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RESEARCH

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Modified nondominated sorting genetic algorithm-based multiobjective optimization of a cross-coupled nonlinear PID controller for a Twin Rotor System

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Abstract

This paper presents an innovative nonlinear PID control scheme based on a modified nondominated sorting genetic algorithm validated using a laboratory helicopter model called the Twin Rotor System. The concepts of controlled elitism and dynamic crowding distance are incorporated into the proposed algorithm to progress towards the best solution from the entire population in order to solve the multiobjective optimization problem with good convergence characteristics. The addition of nonlinear functions to the cross-coupled PID controller structure initiates better error tracking and facilitates smooth output under changing input conditions. The design objective is to implement an optimal nonlinear PID control scheme for the angular displacements of the twin-rotor system, with integral square error and control energy taken as the multiobjective problems. The statistical performance of the controller is analyzed by considering the best, worst, mean, and standard deviations of ISE. In this work, simultaneous control of pitch and yaw angles is considered to get rid of the coupling effect between the two rotors. The results indicate the advantage of the MNGSA-based tuning for the two degrees of freedom MIMO control with standard reference trajectories as per the TRMS330-10 model.

Keywords: Nonlinear PID controller, Twin Rotor System, Modified nondominated sorting genetic algorithm, Integral square error, Evolutionary computation techniques

Introduction

Proportional-integral-derivative (PID) control provides a competent solution to many practical control problems. In an industrial system, the PID controller design is complex due to system nonlinearities such as plant dynamics and uncertainties such as errors in the modeling and disturbances from the external environment concerned with the system. PID controller tuning based on fuzzy logic, neural networks, and other evolutionary computation methods is commonly used [1]. A conventional PID controller is not appropriate for nonlinear systems that are used in many industries. For fixed values of parameters, the PID controller is incapable of adjusting the nonlinear factors to enhance the control performance. In a nonlinear PID (NLPID) controller, many parameters have to be tuned. The nonlinear proportional term provides a higher gain for large errors and a lower gain for small errors, making it much more suitable for working with practical problems [2].

The presence of a nonlinear function in a NLPID controller causes the error to move towards zero at a finite time. Many industrial processes are nonlinear and have a longer time delay. The linear PID controller is competent only for a particular operating range when engaged in a nonlinear process. The NLPID control is used in a second-order robotic process. It is also used in thermoplastic injection molding, which is an essential process in the polymer processing industry. A nonlinear PID controller is significant in superconducting magnetic energy storage (SMES) units associated with a power control system to improve stability in various operating ranges [3]. The PID controller design using a single objective function to minimize the integral square using various population-based evolutionary computation (EC) methods like gravitational search algorithms, particle swarm optimization, genetic algorithms, and covariance matrix adaptation evolution strategies has been developed in [4].

The optimization of controller parameters for an induction generator used in the frequency regulation of a combined wind and thermal power system is proposed in [5]. The proportional, integral, and derivative controllers are optimized in a cooperative manner using the multiobjective nondominated sorting genetic algorithm (NSGA) II. A sensitivity analysis is performed to reduce the parameters involved in the optimization process. The results of this work show effective performance even with parametric uncertainties and wind energy level variation. Power fault diagnosis using the NGSA II algorithm is discussed in [6]. In this work, the Pareto approach is used to remove errors arising from weight setting in the fault diagnosis process. The evaluation of the Pareto optimal solution is accomplished through a technique for ordering performance by similarity to the ideal solution. In this work, instead of considering the constraints with a penalty function, the constraints are transformed into an objective function to formulate the multiobjective optimization problem. Thus, the effect of subjective factors involved in the fault diagnosis process is reduced.

The Twin Rotor MIMO System (TRMS) is a composite model of a Multiple Input Multiple Output (MIMO) system that is multivariable and nonlinear. A PID controller is used for the pitch and yaw angle control of the main and tail rotors of TRMS under specified parameters. In a PID controller design, tuning the controller is considered an optimization problem to solve the desired objective function using evolutionary computation algorithms to track the optimal set point [7]. Nonlinear PID controller design using various conventional computation techniques is discussed in [8]. In [9], an adaptive nonlinear predictive control strategy based on a disturbance observer for a Twin Rotor System is studied. The nonlinear parameterization and second-level adaptation effective in industrial systems are used. In this design, the control algorithm is much more suitable in the presence of uncertainties in the parameter values and disturbances.

The fractional order PID (FOPID) control, super twisting sliding mode (STSMC), and fractional order super twisting sliding mode (FOSTSMC) are used to stabilize a TRMS MIMO system in [10]. In this work, DC motor speed control is carried out to adjust the angle of rotation. The transient response analysis of each controller is done for the validation of the results. The error variation for the main and tail propeller angles is obtained. It has also been found that system performance is improved when each rotor is controlled by a different controller.

A cross-coupled precompensation design for a nonlinear PID controller is evaluated using the single objective evolutionary computation technique in [11]. This method reduces the error rate of the system involved. Cross-coupled controller design has the advantage of tracking the desired contour trajectory with high accuracy and speed. The results of this work validate that tracking accuracy is enhanced with the elimination of overshoot.

The proposed work in [12] deals with the design of MIMO PID controllers to achieve linear quadratic (LQ) performance of a laboratory-based two-degree-of-freedom helicopter system with norm-bounded uncertainties in the cross-coupled gain. It is found that for such an uncertain system, the MIMO PID design problem can be recast as a full-state feedback control for an augmented uncertain system. A simple linear matrix inequality problem is solved to determine the PID parameters in order to achieve robust LQ performance.

The effectiveness of evolutionary algorithms such as differential search algorithm (DSA), real-coded genetic algorithm with simulated binary crossover (RGA-SBX), particle swarm optimization (PSO), and chaotic gravitational search algorithm (CGSA) on the optimal design of cross-coupled nonlinear PID controllers is compared in [13]. A cross-coupled multivariable PID controller structure for the binary distillation column was developed with two inputs and two outputs. This work elaborates on the design of a cross-coupled nonlinear PID controller using single-objective evolutionary algorithms. The results of a multivariable cross-coupled system show that a single-objective nonlinear PID controller performs better. Simulations further show that all four techniques evaluated are suitable for PID controller tweaking offline.

A novel auto-tuning nonlinear PID controller for a nonlinear electric vehicle (EV) model is proposed in [14]. The purpose of the proposed control is to enhance the dynamic performance of the EV regarding internal and external disturbances and minimize its power consumption. Several driving cycles were executed to compare their dynamic power consumption. The results showed that the auto-tuning NLPID had a smooth dynamic response with a minimum rise and settling time compared to other control techniques. Moreover, it achieved low continuous power consumption throughout the driving cycles.

Many processes operated in the chemical processing industry show time-varying and highly nonlinear characteristics. The proposed work in [15] is on an enhanced nonlinear PID (NLPID) controller for the improvement of set point tracking or disturbance rejection responses, along with new tuning formulas for a first-order plus time delay process model. The parameters of the NPID controller are expressed in terms of the ratio of the time delay L to the time constant τ in the process by using the dimensionless approach. Repeated optimizations are performed to obtain the average of optimal parameter values that minimize the integral of the absolute error performance criterion. By using the least-squares method, the calculated optimal values and the rule formulas for the tuning rules are obtained.

Dominance resistance is a challenge for Pareto-based multi-objective evolutionary algorithms to solve high-dimensional optimization problems. The nondominated sorting genetic algorithm still has such disadvantages, even though it is recognized as an algorithm with good performance for many-objective problems. Therefore, a variation of the NSGA algorithm based on fine final-level selection is proposed to improve convergence [16]. The dominance relation is used to sort the solutions in the critical layer, and then favor convergence is employed to evaluate the convergence of individuals in different situations.

The neural network algorithm (NNA) is a recently proposed metaheuristic that is inspired by the idea of artificial neural networks. The performance of NNA on single-objective optimization problems is very promising and effective. In [16], NNA is restructured for its possible use to address multi-objective optimization problems. A novel concept is proposed to initialize the candidate solution, update the position, and select the target solution. To examine the optimization ability of the proposed scheme, it is tested on several benchmark problems, and the results are compared with eight state-of-the-art multi-objective optimization algorithms. Inverse generational distance (IGD) and hypervolume (HV) metrics are also calculated to understand the optimization ability.

Different from the existing works, the constants added to the PID controller enable an extra degree of freedom to enhance the system's performance in the proposed work. The TRMS system used in this work is a nonlinear and effectively coupled system with two degrees of freedom. In the prevailing work, pitch and yaw axes are controlled separately, but in the proposed work, simultaneous control of both axes is done due to the cross-coupled dynamics involved, which consider the influence of one rotor on the other. This overcomes the drawback of system instability that occurs during the separate control of either axis. The desired path tracking is effective when pitch and yaw angle control are done at the same time and in the presence of disturbances. The cross-coupled controller is designed by considering the controller structure as a matrix and every element as a PID controller. There are very few works addressing the setting of accurate controller gains for exact set point tracking of the TRMS in a real-time environment with multiobjective optimization, which is dealt with in this paper.

The design of a multiobjective nonlinear PID controller using the conventional nondominated sorting genetic algorithm (NSGA-II) embraces elitism and a fast nondominated search approach, but it fails to maintain lateral diversity and attain uniform Pareto-front. To overcome this shortcoming, the proposed work involves the modified nondominated sorting genetic algorithm (MNSGA-II), which has the advantages of controlled elitism and a dynamic crowding distance (DCD)-based diversity maintenance strategy for finding the best possible solution. The time integral performance measure is used for set point tracking, and the minimization of the integral square error (ISE) is considered one of the objectives in this paper.

The error and control signals for the main and tail position rotors are considered for the objective function. The optimal nonlinear PID parameters in our work are obtained with the objective of reducing the integral square error. In most cases, the design of PID controllers is done by minimizing integral absolute error (IAE), integral time-weighted absolute error (ITAE), and integral time-weighted squared error (ITSE). Integral square error (ISE) integrates the square of the error over time and prohibits larger errors more accurately. Control systems determined to minimize ISE show fast response with acceptable low-amplitude oscillation. The ISE criterion is used for analyzing the performance measure for a linear tracking optimal control problem in combination with the input constraints. ISE shows better performance indices than IAE and ITAE in steady states and has good robustness against parametric uncertainties [17–19]. Therefore, ISE is chosen as an appropriate performance index in this research work for accurate validation of the result.

For effective set point tracking, the maximization of control energy is also taken as one of the objectives in this paper, which shows a fast response with acceptable low amplitude oscillation. There are many works addressed in the literature with the NSGA-II algorithm, like the wind turbine blade optimization method, Thyristor Controlled Series Compensator (TCSC)-based controller optimization, power system stabilizer optimized controllers to improve the frequency regulation characteristics of wind thermal power systems, and clustering ensembles to integrate the results of multiple base clustering. To the best knowledge of the authors, the application of a modified nondominated sorting genetic algorithm to estimate the model parameters for various operational modes of the Twin Rotor MIMO System is an unaddressed work, which is dealt with in this paper.

The objective of this paper is the design of a cross-coupled nonlinear PID controller for precise trajectory tracking in a Twin Rotor System using a modified nondominated sorting genetic algorithm (MNGSA)-based optimization scheme. The objective of this design is the implementation of a nonlinear PID control strategy for the rotor angular displacement of a TRMS with the aim of reducing the integral square error and increasing the control energy using the multiobjective evolutionary computation technique termed MNGSA. The core contributions of this work are as follows:

- Design of a cross-coupled nonlinear PID control strategy based on MNGSA for accurate trajectory tracking in a TRMS
- The designed PID controller is validated in real time, with optimum gains obtained for the laboratory helicopter model of the Twin Rotor System.
- A MNGSA-based multiobjective optimization scheme is adapted to estimate the model parameters for various operational modes of the TRMS.

Methods

PID controller design implemented for the TRMS system

Twin Rotor MIMO System

In this work, a dynamic, experimental benchmark model called TRMS, which resembles the behavior of a practical helicopter and is used for laboratory purposes, is investigated. The design of a controller in a TRMS system is a challenging task due to factors such as system uncertainties, external disturbances, and changing environmental conditions. These factors impose nonlinearity on the system. The coupling effect between the main and tail rotors needs to be analyzed. The main rotor supports the control of pitch angle. The tail rotor is used for beam control by handling the yaw angle in a skillful manner. The motors manifest aerodynamic force, resulting in a coupling effect between the rotors. The presence of air streams must be considered in the TRMS model [20]. The supply voltage of the DC motors acts as a control input to change the speed of rotation of the propeller [21].

Nonlinear PID controller structure

The nonlinear PID controller structure is given by as follows:

$$K(S) = K_P.fal(e, \alpha, \beta) + \frac{K_I}{S} + K_D S.fal(e, \alpha, \beta) \tag{1}$$

where the PID parameters are denoted asK_P, K_I, and K_D and $fal(\mathrm{e}, \alpha, \beta)$ is a nonlinear function, e is the error position, and α and β are constants.

$$fal(e, \alpha, \beta) = \begin{cases} |e|^{\alpha} sgn(e), |e| > \beta \\ \frac{e}{\beta^{1-\alpha}}, |e| \le \beta \end{cases} \tag{2}$$

The PID control law employs a linear combination of present, accumulative, and predictive forms of tracking error, and other possibilities of this combination are potentially more effective. To facilitate this, according to [22], the nonlinear function given in Eq. 2 is proposed, which has provided better results in practice. With linear feedback, the tracking error approaches zero in infinite time, but with nonlinear feedback of the form given in Eq. 2, the error can reach zero much more quickly in finite time with $\alpha < 1$. Therefore, the value of α is chosen as $0.5 \sim 1$ in the proposed work. With this value of α, the steady-state error is reduced significantly to the extent that integral control can be avoided. The extreme case with $\alpha = 0$ with bang-bang control can bring zero steady-state error without the integral term in the PID. When it provide a smoother control action to track efficiently when $= 0.1 \sim 0.2$ so that these values are chosen. From experimental investigation, it is observed that the nonlinear feedback functions in the form of play an important role in the proposed control scheme.

The cross-coupled nonlinear PID controller is established considering the effect of one rotor on the other, as shown in Fig. 1. It includes four nonlinear PID controllers for controlling the 2×2 TRMS model. The performance of the controller is analyzed by considering two different circumstances.

The simple PID controller controls the vertical and horizontal movements separately. In a simple PID control system, the influence of one rotor on the motion in the other plane is not compensated by the controller structure, whereas in a cross-coupled control system, it is controlled. However, the system is not decoupled. Figure 1 shows the cross-coupled control structure consisting of four PID controllers in which the inputs are independent of each other. The cross-coupled controllers can be designed by presuming the controller structure as a full matrix with each element as a PID controller and by using the tuning method to find out the values of the controller parameters. The gain parameters of the PID controller determine the system's performance. Though TRMS is a coupled system, for tuning using PID control, the effect of tail rotor performance will affect the main rotor dynamics and vice versa.

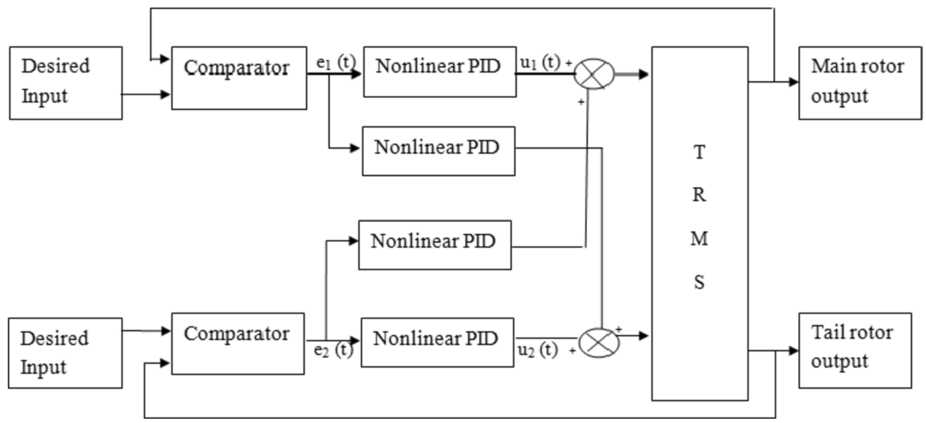

Fig. 1 Cross-coupled nonlinear PID controller

(i) Cross-coupled nonlinear PID controller with fixed α and β values, for which the controller parameters of the main and tail rotors in order to attain the ideal performance is as follows:

$$K = \left[K_{p_r}K_{i_r}K_{d_r}K_{p_{tr}}K_{i_{tr}}K_{d_{tr}}K_{p_t}K_{i_t}K_{d_t}K_{p_{rt}}K_{i_{rt}}K_{d_{rt}}\right] \quad (3)$$

(ii) Cross-coupled nonlinear PID controller with optimized α and β values, for which the controller parameters of the main and tail rotors in order to attain the ideal performance is as follows:

$$K = \left[K_{p_r}K_{i_r}K_{d_r}K_{p_{tr}}K_{i_{tr}}K_{d_{tr}}K_{p_t}K_{i_t}K_{d_t}K_{p_{rt}}K_{i_{rt}}K_{d_{rt}}\alpha\beta\right] \quad (4)$$

where $K_{p_r}, K_{i_r}, \text{and} K_{d_r}$ are PID parameters for the main rotor and $K_{p_t}, K_{i_t}, \text{and} K_{d_t}$ are PID parameters for the tail rotor. $K_{p_{tr}}, K_{i_{tr}}, \text{and} K_{d_{tr}}$ are parameters that influence the effect of the tail rotor on the main rotor and $K_{p_{rt}}, K_{i_{rt}}, \text{and} K_{d_{rt}}$ are parameters that influence the effect of the main rotor on the tail rotor due to cross-coupled dynamics involved and β, α are nonlinear constants.

The objective function for parameter optimization in the cross-coupled nonlinear PID controller is defined on the basis of specifications such as control energy and time-integral performance.

The integral square error

$$ISE = \int_0^\infty e_1^2 dt + \int_0^\infty e_2^2 dt \quad (5)$$

where $e_1(t)$ is the error signal for the main position rotor (elevation or pitch) and $e_2(t)$ is the error signal for the tail position rotor (azimuth or yaw).

$$\text{Controlenergy} = \int_0^\infty u_1^2 dt + \int_0^\infty u_2^2 dt \quad (6)$$

where $u_1(t)$is the control signal for the main position rotor (elevation or pitch) and $u_2(t)$ is the control signal for the tail position rotor (azimuth or yaw).

MNGSA-based optimization scheme for controller tuning

Many works have been reported using evolutionary algorithms for tuning the controller owing to their enhanced performance in the time domain specification. The PID controller tuning for TRMS control using various evolutionary computation methods is studied in [23]. In most of the work, only simulation results are used for performance analysis of the TRMS system. In this work, accurate set point tracking of the TRMS is experimented with in a real-time environment with the aim of obtaining the optimal value of integral square error and control energy in the nonlinear PID control adopted using a modified NSGA-II algorithm. The addition of a nonlinear function to the PID controller initiates better error tracking and reduces overshoot. It also facilitates smooth output under varying input conditions. In this work, simultaneous control of pitch and yaw angles is considered to get rid of the coupling effect that exists between the two rotors. There are very few works addressing the mathematical model of the TRMS and setting accurate controller gains for exact set point tracking of the TRMS in a real-time environment with multiobjective optimization, which is dealt with in this paper.

NGSA II is a multiobjective algorithm useful in many control applications. The main objective of the algorithm is to evolve towards the best solution from the entire population in order to solve the multiobjective optimization problem NGSA uses a nondominated sorting algorithm, which significantly reduces the computational complexity [24]. Figure 2 shows the flow chart of the proposed algorithm. It uses the principle of elitism, where the best solutions of the preceding iteration are kept consistent in the current state. A nondominated solution provides a compromise between all the objectives without degrading them. The Pareto front is the set of optimal solutions obtained. In Pareto dominance, every solution is matched with every other solution in the population. The solution to be selected on the Pareto front is the one that is not dominated by other existing solutions. The procedure for the algorithm is as follows: from the individuals encoded using a definite depiction, an initial population of size N is randomly generated. Genetic operators such as crossover and mutation are used to generate offspring from the initial population set. The next generation is selected according to nondominated sorting and crowding distance comparison. The next generation member on each front is forwarded using the non-dominance principle. Many nondominated fronts are obtained from the initial population and sorted based on objective values. A fitness value or rank is assigned for each member in the Pareto front. The crowding distance for every member in each front is calculated and sorted [25].

The crowding distance (D) depends on the cardinality of the solution sets and their distance to solution boundaries. The crowding distance and rank are the two parameters used to select the parent population from the initial population based on the crowded tournament selection. In the crowded tournament selection, if a solution x_i has a better rank than $x_{j,}$ x_i is selected. If both solutions have the same rank, the crowding distance D_i is compared with the crowding distance $D_{j.}$ If $D_i > D_j$, then x_i is selected according to crowding distance. Then, the processes of mutation and crossover are performed on the parent population for the offspring generation. Elitism is

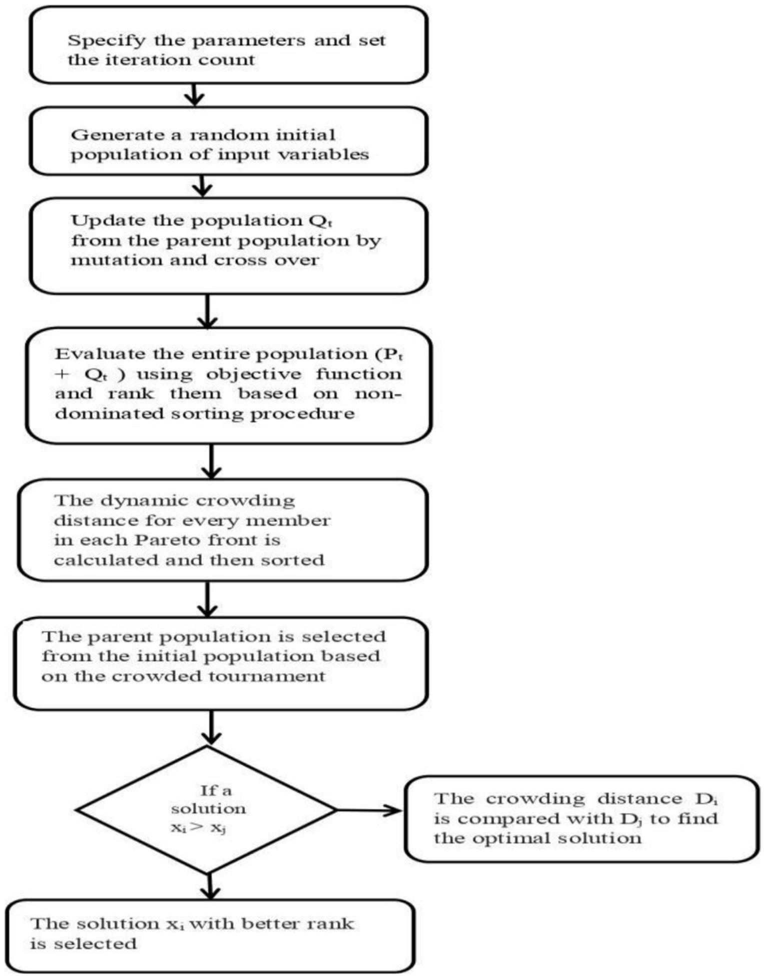

Fig. 2 Flow chart of the proposed algorithm

performed to select the best population of size N based on the objective function. In the Modified NSGA-II (MNSGA) algorithm, the user-provided reference point focuses the search space towards the desired Pareto front. In order to obtain the modified crowding distance, the normalized Euclidean distance of every solution in front is calculated. The closest solution from the reference point is used to sort and rank the solutions obtained. Solutions with a smaller crowding distance are preferred in the tournament selection process to generate a new population. MNGSA shows good results in multiobjective test problems. Dynamic crowding distance (DCD) helps in the maintenance of diversity, depending on the degree of crowding distance between dissimilar objectives. The non-dominance approach in DCD helps to improve the distribution of solutions. The concepts of controlled elitism and dynamic crowding distance incorporated into the NSGA-II algorithms framed the MNSGA [25]. For better convergence characteristics, the algorithmic search process must be exploited in both alignment with the Pareto front and away from the Pareto front in an optimal manner. In most cases, the exploitation of the present-utmost solution of non-domination causes uncontrolled elitism. In the controlled elitism mechanism adopted in MNSGA, the algorithm confines itself to adapting the number of nondominated individuals in the current best front and sustains the desired distribution of individual numbers in every front.

MNGSA is a population-based algorithm where the initial population generation is the first step in the search process. The parameter identification of the system based on a nondominated genetic search algorithm is used for optimizing the objective function. A random initial population of input variables is generated. Mutation and crossover strategies are applied to update the population from the parent population. Then, elitism is performed to select the best population according to its objective function value. The entire population is evaluated using the multiobjective function and ranked based on a nondominated sorting procedure. A nondominated solution is one that provides a suitable compromise between all the objectives without degrading any of them. The Pareto front corresponds to the set of nondominated solutions. The dynamic crowding distance for every member in each Pareto front is calculated and then sorted. In this procedure, the least crowding distance value is eliminated each time, and DCD is calculated for the rest of the individuals. Then, the parent population is selected from the initial population based on a crowded tournament, where the selection is based on ranking and the dynamic crowding distance. The solution with the better rank is selected, but if the two solutions share the same rank, then the optimal solution is based on its dynamic crowding distance. The stopping criteria are checked, and the steps are repeated if necessary. The parameters to be optimized are the controller constants K_p, K_i, and K_d, which are the decision variables, with the objective function being the minimization of integral square error and control energy.

The highest acceptable individual number in each front i among the population is given by N_i

$$N_i = N\frac{1 - rr}{1 - rr^q}rr^{i-1} \tag{7}$$

where q is the highest front number and the rate of reduction is given by rr.

Let N_1^g correspond to the individual's number in the first front. If the value of $N_1^g > N_1$, the crowded tournament selection mechanism is adopted to choose N_1 solutions that exist in the least crowded region. If $N_1^g < N_1$, then $\rho_1 = N_1 - N_1^g$. The maximum allowable individual number in the second front is increased to $N_2 + \rho_1$. This process is repeated to select up to N individuals. This method thus preserves the controlled elitism mechanism.

In the NSGA-II algorithm, CD is calculated as per the equation given below to eliminate the extra individuals.

$$\mathrm{CD_i} = \frac{1}{\mathrm{N_{obj}}}\sum_{\mathrm{k=1}}^{\mathrm{N_{obj}}}\left|\mathrm{f^k_{i+1}} - \mathrm{f^k_{i-1}}\right| \tag{8}$$

where the objective number is given by $\mathrm{N_{obj}}$, $\mathrm{f^k_{i+1}}$ represents the kth objective corresponding to $\mathrm{i+1}$th individual and $\mathrm{f^k_{i-1}}$ represents kth objective corresponding to $\mathrm{i-1}$th individual after sorting the population based on crowding distance. In the dynamic crowding distance technique, the least crowding distance value is eliminated each time, and then, the crowding distance is calculated for the rest of the individuals as per the equations given below.

$$DCD_i = \frac{CD_i}{log\left(\frac{1}{Vcd_i}\right)} \tag{9}$$

$$Vcd_i = \frac{1}{N_{obj}} \sum_{k=1}^{N_{obj}} \left(\left| f_{i+1}^k - f_{i-1}^k \right| - CD_i \right)^2 \tag{10}$$

If an individual is conserved in the nondominated set then the other individuals with the same characteristics have a higher probability to be maintained. The uniform distribution of the solutions over the front which is nondominated is measured by minimal spacing S_p

$$S_p = \sqrt{\frac{1}{|Q|} \sum_{i=1}^{|Q|} (de_i - de)^2} \tag{11}$$

where $de_i = min_{k \in Qandk \neq i} \sum_{m=1}^{M} \left| f_i^m - f_k^m \right|$, $f_i^m \left(or f_k^m \right)$ is the objective value (m) of the solution i in the last set that corresponds to nondominated solutions Q and de gives the average value of all the de_i.

Results and discussion

The system performance is conducted with the standard reference trajectories as per the TRMS330-10 model used in our work. The best optimal parameter value of controller constants obtained by the algorithm is validated with the cross-coupled conventional PID controller for the Twin Rotor MIMO System. The output response of the pitch and yaw rotor of TRMS is obtained, which shows the saturation of the pitch and main rotors with respect to the standard reference input.

The implementation of the MNGSA-based multiobjective nonlinear PID controller tuning is considered for simulating the TRMS setup, where MATLAB software is used. Independent population initializations are made to acquire useful performance from the algorithm. The population size is fixed at 100. The sampling time is 0.01 s. The best mean, worst mean, and standard deviations of the ISE measure and control energy in 20 independent trials are reported.

In this work, the Twin Rotor System is run in a real-time environment to provide appropriate validation of the simulation case studies carried out. ISE and control energy are determined for the desired pitch/yaw angle response with set point regulation. Simulations are carried out using a stopping criterion, with the maximum number of function evaluations set at 1500. Optimum nonlinear PID parameters are obtained with the objective of simultaneously minimizing the ISE and maximizing the control energy. The Pareto-optimal solution obtained from the MNSGA-II algorithm optimizes both objective functions.

The performance of the proposed controller is tested in real time using the Twin Rotor System. The statistical performance of the designed nonlinear PID controller with optimized β and α is compared for various evolutionary computation techniques such as the differential search algorithm (DSA) [8], particle swarm optimization algorithm (PSO) [8], real-coded genetic algorithm (RGA) [8], chaotic gravitational search algorithm (CGSA) [8], and the proposed modified nondominated sorting genetic algorithm (MNGSA). The initial stage of the algorithm selects the range of parameters so that depending on the overshoot, various appropriate settings of search space are provided for the nondominated search procedure. The design parameter vector is the vector of control gains, which are the proportional, integral, and derivative constants. The nonlinear control design optimization procedure based on MNGSA is evaluated to solve the objective function. In this work, the integral square error and control energy are considered for the objective function. The purpose is to accomplish a control structure with two degrees of freedom. To achieve this, the parameters of the nonlinear PID control design are tuned first, and then, the results are integrated for the two degrees of freedom system. Performance analysis of the proposed work shows the advantage of the proposed MNGSA algorithm-based multiobjective-based tuning for two degrees of freedom MIMO control. Table 1 shows the performance comparison of the designed cross-coupled nonlinear PID controller for various optimization-based tuning techniques. Table 2 shows the performance comparison of a conventional PID controller with various other optimization-based tuning techniques. Table 3 shows the performance comparison of the best optimal parameter value for the designed cross-coupled nonlinear PID controller with various other algorithms.

The work in [26], which is compared with the proposed work, addresses the simultaneous tuning of multi-loop linear PID using a new variant of the fully informed particle swarm optimization technique. It shows the implementation of a linear PID controller to stabilize and control a Granty crane system. In [27], a multiobjective genetic algorithm used in the design of fractional order PID and integral order PID for trajectory tracking control of a TRMS system is discussed.

Table 1 Performance comparison of the designed cross-coupled nonlinear PID controller with various optimization-based tuning techniques

Parameter	DSA	PSO	RGA	CGSA 9	CGSA 10	NGSA	MNGSA
Best optimal value of ISE	13.103	8.8527	9.954	25.307	25.307	29.455	29.006
Worst optimal value of ISE	44.748	21.470	24.870	110.702	139.470	44.551	35.703
Mean optimal value of ISE	22.533	12.251	14.448	109.702	139.473	36.088	31.597
Standard deviation value of ISE	7.807	2.222	2.731	22.953	27.474	4.740	2.127

Table 2 Performance comparison of a conventional PID controller with various other optimization-based tuning techniques

Parameter	DSA	PSO	RGA	CGSA 9	CGSA 10	NGSA	MNGSA
Best optimal value of ISE	94.67	75.77	85.77	81.51	76.90	29.455	29.006
Worst optimal value of ISE	116.37	139.45	118.21	139.09	205.03	44.551	35.703
Mean optimal value of ISE	103.42	105.75	101.56	110.71	125.41	36.088	31.597
Standard Deviation value of ISE	6.56	28.06	16.79	21.97	41.85	4.740	2.127

Table 3 Performance comparison of the best optimal parameter value for the designed cross-coupled nonlinear PID controller with various other algorithms

Parameter		DSA	PSO	RGA	CGSA 9	CGSA 10	NGSA	MNGSA	FIPSO [26]	MOGA [27]
Best optimal parameter	K_p	4.44	5.00	4.78	4.01	4.09	3.51	3.50	4.85	11.646
	K_i	3.02	5.00	4.40	4.99	5.00	4.89	3.77	3.49	19.25
	K_d	5.00	2.17	2.66	5.00	5.00	4.98	4.70	4.04	33.01

Figures 3 and 4 show the Pareto front obtained from the NSGA-II and MNSGA-II algorithms.

It is observed that the Pareto front obtained from MNSGA is uniformly distributed because of the dynamic crowding distance and controlled elitism behavior. It is observed that the minimal spacing is less in the MNSGA response, whereas the NSGA-II Pareto front is not uniform. The Pareto front obtained from the MNSGA algorithm has uniform distribution characteristics compared to NSGA-II due to the properties of dynamic crowding distance and controlled elitism. The output response of the pitch/main and yaw/tail rotors of the TRMS system is depicted in Figs. 5 and 6.

It is observed that the designed PID controller tracks the reference signal very closely. The reference signal has a smooth increase, and no overshoot is needed for increasing the reference signal tracking. It has smoother and faster transient performance and enhanced steady-state performance with a slow rise time. These results demonstrate the effectiveness of the proposed MNSGA-based tuning for the two degrees of freedom MIMO control with standard reference trajectories as per the TRMS-330 model.

Conclusion

In this work, the combination of modified nondominated sorting genetic algorithm-based tuning for a nonlinear PID controller design with multiobjective optimization is implemented for a Twin Rotor System. All the parameters of the controller are obtained by the dynamic crowding distance and controlled elitism mechanisms adopted in the proposed algorithm, with the integral square error and control energy

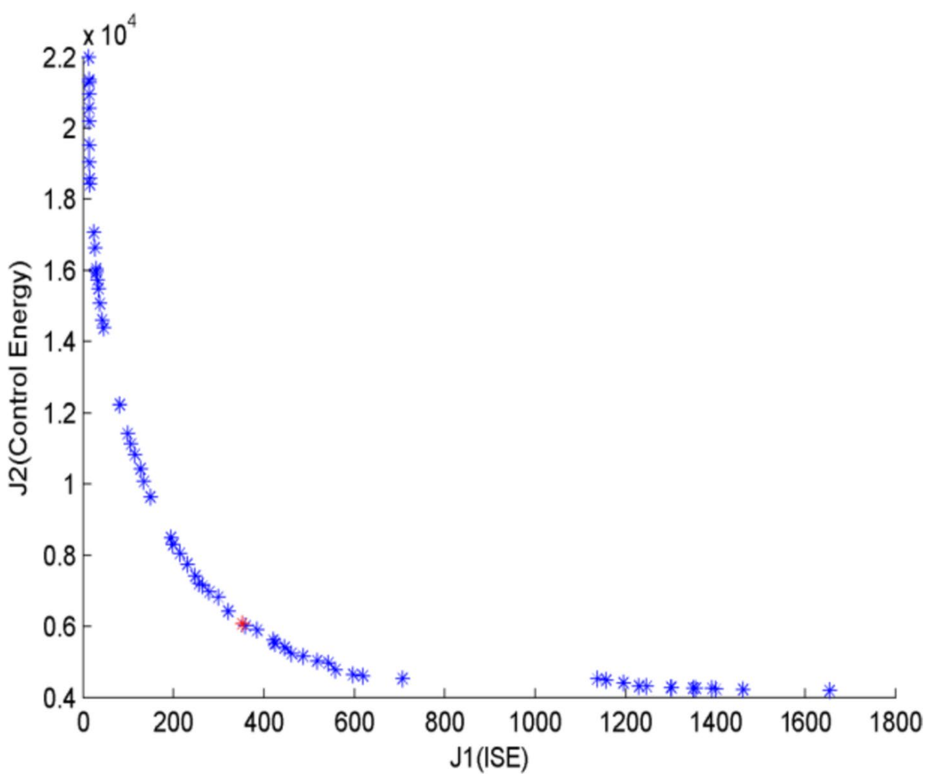

Fig. 3 Pareto front obtained from the NSGA-II algorithm

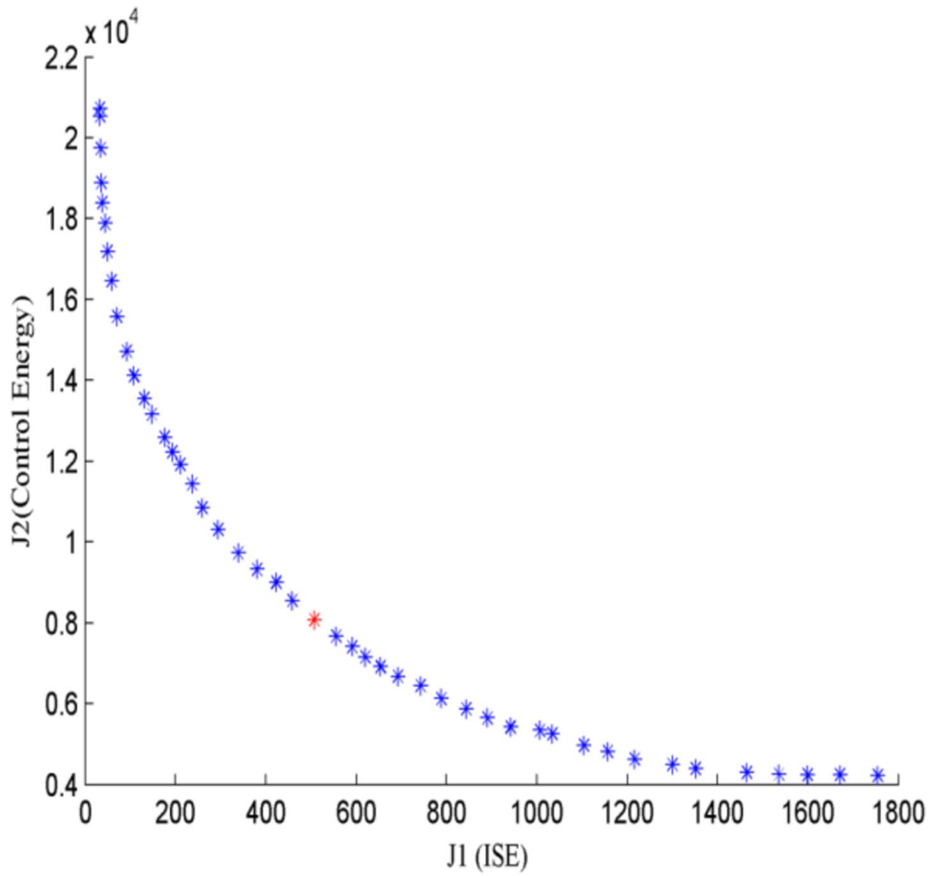

Fig. 4 Pareto front obtained from the MNSGA algorithm

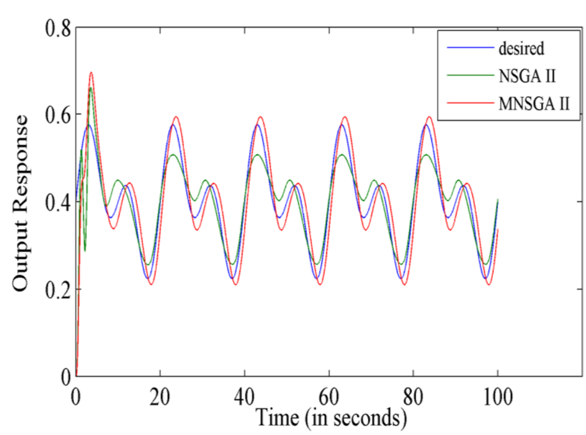

Fig. 5 Pitch/main rotor response of the designed cross-coupled nonlinear PID controller with optimized nonlinear constants

taken as the performance index measures. The proposed work experiments with the control of a Twin Rotor System with two degrees of freedom using a MNSGA-based strategy for tuning the PID parameters. Different from the existing works, the

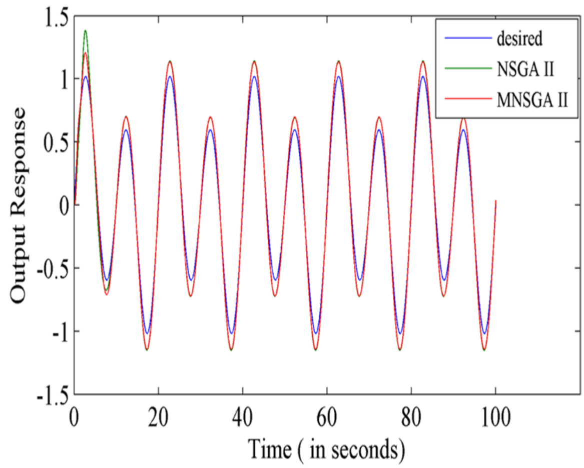

Fig. 6 Yaw/tail rotor response of the designed cross-coupled nonlinear PID controller with optimized nonlinear constants

inclusion of additional constants in the PID controller design has enabled an extra degree of freedom to enhance the system performance in the proposed work. In addition, simultaneous control of both axes is done in this work due to the cross-coupled dynamics involved, which consider the influence of one rotor on the other. This overcomes the drawback of system instability that occurs during the separate control of either axis. The minimization of ISE is taken as the objective function since it integrates the square of the error over time and prohibits larger errors more accurately. Control systems determined to minimize ISE show fast response with acceptable low amplitude oscillation. From the simulation results, it is observed that the innovative control strategy enables the Twin Rotor System to achieve a precise position and track the desired path more competently. The control parameters converge to an appropriate solution rapidly. Thus, the design of an optimal control strategy for the Twin Rotor System beam positioning in a real-time environment is based on the nondominated sorting approach with an accurate controller design is an unaddressed work that is dealt with in this paper. Future research can focus on model predictive controller design to enhance the tuning process.

Abbreviations

CGSA	Chaotic gravitational search algorithm
DCD	Dynamic crowding distance
DSA	Differential search algorithm
EC	Evolutionary computation
EV	Electric vehicle
FOPID	Fractional order PID
FOSTSMC	Fractional order super twisting sliding mode control
HV	Hyper volume
IGD	Inverse generational distance
ISE	Integral square error
LQ	Linear quadratic
MIMO	Multi Input Multi Output
MNGSA	Modified nondominated sorting genetic algorithm
NLPID	Nonlinear PID
NNA	Neural network algorithm
NSGA	Nondominated sorting genetic algorithm
PID	Proportional-integral-derivative
PSO	Particle swarm optimization

RGA-SBX	Real-coded genetic algorithm with simulated binary crossover
STSMC	Super twisting sliding mode control
TRMS	Twin Rotor MIMO System

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Authors' contributions
All the authors contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All the authors have read and approved the manuscript.

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Availability of data and materials
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Declarations

Competing interests
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