuzzy PCRC is compared via computer simulation with different power range operations. Overall, the results show the MPC-Fuzzy PCRC strategy provides a greater level of operational safety and optimum operation of the TRIGA reactor.

1. Introduction

The Reaktor TRIGA PUSPATI (RTP), TRIGA MARK II type is the only nuclear research reactor available in Malaysia. The reactor is used to generate neutrons for various research purposes such as medical, material study, and industrial applications. The generation of thermal power or core power is varied based on the movement of the control rods and can be regulated by the core power control system.

In general, the automatic core power control is a part of the Instrumentation and Control (I&C) system which is designed to provide efficient and safe power production [1]. At present, the tracking performance of the power control system at RTP is deemed unsatisfactory due to slow tracking, unsmooth transient response, and a long settling time. As a result, continuous improvement is still required for developing a stable and safe core power control system.

The core power control is physically designed based on common safety parameter constraints such as step reactivity limiting [2], reactor period limiting [3], power change rate-limiting [4], and control rod speed limiting [5]. To date, the effects of the combination of all these safety nuclear reactor parameter constraints in the other type of controller which is capable of naturally handling constraints of the plant have not been extensively studied. Generally, control rod speed or velocity constraint is the most popular safety constraint which is much easier to design for implementation in a practical system. However, in TRIGA research reactor is require tight multiple parameter constraints to regulate reactor power [6].

The RTP uses a conventional core power control known as Feedback Control Algorithm (FCA) [7]; [8] for the power manoeuvring up to 1 MWth based on the conventional Control Rod Velocity Design (cCRVD) and conventional Power Change Rate Constraint (cPCRC). In our recent works, the new PCRC based on the fuzzy logic approach [9] and changes in the maximum rod speed limiter values [10] have been designed to provide better results than the FCA-conventional PCRC method in terms of reducing chattering error. However, the result produced is not fully optimized in terms of settling and rise time. Hence, in this paper, the model-based controller using Model Predictive Control (MPC) and combination Fuzzy PCRC of the strategies in [9] is studied and analyzed to further improve the power tracking performance of the RTP.

Most studies using analytical for designing the MPC core power control as the current practices [11], [12], and other possibilities methods such as System Identification (ID) help to simplify the process and convert the non-linear model based on zero dimension approach in ordinary differential equation (ODE) to state-space form. In this study, to evaluate the effectiveness of the developed MPC and Fuzzy PCRC strategies, a set of performance criteria based on a descriptive approach which is most commonly used in this core power control application area such as settling time, rise time, per cent overshoot, chattering error, offset error, workload, and energy released.

This paper is organized as follows. The modelling of RTP using system identification is presented in Section 2 and the current FCA-Fuzzy PCRC RTP core power control system is briefly described in Section 3. The proposed model predictive control strategy is presented in Section 4. The results and discussion on the implementation of an MPC-Fuzzy PCRC strategy are given in Section 5. Finally, conclusions are given at the end of the paper.

2. Reaktor TRIGA PUSPATI model using System Identification

The TRIGA model is based on point kinetics, and it includes six groups of delayed neutrons, as well as reactivity feedback from control rod movement, fuel temperature, and moderator coolant temperature changes [13].

The linearized model, which is extensively used in RTP modelling can be expressed in state-space form as [14][15]:

$$\left.\begin{array}{c}\dot{x} = Ax + Bu \\ y = Cx + Du \\ A = \begin{bmatrix} -\frac{\beta}{\Lambda} & \lambda_1 & \lambda_2 & \lambda_3 & \lambda_4 & \lambda_5 & \lambda_6 & \frac{\alpha_f}{\Lambda}\psi_0 & \frac{\alpha_m}{\Lambda}\psi_0 & \frac{\psi_0}{\Lambda} \\ \frac{\beta_1}{\Lambda} & -\lambda_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{\beta_2}{\Lambda} & 0 & -\lambda_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{\beta_3}{\Lambda} & 0 & 0 & -\lambda_3 & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{\beta_4}{\Lambda} & 0 & 0 & 0 & -\lambda_4 & 0 & 0 & 0 & 0 & 0 \\ \frac{\beta_5}{\Lambda} & 0 & 0 & 0 & 0 & -\lambda_5 & 0 & 0 & 0 & 0 \\ \frac{\beta_6}{\Lambda} & 0 & 0 & 0 & 0 & 0 & -\lambda_6 & 0 & 0 & 0 \\ \frac{N_0}{\mu_f} & 0 & 0 & 0 & 0 & 0 & 0 & -\frac{\Omega}{\mu_f} & \frac{\Omega}{\mu_f} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{\Omega}{\mu_m} & \frac{(\Omega+2M)}{\mu_m} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \\ B = [0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ G_r]^T \\ C = [1\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0] \\ D = [0] \end{array}\right\} \quad (1)$$

where A is the state matrix, B is the input matrix, C is the output matrix, D is the disturbance matrix, core state $x = \left[\delta N\ \delta\eta_1\ \delta\eta_2\ \delta\eta_3\ \delta\eta_4\ \delta\eta_5\ \delta\eta_6\ \delta T_m\ \delta T_f\ \delta\rho\right]^T$, core input $u = [z_r]$, and core output $y = [N]$.

All the parameters used in this paper are summarized in Table 1.

Table 1. Nomenclature.

ψ	Relative neutron density	Λ	Mean neutron generation time (*s*)
ψ_o	Relative neutron density at initial equilibrium state	β	The total fraction of effective delayed neutron (Δk/k)
G_r	Reactivity worth of the control rod (*Δk/k/m*)	β_i	The *i*-th group of the delayed neutron (*Δk/k*)
N	Actual core power (*W*)	α_f	Reactivity due to change in temperature fuel (*Δk/k/°C*)
N_o	Nominal core power (*W*)	α_m	Reactivity due to change in temperature moderator (*Δk/k/°C*)
μ_m	Heat capacity of coolant (Ws°C^{-1})	η_i	The *i*-th group of normalized precursor concentration (m^{-3})
μ_f	Heat capacity of fuel (Ws°C^{-1})	T_f	The average temperature of the fuel (°*C*)
Ω	Global heat transfer coefficient ($W\,^0C^{-1}$)	T_m	The average temperature of coolant (°*C*)
λ_i	Decay constant of the *i*-th group of delay neutron precursor (s^{-1})	ρ	Total reactivity
M	Heat capacity of a mass flow rate of coolant ($W\,^0C^{-1}$)	z_r	The velocity of the control rod bank (ms^{-1})

In order to have high consistency and accuracy in the RTP model included the control rod position dynamic in [8] can also be derived based on a set of actual input and output data using System ID. The plant model's linearized state-space model based on System ID can be represented as [16]

$$\begin{cases} x(t+t_s) = A_{SID}x(t) + B_{SID}u(t) + K_{SID}e(t) \\ y(t) = C_{SID}x(t) + D_{SID}u(t) + e(t) \end{cases} \quad (2)$$

where A_{SID}, B_{SID}, C_{SID} and D_{SID} are coefficient matrices estimate using System ID, K_{SID} represents the noise matrix of the model and $e(t)$ is the disturbance that exists in the model output.

Based on the measurement of input, which is control rod velocity values, and output, which is core power data, a mathematical model of the RTP is built. A square wave signal is employed as a perturbed input to the system in this study, and 2401 observations of input and output data sets from a non-linear model simulation were collected at 0.5 seconds. The square wave signal is used as a representation of the output from the controller in automatic operation mode and is still capped at a maximum value of 23 steps/cycle and a minimum value of 0 step/cycle.

The measured input and output data are divided into two sets in System ID; the first set is used for estimation, while the second set is used for validation. The first 819 samples of data were used for estimation, while the remaining samples were used for validation. The System ID Toolbox in the Matlab environment is used to determine a suitable model structure for the RTP. In Matlab System ID Toolbox, there are a few model structures that are often utilised in real-world applications. Model-based Predictive Control (MPC) state-space model identification with 12th model order, 0.5 s model sample time (t_s), and state-space core model structure is employed in this study.

Model validation is the last step in the System ID process. The second set of data, sampled from 1583 to 2401, will be utilised for validation reasons, as stated at the beginning of this subsection. Model validation evaluates the discrepancy between actual and simulated data to determine whether the identified model appropriately describes the process under investigation. If the best fit is more than 95%, the created model is acceptable. Eq. (3) can be used to calculate the best fit.

$$Best\ Fit = \left(1 - \frac{|y-\hat{y}|}{|y-\bar{y}|}\right) \text{x } 100 \quad (3)$$

where y is the actual measure output, $\hat{y}$ is simulated or predicted model output and $\bar{y}$ is the mean of y. 100% corresponds to a perfect fit, and 0% indicated that the fit is no better than guessing the output to be a constant where $\hat{y} = \bar{y}$.

The best fit result for the RTP model using System ID is illustrated in Figure 1.

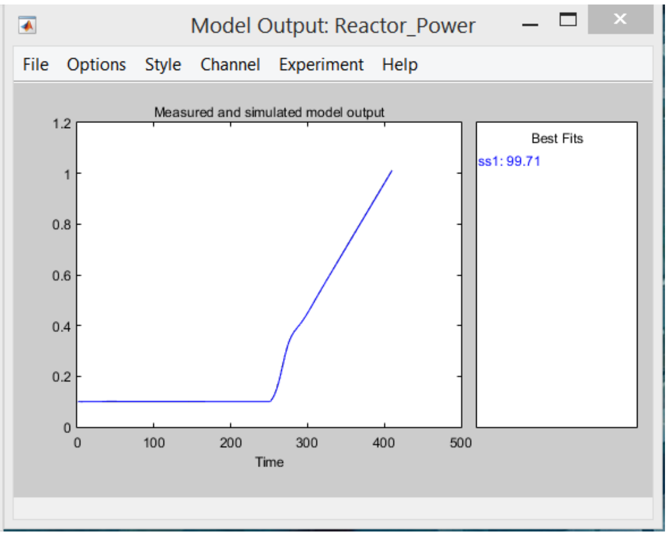


Figure 1. Development of state-space RTP model via System ID in Matlab

3. Feedback Control Algorithm-Fuzzy PCRC core power control system

The RTP feedback core power control system for power manoeuvring is illustrated in Figure 2. The term input refers to a Power Demand (PDM) and the output is the neutron power at the core. The core power is measured by an ex-core neutron detector and Neutron Measurement System (NMS) as signal processing. The NMS provides two signals which are core power (*N*) and the rate of power change (Log Rate). The error deviation in percentage between the PDM and the core power output is used as the inputs for the signal filter and Proportional-Integral (PI) controller. The controller output in form of the control rod velocity is fed to the Control Rod Velocity Design (CRVD) to constraint the reactivity insertion rate in the core. The Fuzzy PCRC is used to penalize control rod velocity signal using a different gain during a specific power level condition before entering to Control Rod Drive Mechanism (CRDM). Using the said configuration, the core power control has a 1.25% full power (FP) chattering error with a large settling time in the case of a sudden change in power demand.

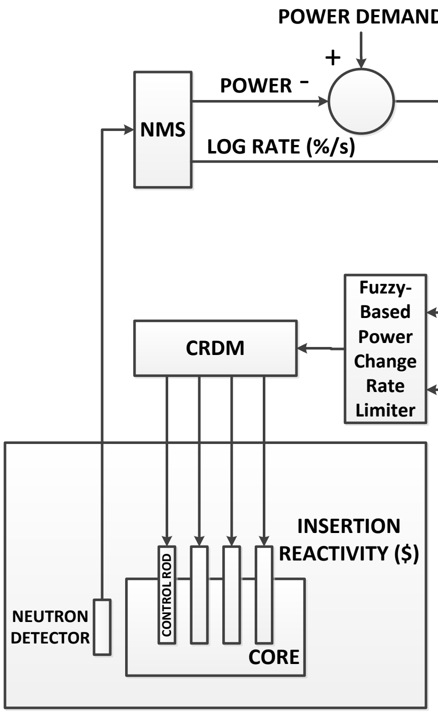


Figure 2. Block diagram of core power control with Fuzzy PCRC

The FCA consist of PCRC, signal filter, PI controller, cCRVD, and CRDM. The PI controller with a signal filter is designed as follows [9]; [15]:

$$\left.\begin{aligned} u_c = &\quad K_P E_{fi} + K_I \int_{t_0}^{t} E_{fi} dt \\ E &= \left[G_1 log\left(\frac{PDM}{N}\right)\right]_{\pm 1} \\ E_{fi}(k) &= 1.47197E(k) + 0.882\left[E_{fi}(k-1) - E(k-1)\right] \end{aligned}\right\} \qquad (4)$$

where u_c is the output signal from the controller, G_1, K_P, K_I, are controller tuning gain for FCA, and E_{fi} is input filter calculation based on the error signal (E).

In fuzzy logic rules, the most commonly used parameterized membership functions (MFs) are triangular, trapezoids, bell curves, Gaussian and sigmoidal functions [17]. However, this study only considered a single type of MFs which is triangular.

In this study, the range of rate of power change need to specify for each condition; very fast (more than u_c), fast (u_c), slow (u_b), very slow (u_{ab}) and no change (u_a), The rules with triangular MFs are shown in Figure 3.

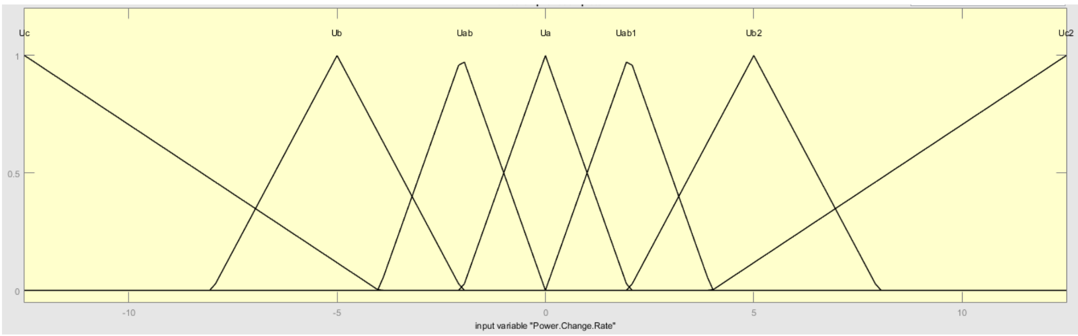


Figure 3. The triangular MFs for the Fuzzy PCRC.

Before applying the fuzzy operator, the rule weight is first assigned. Each rule has weight, w_i can vary from 0 to 1.0, which is applied to each part of the antecedent or single fuzzy degree of membership. Based on Eom et al., by setting w_i is 1.0 for the purpose to provide maximum penalize value in order to stop control rod moving and w_i is 0 for introducing not constraint effect on the control rod velocity value calculated by the controller. However, there is no rule of thumb to decide the value of w_i and the number of fuzzy rules needed for each power increment. For the case of RTP, the chattering error at steady-state maybe can be reduced by the fine movement of control rod velocity when near to power demand by introducing small weight without zero value. Thus, in this study, the w_i value is changed to smaller than 1.0 which can decrease the sensitivity on the system and effect of one rule relative to the others. At this stage, the PCRC is limited to ±12.5% FP/s.

The proposed value of w_i has been assigned to each rule based on a set of inputs consisting of the rate of power change with their corresponding output values in [9] for the triangular MFs Fuzzy PCRC. The rules can be expressed as

$$\left.\begin{array}{r} Rule\ 1.\ If\ (Power.Change.Rate\ is\ u_c)\ then\ (output\ is\ V_s^{c})\ (w_c = 1.0) \\ Rule\ 2.\ If\ (Power.Change.Rate\ is\ u_b)\ then\ (output\ is\ V_s^{b})\ (w_b = 0.15) \\ Rule\ 3.\ If\ (Power.Change.Rate\ is\ u_{ab})\ then\ (output\ is\ V_s^{ab})\ (w_{ab} = 0.01) \\ Rule\ 4.\ If\ (Power.Change.Rate\ is\ u_a)\ then\ (output\ is\ V_s^{a})\ (w_a = 0.001) \\ Rule\ 5.\ If\ (Power.Change.Rate\ is\ u_{ab1})\ then\ (output\ is\ V_s^{ab})\ (w_{ab} = 0.01) \\ Rule\ 6.\ If\ (Power.Change.Rate\ is\ u_{b2})\ then\ (output\ is\ V_s^{b})\ (w_b = 0.15) \\ Rule\ 7.\ If\ (Power.Change.Rate\ is\ u_{c2})\ then\ (output\ is\ V_s^{c})\ (w_c = 1.0) \end{array}\right\} \quad (5)$$

In addition, the following scaled control inputs to relate between the rule weight and control rod velocity calculated by the controller are considered:

$$V_s^i = w_i u_{step} \quad (6)$$

where variable w_i (for $i = a, b, c, ab$) is an adjustable weighting parameter and can be varied at different levels of the penalty based on the rate of power change.

4. TRIGA model predictive core power control

In general, the MPC controller performs all estimation and optimization calculations using a discrete-time. Therefore, the discrete form of the RTP as presented previously in Eq. **Error! Reference source not found.** can be expressed as:

$$\begin{cases} x(k+1) = Ax(k) + B_u u(k) + B_{v_o} v_o(k) + B_d d(k) \\ y(k) = Cx(k) + D_{v_o} v_o(k) + D_d d(k) \end{cases} \quad (7)$$

where k is the time index; x is the state of the model, u is the vector of manipulated variables (control rod velocity), v_o is the vector of measured disturbances, d is the vector of unmeasured disturbances, and y is the output vector (core power). Whereas A, B, C, and D are the constant state-space matrices.

The model used for both prediction and state estimation is augmented with the disturbance $d(k)$ to ensure zero offset tracking in the steady-state. However, for this study, the designed MPC did not consider measured and unmeasured disturbance inputs by setting $B_{v_o}(k)$, $B_d(k)$, $D_{v_o}(k)$, and $D_d(k)$ to zero. Then, Eq. (7) can be rewritten as:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) \\ y(k+1) = Cx(k+1) + Du(k) \end{cases} \quad (8)$$

where the variables are considered as the deviations from the nominal values based on the operating zone where the model is defined.

In general, the controlled quality is defined as the velocity of the control rod that can be considered as $u = 0$ when the actual core power is stable at the desired power level. Thus, the objective cost function J for the MPC system is defined as [18]:

$$J = (R_s - Y)^T (R_s - Y) + U^T R_W U \quad (9)$$

where $Y = [y(k+1) \quad y(k+2) \quad \cdots \quad y(k+N_p)]^T$; $R_s = [0.75 \quad 0.75 \quad \cdots \quad 0.75]^T r(k)$; r is the reference trajectory (power demand) of core power; $U = [u(k) \quad u(k+1) \quad \cdots \quad u(k+N_c-1)]^T$; N_p is the prediction horizon; N_c is the control horizon; $R_W = R_1 \begin{bmatrix} 0.75 & 0 & \cdots & 0 \\ 0 & 0.75 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0.75 \end{bmatrix}$, R_W is the weight matrix with N_c x N_c dimensions and R_1 is a tuning parameter for the desired closed-loop performance.

Defining $\emptyset = \begin{bmatrix} CB & 0 & 0 & \cdots & 0 \\ CAB & CB & 0 & \cdots & 0 \\ CA^2B & CAB & CB & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{N_p-1}B & CA^{N_p-2}B & CA^{N_p-3}B & \cdots & CA^{N_p-N_c}B \end{bmatrix}$ and $F = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{N_p} \end{bmatrix}$ gives:

$$Y = Fx(k) + \emptyset U \quad (10)$$

To find the optimal solution, the derivative of J with respect to U is needed. After $\frac{\partial J}{\partial U} = 0$ is defined, the optimal solution of the control system is defined as:

$$U = (\emptyset^T \emptyset + R_W)^{-1} \emptyset^T (R_s - Fx(k)) \quad (11)$$

As the movement of the control rod is mechanically limited, the limit on $u(k)$ is existent. The maximum velocity of the control rod is set to 23 steps per cycle, and the height of the reactor core is about 0.381 m. It is about 21,525 steps for the control rod to move from the bottom to the top of the reactor core. Consequently, the range of $u(k)$ is obtained:

The velocity of the control rod, $u(k)$ = 23 step per cycle x 0.0177 mm per step.

$$-0.4 \leq u(k) \leq 0.4 \tag{12}$$

Since the limits on $u(k)$ are existent, quadratic programming (QP) is utilized for optimization. Another objective cost function J_{QP} is defined as [19]:

$$J_{QP} = \frac{1}{2} U^T (\emptyset^T \emptyset + R_W) + \left(\emptyset^T \left(-R_s + Fx(k)\right)\right)^T U \tag{13}$$

where J_{QP} is qualitatively equivalent to J for the MPC system.

Defining control rod velocity constraint gives:

$$\begin{cases} -A_{QP} U \leq M \\ A_{QP} U \leq M \end{cases} \tag{14}$$

where $M = [0.4 \quad 0.4 \quad \cdots \quad 0.4]^T$ and A_{QP} is a unit matrix with N_c x N_c dimensions.

In this section, the previous Fuzzy PCRC proposed in [9] is integrated with the general MPC algorithm in Eq. (7) – (14) and later will be compared with Fuzzy PCRC with FCA in Section 5.

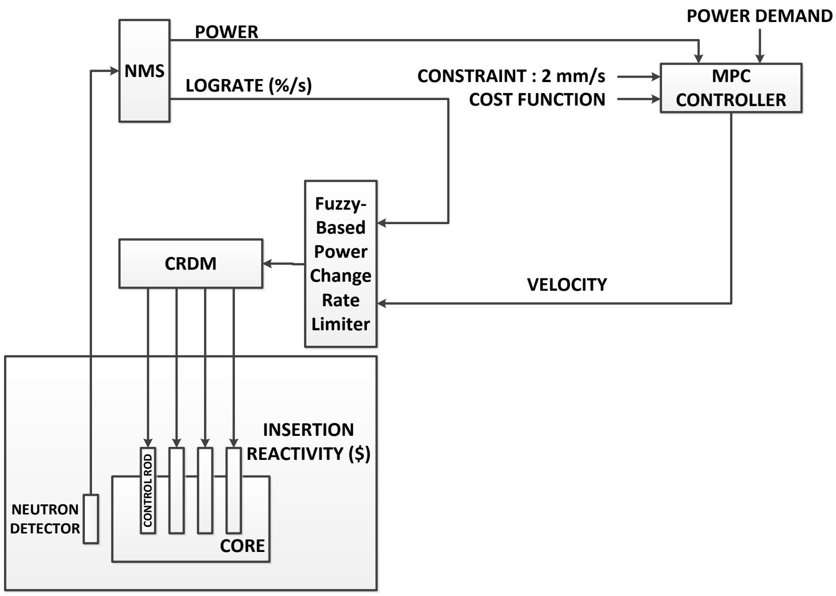


Figure 4. The block diagram of the MPC with triangular MFs Fuzzy PCRC.

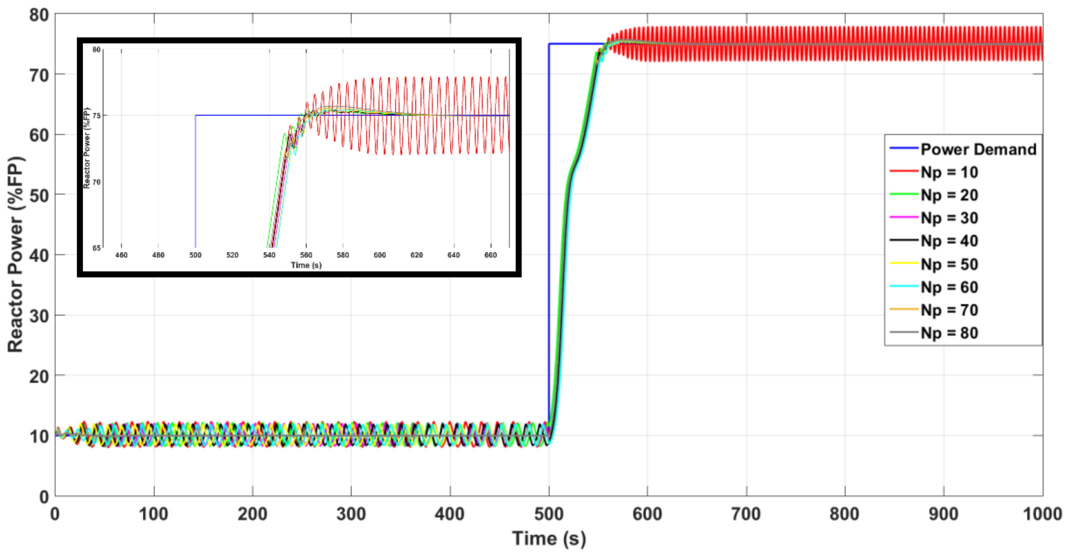
To ensure the simplicity of the developed function, the MPC-Fuzzy PCRC in Figure 4 is designed using the same approach as FCA-Fuzzy PCRC. The triangular MFs MPC-Fuzzy PCRC is designed as follows:

$$\breve{u}_{PCRC} = \left[1 - \left(\frac{u_a w_\mathrm{a} + u_b w_\mathrm{b} + u_c w_\mathrm{c} + u_{ab} w_\mathrm{ab}}{u_a + u_b + u_c + u_{ab}}\right)\right] u_{MPC} \tag{15}$$

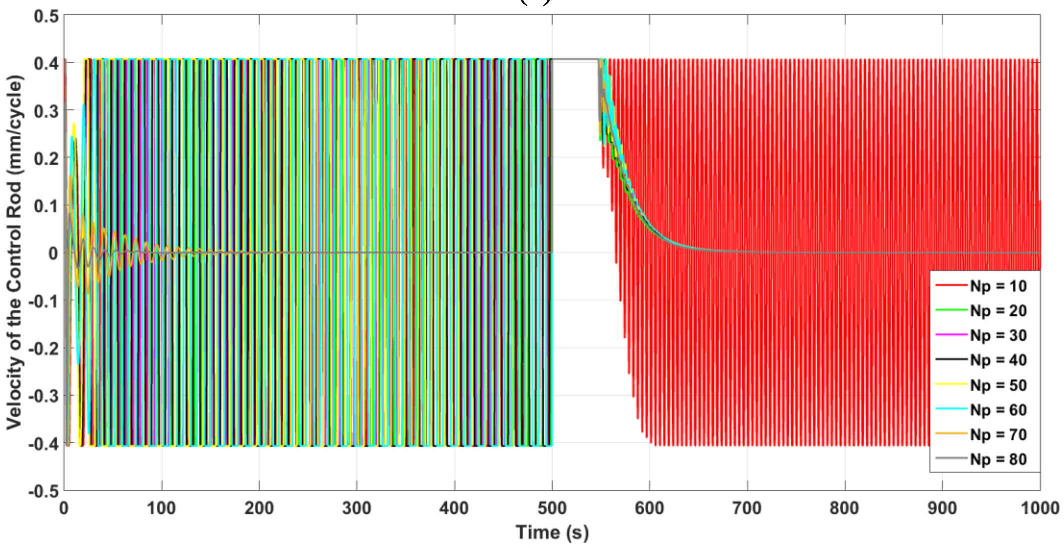
where variable u_i (for $i = a, b, c, ab$) is fuzzy set for triangular MFs, variable w_i (for $i = a, b, c, ab$) is adjustable weighting parameter, and u_{MPC} is the control rod velocity signal calculated using the MPC controller.

5. Results and discussion

The linearized model of the RTP is modelled using System ID Eq. (2) presented in Section 2. The validation of the RTP simulation model using the experimental data has been reported in our previous work [8]; [10]. The control horizon is determined by the rule of thumb in the Matlab simulation manual [20], in which the control horizon is set to 10% to 20% of the prediction horizon and has a minimum of 2 to 3 steps. In this study, the control horizon is set to 5 steps and each step is equal to 0.2 s, thus the interval time is equal to 1 s, by considering the time delay produced by the motor. Based on the considered rule of thumb, the prediction horizon is chosen to be within 10 to 200 steps. Within the selected range, the optimum prediction horizon is determined by testing all the prediction horizon values. For simplicity, the prediction values are divided into 2 groups. The first group is 10 steps to 80 steps in the range of 6% to 50% to test the rule of thumb in Matlab simulation manual and the second group is between 90 to 200 steps in the range of 2% to 5% to test beyond the rule of thumb in the first group. The considered prediction values are not more than 200 steps, equal to 40 s because it is not suitable for reactor operation to have tool long prediction values, which consequently will produce a long settling time. The result of power tracking response and actuation signal based on these two groups are shown in Figure 5 and Figure 6.



(a)



(b)

Figure 5. (a) The power tracking performance for prediction horizon 10 to 80, (b) The velocity control signal for prediction horizon 10 to 80

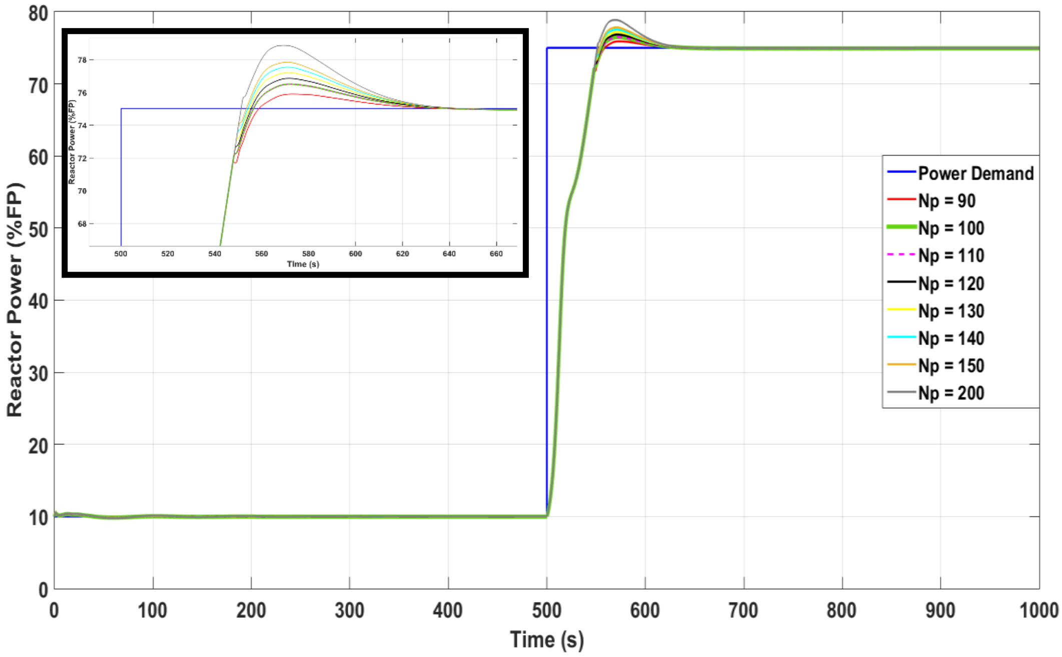


Figure 6 (a)

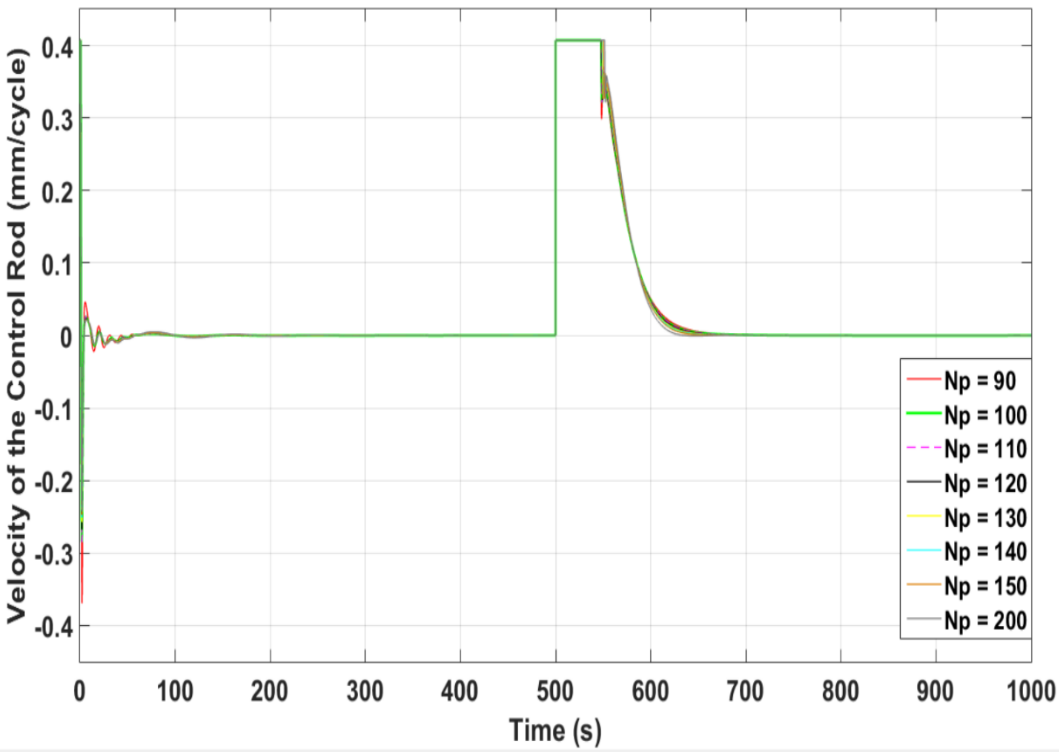


Figure 6 (b)

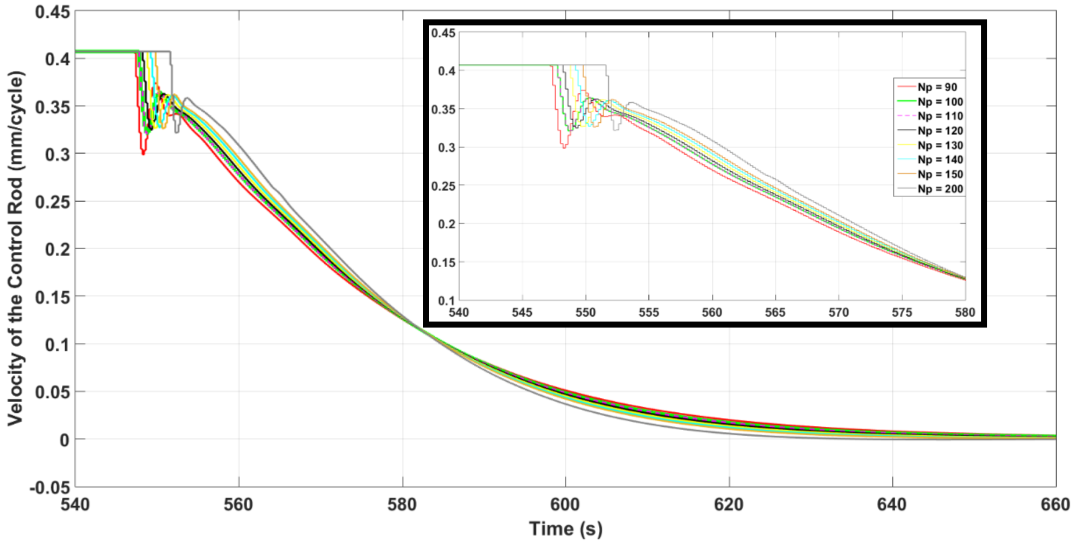


Figure 6 (c)

Figure 6. (a) The power tracking performance for prediction horizon 90 to 200, (b) The velocity control signal for prediction horizon 90 to 200, (c) Closed view of the actuation signal for prediction horizon 90 to 200

Small values of the prediction horizon in the first group as shown in Figure 5 tend to produce oscillations in the control rod movement and the power output, thus it is not suitable for safe operation in a reactor. The prediction horizon above 70, however, produces minimal oscillation in both signals and disappears when the prediction horizon reaches above 90. All prediction horizon values in the second group have small power overshoot, in which the maximum overshoot is around 6.7% which is less than 10% for safety requirements. Based on the result in Figure 6, this study chose the prediction horizon equal to 100, by taking into consideration that the value complies with the minimum criterion for the safe operation in core power control, which are minimum overshoot, less oscillation, and continuous increase reactor power.

The MPC parameters are set to 100 steps of prediction horizon N_p, which equal 20 seconds, 5 steps control horizon N_c, to update the control signal for every 1 second, and $R_1 = 0.1$. The performance of the MPC is compared with FCA-Fuzzy PCRC through the power manoeuvring of the core power and actuation signal of CRDM. Figure 7 shows that the MPC control strategy can significantly improve the power tracking performance compared to the FCA-Fuzzy PCRC during a transient. However, when core power is a power above 70% FP, all MPC produced small ripple and overshoot. In terms of smoothness of the actuation signal, the FCA-Fuzzy PCRC provide a better signal to CRDM. The signal fluctuation occurred when MPC reduce the control rod velocity from a maximum value to zero due to a mismatch in model prediction. The MPC struggled to eliminate the prediction error, thus producing higher control effort and consequent increase in the chattering error.

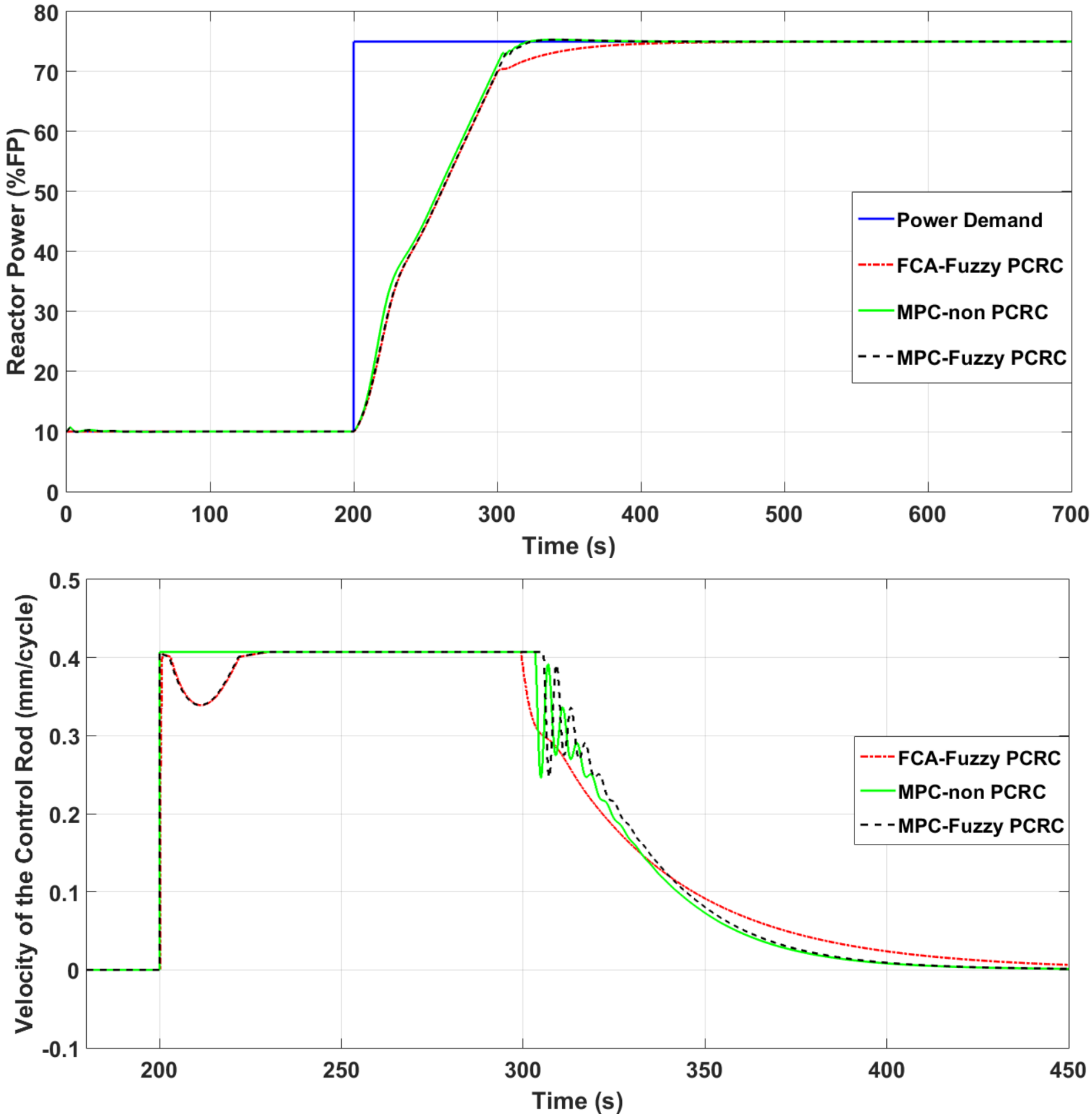


Figure 7. Comparison of different controller types for limiting the rate of power increment by increasing the power to 75% FP

The final cost value is calculated using the linear MPC with 1.220e-7 respectively. Both MPC controllers have achieved their objectives by minimizing cost value to reduce the control effort. The quantitative performance comparison is in Table 2.

Table 2. Transient and steady-state response for FCA and MPC-Fuzzy PCRC core power control at 750kW

Type	*Settling Time, T_s (s)*	*Rise Time, T_r (s)*	*Percent Overshoot, P_{os} (%)*	*Chattering Error during transient, Δe_{ce} (%)*	*Chattering Error during steady-state, Δe_{ce} (%)*	*Offset Error, Δe_{oe} (%)*	*Work Load (mm/cycle) / Energy Released (kW-h)*
FCA-Fuzzy PCRC	113.5	86.0	0.00131	0.02621	0.026213	+0.00098	105.55 / 5299.06
MPC-non PCRC	110.0	84.5	0.32777	0.31427	0.000468	+0.01397	105.85 / 5391.29
New MPC-Fuzzy PCRC	110.5	85.5	0.32814	0.31439	0.000469	+0.01422	105.85 / 5352.49

By referring to Table 2, the MPC-non PCRC type provides the most responsive reactivity compared to other control strategies with the reduction in settling and rise times. In addition, it is also capable of optimizing total energy released from the reactor core significantly. The combination of Fuzzy PCRC and MPC type does not produce any significant improvement compared to the MPC-non PCRC. However, the effect of input-output fuzzy rules is maintained to improve the chattering error when different controller type is used. The absent PCRC in MPC caused the control movement to maintain maximum control rod velocity. Overall, based on Table 2, the MPC is the best control strategy in terms of reducing settling and rise time. However, overshoot, smoothness of the actuation signal and offset error still need to be improved for MPC to be chosen. The FCA is the best solution to eliminate the offset error during steady-state.

The MPC-non PCRC and MPC-Fuzzy PCRC are also tested with 3 mm/s control rod velocity and highest reactivity insertion rate by using Regulating (RG) rod. It can be observed that the rate of power change for the MPC-non PCRC is more than 12.5% FP/s. By increasing rod velocity, can significantly improve tracking performance for wide-range power demand. The smoothness of the actuation signal can be observed by using MPC-Fuzzy PCRC. However, without the PCRC component, the tracking performance considered is not safe in terms of the rate of power change which is not a bounded constraint and more than the currently permitted 12.5% FP/s during a transient as shown in Figure 8. Therefore, MPC-Fuzzy PCRC is introduced for high control rod velocity and reactivity insertion rate.

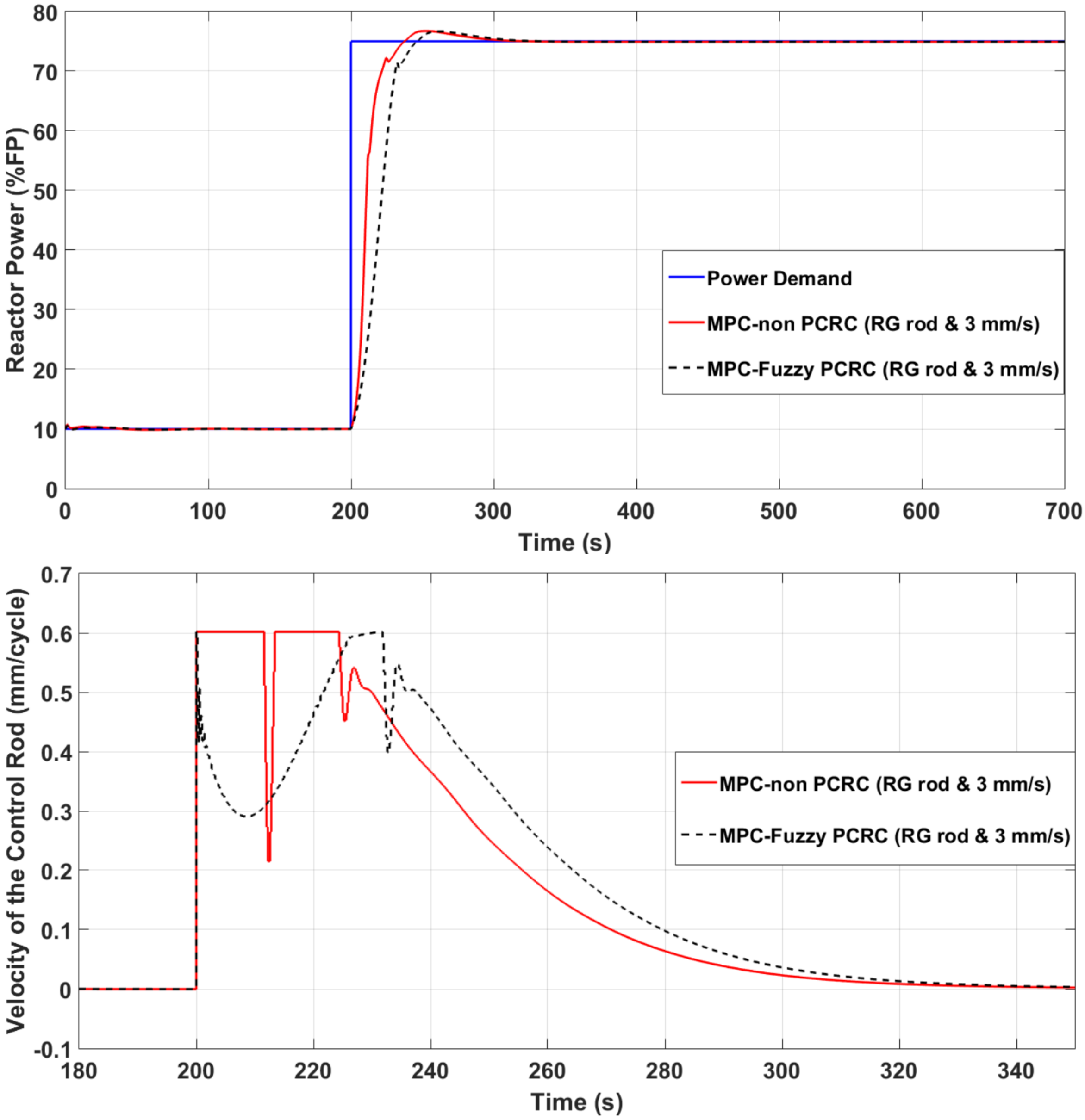


Figure 8. The power tracking performance and velocity control signal between MPC-non PCRC and MPC-Fuzzy PCRC using RG rod at 3 mm/s rod velocity

6. Conclusion

A study of the MPC-Fuzzy PCRC core power control strategies for the TRIGA reactor is presented to provide a greater level of operational safety and is very useful for types of nuclear that require tight multiple parameter constraints to regulate reactor power. Instead of using FCA-Fuzzy PCRC, the new MPC-Fuzzy PCRC control strategies consider other alternative solutions to optimize the TRIGA core power control performance. Overall, the results show that the response from the MPC-Fuzzy PCRC offers better results than the FCA-Fuzzy PCRC, which reduces the chattering error during steady-state by up to 98%, the settling time by up to 2.6%, and the rise time up to 0.6%. The optimised energy released from the reactor core is slightly improved by 1.0% for the same workload with MPC-Fuzzy PCRC. The significant finding from this study is that the MPC and Fuzzy can mutual understand and collaborate for different functions assigned. The MPC controller can provide a fast response due to model prediction ability and fuzzy logic to penalize control rod velocity signal based on power change rate to improve the drivability of the CRDM.

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