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Improving TRIGA PUSPATI reactor performance with a PI Controller and PSO-Optimized Fractional Order Lead-Lag Compensator

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ABSTRACT Controlling the power level in the TRIGA PUSPATI Reactor (RTP) is crucial for both producing accurate power output and managing reactor activity and power distribution. Currently, the RTP uses a Feedback Controller Algorithm (FCA) based on a Proportional-Integral (PI) controller to improve steady-state error during operation. However, this existing model faces issues such as delays in reaching a steady state and an inability to minimize errors due to insufficient power accuracy and an ineffective controller. To address these issues, a new structure called the Fractional Order Lead-Lag Compensator (FOLLC) has been introduced. Traditionally, the FOLLC structure is identified through loop shaping using Bode plots and root locus in the frequency response domain. In this study, however, the Particle Swarm Optimization (PSO) technique has been employed to estimate the values of the compensator's poles and zeros. Integrating the compensator with the PSO approach improved the reactor core system's ability to reach and maintain the desired power output while minimizing deviations from the target power level, achieving Residual Mean Percentage (RMP) values between 0.75% and 2.35%. In comparison, the model without a compensator had much higher RMP values of 3.45% to 27.48%, showing a less accurate match with the real plant. This integration enhanced the overall performance of the reactor core system.

KEYWORDS: Proportional-Integral (PI) controller; Lead-lag compensator; Particle Swarm Optimization (PSO); System Identification (SI)
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INTRODUCTION

This year in 2024, RTP has achieved 42 years old in operation using its original fuel since commissioning. The latest modernization was the Reactor Digital Instrumentation Control System (ReDICS) replacement into digital from analogue control conducted in 2014. The replacement had been done in controlling system part, however, the system such as the cooling system, reactor core system and certain auxiliary systems are not replaced or substituted even though these systems are old enough. Therefore, the parameters such as rod worth, delayed neutron, spent fuel, heat transfer and a few more parameters were not in the initial state and have become less significant compared to early installation. Few studies had been showed that the performance of the RTP had been degraded (Ghazali *et al.*, 2016; Minhat *et al.*, 2018; Minhat *et al.*, 2020) from the real data of output power level and power demand.

The accuracy of power control is crucial for optimizing fuel consumption, reducing heat and safety issues, especially when operating at a power demand of 1000 kW. When the goal is to produce a specific isotope or element, the operator of the RTP will adjust the power to a lower level for a longer period or vice versa. If a low power level is insufficient to produce the target element, the controller will extend the time and exposure accordingly. To ensure extended fuel consumption and minimize heat generation, the reactor system must precisely control the time, power demand level, and exposure. Currently, the existing model at RTP faces issues such as delays in achieving a

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steady state and an inability to minimize errors due to inadequate power accuracy and an ineffective controller. Effective power control in RTP is essential not only for producing accurate power output but also for managing activity and power distribution. Despite addressing factors like aging, and implementing preventive and corrective maintenance, as well as any necessary amendments, the model's accuracy has not significantly improved, with steady-state errors ranging between 0.235 and 0.7 (Ghazali *et al.*, 2016; Minhat *et al.*, 2018). Therefore, this study will introduce a new structure with an optimized compensator using PSO to estimate the poles and zeros, aiming to further enhance the reactor core system's performance.

METHODOLOGY

The project begins with data collection from the real plant at RTP. Using the collected input and output data, a model of the RTP plant is developed through a System Identification (SI) approach. Next, a compensator is designed and integrated into the RTP controller to enhance performance accuracy, with its parameters estimated using PSO to minimize error. Finally, the model is evaluated against performance metrics to ensure an accurate representation of the RTP.

Datasets

All parameters of the core reactor system were collected by the Wide Range Nuclear Monitoring System (WRNMS) and stored in a computer. According to the ReDICS in the RTP system, the data acquisition system encompasses a total of 342 parameters. However, for this study, the parameters considered are fuel temperature, coolant temperature, reactivity, and core power. Real input and output data were gathered at four different power levels 250 kW, 500 kW, 750 kW, and 1000 kW for each power level. The data collection was limited to 10,000 samples with a sampling time of 0.5 seconds, which was considered sufficient to complete the RTP system within the required timeframe.

System Identification (SI) Modelling

Since the model is a black-box model structure, no previous knowledge is required. The approach of transfer function model had been employed in this research to represent all subsystem models by using SI approach technique. The output of the SI modelling is in the form of a transfer function or called model for each subsystem which represents the relationships between real input and output data which is unique for each model. The subsystem model of RTP reactor system is depicted in Figure 1.

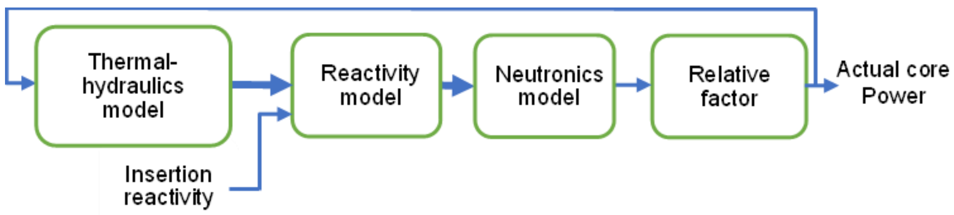

Figure 1. The block diagram of the subsystem model of the RTP reactor system

All the models are above 95% best fit except for the thermal-hydraulics model's coolant temperature, 92.79%. It was hard for the coolant temperature to get the higher best fit since the actual coolant temperatures were fluctuating along the process. However, the models with above 90% best fit show that the model can be accepted and considered as almost identical to the real plant. The transfer functions are presented as

$$T_f(s) = \frac{2.514s^2 + 0.1122s + 8.076e^{-5}}{s^2 + 2.3831e^{-2}s + 2.973e^{-6}} \quad (1)$$

$$T_c(s) = \frac{377.1s + 189.6}{s^2 + 10.48s + 0.5157} \quad (2)$$

where T_f is the transfer function for fuel temperature and T_c is the transfer function for coolant temperature.

The reactivity model generates the total reactivity from insertion reactivity and feedback reactivity due to fuel and coolant temperatures. The transfer functions are presented as

$$P_{ext}(s) = \frac{2.409s + 8.816e^{-4}}{s^2 + 2.449s + 8.97e^{-4}} \quad (3)$$

$$P_f(s) = \frac{-8.08e^{-5}s - 5.092e^{-4}}{s + 5.908} \quad (4)$$

$$P_c(s) = \frac{3.895e^{-5}s + 1.714e^{-8}}{s + 3.164e^{-4}} \quad (5)$$

where P_{ext} is the transfer function for insertion reactivity due to control rod motion, P_f is the transfer function for feedback reactivity due to fuel and P_C is the transfer function for feedback reactivity due to coolant.

For nominal core power due to neutron from neutronics model, the input-output were reactivity value and nominal core power, respectively. Based on rods movement, the reactivity model produced the reactivity value and was utilized in the neutronics model to form the nominal core power before converted into actual core power. The model of nominal core power due to neutron from SI technique is defined as

$$P_0(s) = \frac{1485.45^2 + 64.667075s + 21.75}{1537s^2 + 1542s + 5} \quad (6)$$

P_0 is the transfer function for nominal core power due to neutrons.

Design of Fractional Order Lead-Lag Compensator

The reactor system models alone could not generate power demand with high accuracy. Therefore, adding a compensator was crucial to improve accuracy, increase stability, and enhance the steady-state and transient response of the closed-loop control system. The feedback and cascade configuration are used as compensators in the structure, as shown in Figure 2. Before applying the compensator to control the reactor system, its parameters needed to be estimated. This process began with the lowest-order FOLLC, with parameters estimated based on real input and output data. The transfer function of the classical lead-lag compensator is defined as (Tavazoei & Tavakoli-Kakhki, 2013)

$$C(s) = K\left(\frac{\lambda s + 1}{x\lambda s + 1}\right)^j \quad (7)$$

where $j \in (0, \infty)$, K is a low-frequency gain of the compensator with $\lambda > 0$ is the associated time-constant and $x > 0$ is the scaling factor of the time constant and j is the order number. The pole and zero are associated with λ and are defined as $p = 1/x\lambda$ and $z = 1/\lambda$ (Memlikai *et al.*, 2021).

According to Equation (7), the structure of the compensator in this study starts with the lowest order which is *j=1*, therefore the equation for denominator and numerator is in the form of a continuous *s*-domain as

$$C(s) = K\left(\frac{s+z}{s+p}\right) \tag{8}$$

For cascade structure, the input is a set point in term of nominal neutron power which is fed into the compensator and a summation function to yield an error. This error is the difference between the actual/real data and the predicted output. The error in cascade compensator can be expressed as

$$e_c = u(t)(1 - R(t)C_c(t)) \tag{9}$$

where, $R(t)$ is reactor system output and $C_c(t)$ is cascade compensator output. Meanwhile in feedback compensator, the difference is the reactor system output is being fed into the compensator while the feedback error is the same as in cascade compensator i.e. the error is the difference between the actual/real data and the predicted output. The error in feedback compensator can be expressed as

$$e_f = u(t)\big(1 - R(t)\big) + R(t)C_f(t) \tag{10}$$

where, $R(t)$ is reactor system output and $C_f(t)$ is feedback compensator output.

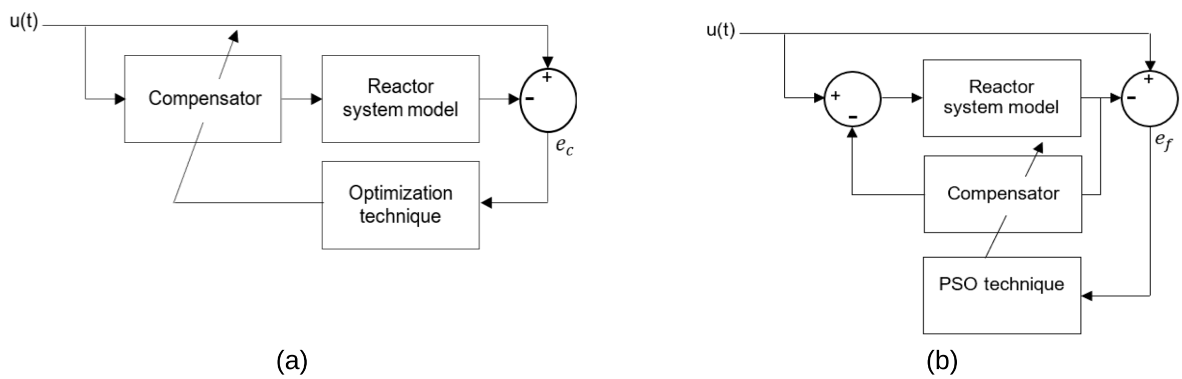

Figure 2. Block diagram for (a) cascade compensator and (b)feedback compensator

Parameter Estimation using Particle Swarm Optimization

Generally, after designing and structuring both compensators, the PSO take place to optimize the poles and zeros. Followed by performances test of the pole and zero in the subsystem, the decision of the optimum pole and zero for each model were determined. The determination is based on the final output for each model which is nearer to the real plant. To begin with, the PSO was specified with the setting of variables search space size within [0 200], dimension =2, swarm =10, and iteration number = 5. Then PSO started to initialize the population randomly and generated the position and velocity within the range.

In every iteration, each particle will be updated to get personal best value (*pbest*) and global best value (*gbest*). While the particles were moving in search space, they remember the position and memorize the location of their best result so far. At the same time, the velocity of the particle movement was measured. The velocity is affected by weight value besides prior weight value as well as cognitive and social components. Then, the fitness evaluation was done after the position of the particle had been assigned into objective function. Then after both *pbest* and *gbest* values were attained, the position and the velocity of particle were updated to a new position. The updated position and velocity of the particle are expressed as Equation (11) and Equation (12) correspondingly.

$$\rho_i^{dnew} = \rho_i^d + v_i^{dnew} \tag{11}$$

$$v_i^{dnew} = (W_0 \times v_i^d + c_1 \left(r_1\left(p_i^d - \rho_i^d\right)\right) + c_2 \left(r_2\left(p_g^d - p_i^d\right)\right) \tag{12}$$

where ρ_i^d and v_i^d are position vector and velocity of the i-th particle in the dimensional search space in previous step, respectively. The parameter c_1 and c_2, are acceleration coefficient for cognitive and both values are constant and equal to 2 as suggested by Kennedy & Eberhart (1997). The social component, r_1 and r_2 are two different random numbers between [0 1] and W_0 is inertia weight. While p_i^d and p_g^d are personal best position and global best position in the D-dimensional search space. The inertia weight (also called momentum) was integrated to influence the velocity at previous step and to improve the performance of basic PSO subsequently. For standard PSO in this study, the inertia weight was defined as (Latiff & Tokhi, 2009)

$$W_0 = 1 - 0.9 \times \left(\frac{i}{i_{max}}\right) \tag{13}$$

where i is iteration number and i_{max} the maximum number of iterations. The flow of the PSO was carried on until the maximum number of iterations was met. Finally, the best result for pole and zero with the lowest MSE together with best fitness and mean fitness was achieved.

Model Evaluation

The accuracy of the models was evaluated using three metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), and Residual Mean Percentage (RMP). MSE measures the average squared difference between predicted and actual values, while RMSE, similar to MSE, provides the error in the same units as the data by taking the square root of MSE. RMP evaluates the model's accuracy in percentage terms, indicating how well the predictions align with actual values. These metrics are defined as (Pan *et al.*, 2021; Saini *et al.*, 2021)

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{14}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{15}$$

$$\text{RMP} = \left(\frac{y_i - \hat{y}_i}{y_i}\right) \times 100\% \tag{16}$$

y is real plant data set or actual value and $\hat{y}$ is prediction data set and i is the numbers of data until n the total number of samples.

RESULT AND DISCUSSION

The models were improved by adding the compensator method to achieve a better power level as required up to. These two types of the compensator, i.e. cascade and feedback compensator, were applied to the system depending on the formation of the compensator type. Then, optimization techniques were applied to each compensator type to improve poles and zeros for each model as shown in Table 1.

Table 1. Poles and Zeros for Compensator

Cascade compensator	Feedback compensator
$\frac{s+198.96}{s+197.87}$	$\frac{s+6.5202}{s+128.9529}$

Four performance indices were used to assess the values of poles and zeros for each compensator, as shown in Table 2. The goal of this analysis is to create a reactor core system model that closely resembles the real plant. To achieve this, it is crucial to minimize the error between the real plant and the optimized reactor core system model. This involves optimizing the poles and zeros using PSO to minimize the MSE and RMSE values. Consequently, the objective function aims to minimize the MSE and RMSE to generate optimal pole and zero values. In PSO, fitness measures how closely the obtained result aligns with the target or objective function. In this study, fitness is determined by evaluating the error between the MSE and RMSE after applying them to the reactor core system model. The best fitness represents the particle within the population that converges to the best solution. A lower best fitness indicates lower MSE and RMSE values, suggesting a closer resemblance between the reactor core system model and the real plant.

Table 2. Comparison between Cascade and Feedback Compensator

Performance	Cascade compensator	Feedback compensator
MSE	0.0873	0.0708
RMSE	4.179E-3	3.9268E-3
Best fitness	270.7149	190.0434
Mean fitness	772.4379	375.7147

From Table 2, it is observed that the feedback compensator achieved the smallest best fitness value of 190.0434 and a lower mean fitness of 375.7147 compared to the cascade compensator. This suggests that the feedback compensator enhances control performance by adapting the controller output to minimize errors. Its adaptability allows the feedback compensator to effectively handle and mitigate external disturbances, making it the most robust compensator among those evaluated. The lower mean fitness value further indicates the feedback compensator's superior performance in maintaining stability and reducing the impact of disturbances on the system. Therefore, the feedback compensator proves to be an effective solution for improving control in the presence of external disturbances. In contrast, the cascade compensator exhibited the highest best fitness and mean fitness values, at 270.7149 and 772.4379, respectively.

Table 3 shows the mean power and RMP for data from the real plant, the SI model with a PI controller, and the SI model with a PI controller optimized with feedback and cascade compensators. Overall, both compensators demonstrate a trend of increasing mean power and decreasing RMP, indicating that the models are becoming more refined and closely aligned with the real plant's core reactor system. The RMP values for the SI model ranged from 3.45% to 27.48% for the PI controller, 1.70% to 2.35% for the PI with cascade compensator, and 0.75% to 1.43% for the PI with feedback compensator. While the feedback compensator shows slightly better performance and lower error compared to the cascade compensator, the difference is minimal. Therefore, both compensators provide good performance, enhanced accuracy, and results that are closely aligned with the real plant

Table 3. Comparison between Mean Power and RMP of Each Power Level for Compensators

Power level (kW)	Mean Power(kW)				RMP (%)		
	Real Plant	PI	PI+ Cascade	PI+ Feedback	PI	PI+ Cascade	PI+ Feedback
250	240.64	232.33	236.53	238.74	3.45	1.70	0.75
500	481.43	394.76	471.20	475.60	18.00	2.12	1.21
750	714.69	605.34	697.96	704.49	15.30	2.34	1.43
1000	942.05	683.21	919.88	928.87	27.48	2.35	1.40

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CONCLUSION

In conclusion, the modelling approach for all subsystems in the reactor core system focused on developing thermal-hydraulics, reactivity, and neutronics models. These models were evaluated based on the highest best fit and the lowest FPE and MSE values to ensure they closely resembled the real plant. Most models achieved a best fit of over 95%, except for the thermal-hydraulics model's coolant temperature, which had a 92.79% fit due to fluctuations in actual coolant temperatures. Nevertheless, models with a best fit above 90% are considered nearly identical to the real plant and acceptable for use. To further improve the models, compensators were introduced by embedding poles and zeros, which were estimated using PSO in both cascade and feedback compensator structures. With the same parameter settings in PSO, the accuracy of the poles and zeros estimation, as well as all the subsystem models, was evaluated. Starting with the lowest order, both compensators successfully improved the accuracy of the models. The evaluation of each model through RMP demonstrated that the proposed compensators, using the PSO approach to estimate poles and zeros, enhanced the accuracy of all models and improved the overall performance of the RTP.

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