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Multi-objective Optimization of PID Controller using Pareto-based Surrogate Modeling Algorithm for MIMO Evaporator System

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ABSTRACT

Most control engineering problems are characterized by several objectives, which have to be satisfied simultaneously. Two widely used methods for finding the optimal solution to such problems are aggregating to a single criterion, and using Pareto-optimal solutions. This paper proposed a Pareto-based Surrogate Modeling Algorithm (PSMA) approach using a combination of Surrogate Modeling (SM) optimization and Pareto-optimal solution to find a fixed-gain, discrete-time Proportional Integral Derivative (PID) controller for a Multi Input Multi Output (MIMO) Forced Circulation Evaporator (FCE) process plant. Experimental results show that a multi-objective, PSMA search was able to give a good approximation to the optimum controller parameters in this case. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) method was also used to optimize the controller parameters and as comparison with PSMA.

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1. INTRODUCTION

In real control engineering world, engineers are often faced to track several objectives simultaneously. Most controllers are needed that provide a fast response, small overshoot, no oscillation and economical control. There are mainly two ways of tackling this problem: aggregating the objectives to a single objective or solving a multi-objective optimization problem using Pareto-based method. Aggregating several objectives into a single objective has the advantage of solving a simpler problem, but on the other hand many design iterations are required to obtain an acceptable compromise. On the other hand, the multi-objective approach is claimed to lead to a set of solutions each of which dominates the others in some sense.

There are several of methods published and widely used to do multi-objective optimization for engineering problem such as NSGA and SPEA that are based on genetic algorithm and evolutionary algorithm. However despite of ability to achieve good optimization results [1], [2], both methods are known to need many function evaluations. In real engineering problem the cost of evaluating design is probably the biggest obstacle that prevents extensive use of optimization procedures. In the multi-objective world, this cost is multiplied, because there are multiple results to obtain. Evaluating directly a finite element model can take several days, which makes is very expensive to try hundreds or thousands design. Thus Pareto-based surrogate modeling algorithm (PSMA) is proposed for the determination of simpler models that involves less computational and gives good approximation results of the complicated model.

Surrogate Modeling (SM) also known as metamodeling or model reduction is said to be a model of a model or an approximation of a model. It is a supplementary model that can be alternatively used to interpret a more detailed model [3]. SM are usually consists of mathematical functions. These are functions with calibrated parameters, which are used as abstractions and simplifications of the simulation model [4]. In computer simulation, a SM is used to substitute a computationally expensive simulation model with a more efficient one. The basic idea of SM is to construct an approximate model using function values at some sampling points, which are typically determined using experimental design methods [5]. A SM exposes the system's input-output relationship through a simple mathematical function [3]. Thus the simulation time for SM is less than that of the actual simulation model.

Recently, as studied in [6], SM had been used to optimize various type of system, included the nonlinear system. Some of the systems that were successfully optimized using the SM technique are the Cartesian Coordinates Control of Hovercraft System [7] and the unmanned underwater vehicle [8], [9]. Through their study, they also had proved that the SM technique can optimize various types of controller parameters, for example, the fuzzy logic controller and the PID controller.

The core of SM is a metamodel that gives the prediction of a system's output. Although the output from metamodel is an approximate of actual measurement of complex model, it gives a good approximate of the actual value. The evaluation of output value is fast and provides enough information during design phase of a system [10]. Examples of metamodel are Radial Basis Functions Neural Networks (RBFNN), Kriging Models (KR), Polynomial Regression (PR), Multivariate Adaptive Regression Splines (MARS), and Support Vector Machines (SVM). In comparison, RBFNN shows a generally better performance. Based on different types of problems (i.e., different orders of nonlinearity and problem scales) it is concluded that RBFNN is the most dependable method in most situations in terms of accuracy and robustness [11]. In this project, a RBFNN was used as the metamodel to approximate the mapping of the controller gains and the objective function.

2. MODELING OF THE SYSTEMS

2.1. Radial Basis Function Neural Network

Radial Basis Function Neural Network (RBFNN) was used as the Metamodel to approximate the mapping of the controller parameters and the objective function. The radial basis functions were first used to design Artificial Neural Networks in 1988 by Broomhead and Lowe [12]. The architecture of the RBF NN used in this work is illustrated in Figure 1.

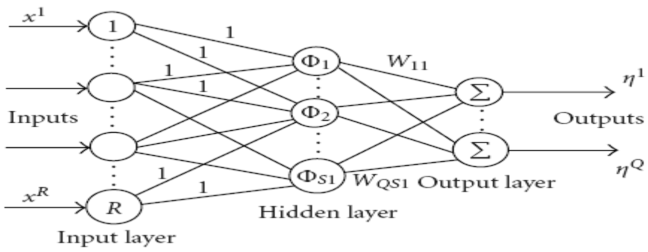


Figure 1. Radial Basis Function Neural Network

The network consists of three layers: an input layer, a hidden layer and an output layer. Here, R denotes the number of inputs while Q the number of outputs. Equation (1) is used to calculate the output of the RBF NN for Q = 1, the output of the RBFNN in Figure 1 is calculated according to

$$\eta(x,w)=\sum_{k=1}^{S1} w_{1k}\phi\left(\left\|x-c_k\right\|\right)_2 \tag{1}$$

Where $x \in \mathbf{R}^{R\times 1}$ is an input vector, $\phi(.)$ is a basis function, $\|.\|_2$ denotes the Euclidean norm, w_{1k} are the weights in the output layer, S1 is the number of neurons (and centers) in the hidden layer and $c_k \in \mathbf{R}^{R\times 1}$ are the RBF centers in the input vector space. Equation (1) can also be written as Equation (2)

$$\eta(x,w)=\phi^T(x)w \tag{2}$$

Where basis function in Equation (3)

$$\phi^T(x)=\left[\phi_1\left(\|x-c_1\|\right)\ldots\phi_{S1}\left(\|x-c_{S1}\|\right)\right] \tag{3}$$

And weight layer in Equation (4)

$$w^T=\left[w_{11}\ w_{12}\ldots w_{1S1}\right] \tag{4}$$

The output of the neuron in a hidden layer is a nonlinear function of the distance given by Equation (5):

$$\phi(x)=e^{-x^2/\beta^2} \tag{5}$$

Where β is the spread parameter of the RBF. For training, the least squares formula was used to find the second layer weights while the centers are set using the available data samples. Thus, the approach of Pareto-based Surrogate Modeling Algorithm (PSMA) for multiobjective optimization as summarized in [6-9] was used in this project.

2.2. Forced Circulation Evaporator

In addition, a metamodeling approach for PID controller in an evaporator process has been successfully presented in [13], [14]. Figure 2 shows the forced circulation evaporator derived by Newell and Lee [15] in 1989. This evaporator has become a well-known and very difficult benchmark used by control engineers to evaluate their methodologies. A feed stream enters the evaporator with concentration X1, temperature T1 and flow rate F1. It will mix with recirculation liquor, which is pumped through the evaporator at flow rate F3. The evaporator itself is a heat exchanger, which is heated by steam flowing at a rate F100, with temperature T100 and pressure P100. The mixture of feed and recirculation liquor boils inside the heat exchanger, and the resulting mixture of vapor and liquid enters the separator, which the liquid level is L2. The operating pressure inside the evaporator is P2. Some portion of liquid from separator drawn out as product with concentrationX2, with flow rate F2 and temperature T2; most of it becomes the recirculation liquor with flow rate F3. The vapor from the separator flow to a condenser at flow rate F4 and temperature T3, where it is condensed by cooled water flowing at flow rate F200, with entry temperature T200 and exit temperature T201.

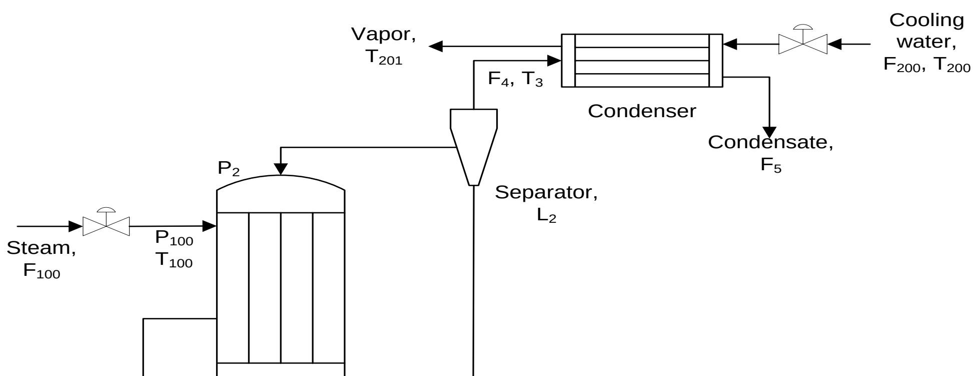


Figure 2. Forced Circulation Evaporator

The constant value and description are shown in Table 1, while the variables names, descriptions, steady state value, and engineering units are shown in Table 2.

Table 1. Constant value and description

Constant	Description	Value	Units
ρA	Liquid density and cross-sectional area of separator	20	kg/m
M	Amount of liquid in the evaporator	20	kg
C	Constant that converts the mass of vapor into an equivalent pressure	4	kg/kPa
C_p	Heat capacity of the liquor	0.07	kg/min
Λ	Latent heat of vaporization of the liquor	38.5	kg/min
λ_s	Latent heat of steam at the saturated conditions	36.6	kg/min
U_{A2}	Overall heat transfer coefficient times the heat transfer area	6.84	kW/K

Table 2. Evaporator variables and steady state value

Variable	Description	Value	Units
F_1	feed flow rate	10.0	kg/min
F_2	product flow rate	2.0	kg/min
F_3	circulation flow rate	50.0	kg/min
F_4	vapor flow rate	8.0	kg/min
F_5	condensate flow rate	8.0	kg/min
X_1	feed composition	5.0	percent
X_2	product composition	25.0	percent
T_1	feed temperature	40.0	deg C
T_2	product temperature	84.6	deg C
T_3	vapor temperature	80.6	deg C
L_2	separator level	1.0	metres
P_2	operating pressure	50.5	kPa
F_{100}	steam flow rate	9.3	kg/min
T_{100}	steam temperature	119.9	deg C
P_{100}	steam pressure	194.7	kPa
Q_{100}	heater duty	339.0	kW
F_{200}	cooling water flow rate	208.0	kg/min
T_{200}	cooling water inlet temperature	25.0	deg C
T_{201}	cooling water outlet temperature	46.1	deg C
Q_{200}	condenser duty	307.9	kW

3. RESEARCH METHOD

Two control variables are chosen out from FCE as objectives function and controlled by using PID controller. The control variables are L2 and P2 with manipulated variables of the plant are F2 and F200. The design objective will be a six parameter optimization problem of determining the optimal parameter gains [Kp1 Ki1 Kd1 Kp2 Ki2 Kd2] to minimize the output of L2 and P2. Table 3 shows parameter coefficient with their range which cover both PID controllers. This range is used in order to obtain a good comparison between PSMA and NSGA-II.

The simulation for both controllers was done using MATLAB SimulinkTM as illustrated in Figure 3. All values were initialized at the operating points as stated in Table 2. Simulation time was set to be 300 seconds and run using ode14x (extrapolation) solver. The set point for P2 is 50.5 kPa over the simulation time while L2 was given a varying step input from initial 1.0m to 2.5m and going down back to 1.0m. Table 4 shows the control variable constraints.

Table 3 PID variables and design space

	Variables					
Limit	K_{p1}	K_{i1}	K_{d1}	K_{p2}	K_{i2}	K_{d2}
Lower	-130	-2	-60	-410	-20	-10
Upper	-100	2	-50	-390	-10	-5

Table 4 Variable constraints

Variable	Lower limit	Upper limit
F_2	0 kg/min	50 kg/min
F_{200}	0 kg/min	400 kg/min

The performance criterion to measure the output tracking in this case was the Integral Square Error (ISE) given by:

$$\text{ISE} = \int (y_d(t) - y(t))^2 \, dt \tag{6}$$

Where y_d is the desired output (set point) while y is the actual output. This criterion has been used because of the ease of computing the integral both analytically and experimentally. The most efficient value of Pareto frontier is defined by calculating Euclidean distance between ISE and initial point, zero:

$$Cost = \sqrt{\sum_{i=1}^{n} (ISE)^2} \tag{7}$$

Figure 3 shows PID Forced Circulation Evaporator as implemented in Matlab® Simulink®.

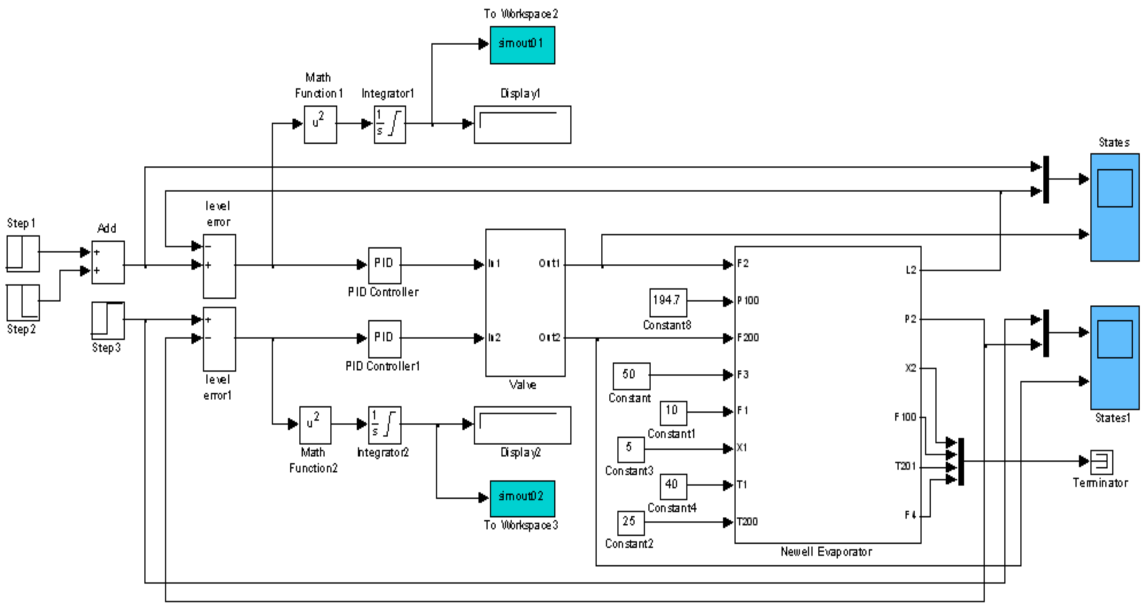


Figure 3. PID Forced Circulation Evaporator as implemented in Matlab® Simulink®

3.1. Pareto based Surrogate Modeling Algorithm

Table 5 show the objective function, initial design space (D) and larger design space (D') used for PSMA simulation.

Table 5. Objective function, initial data sets and large data sets

Objective function	PID Parameter	Initial data sets (*D*)	Large data sets (*D'*)
	K_{p1}	*{-130, -120, -110}*	*{-130, -125,…, -110}*
F2	K_{i1}	*{-2, 0, 2}*	*{-2, -1,…, 2}*
	K_{d1}	*{-60, -55, -50}*	*{-60, -55, -50}*
	K_{p2}	*{-410, -400, -390}*	*{-410, -405,…, -390}*
P2	K_{i2}	*{-20, -15, -10}*	*{-20, -17.5,…, -10}*
	K_{d2}	*{-10, -5}*	*{-10, -7.5, 5}*
Total number of data configurations		486	5625

The step size of D and D' specifically sets by user where D'' use smaller resolution thus multiplies the total number of data configuration. Different with NSGA-II, the value between bound are created randomly. The initial data sets should not too small for proper training and should not be too large to minimize the training time. The initial data sets are used to simulate ISE for both operating pressure P2 and separator level, L2 simultaneously. RBFNN then use ISE value from initial data sets and predict the output for large data sets.

In this PSMA simulation, the basis function centers, c_k is set equal to the input vector from the training set or maximum number of initial data sets, 486. The spread value of 10 is used in the training process. The larger the spread of the data the smoother will be the function approximation. A large spread implies a lot of neuron will be required to fit a fast changing function. Where a small spread is means less neuron will be required to fit a smooth function and the network may not generalize well.

3.2. Non dominated Sorting Geneting Algorithm

The NSGA-II [16] is selected as comparison to PSMA because of widely used and capable algorithm. The principle behind NSGA-II is that the non dominated solution that usually occur for multiobjective optimization problems are all treated as equals. This allows the algorithm to evolve a set of non-dominated solution that is equally well suited for solving the specific problem given the performance measures specified. By using the algorithm for tuning of PID controller for the FCE, it will be possible to obtain varied set of different solution that should perform well with regards to minimization of all specific performance measures. NSGA-II run-time parameters used for this problem are summarized in Table 6.

The choice of real valued representation was made to ensure that the precision of the parameters would not be compromised by a choice of precision, which can happen for binary representation. A crossover probability of 0.9 ensures a good mixing of genetic material and mutation probability can be expressed as

$\frac{1}{n_{param}}$ where n_{param} is the number of parameters in an individual which for this application is six. Simulated binary crossover parameter (SBX) and the mutation parameter were decided to use 20 and 20 respectively since they provide a reasonable distribution of solutions for the different operations.

Table 6. NSGA-II run-time parameters

Representation type	Real values
Crossover probability	0.6
Mutation probability	0.167
SBX parameter	20
Mutation parameter	20
Population	100
Generation	100

4. RESULTS AND ANALYS

4.1. Simulation Result of PSMA

Figure 4 show the simulation result of P2 and L2 using initial data sets with 486 total number of data configurations.

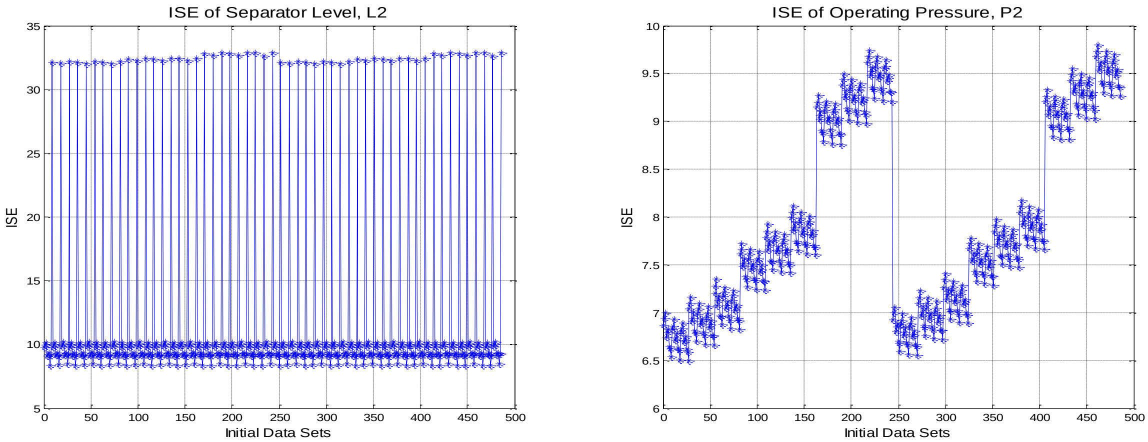


Figure 4. ISE of separator level and operating pressure for initial data sets.

The ISE values are used to train the RBFNN which will then be used as the metamodel of the FCE to evaluate the ISEs for the corresponding large data sets of the controller parameters. The results of RBFNN training using 486 centers and 10 spread are shown in Figure 5.

After the training stage RBFNN is used to perform the simulation for large data space controller parameters sets which consist of 5625 data sets. The result is shown in Figure 6. The estimated ISE for L2 and P2 then plotted into pareto set as in Figure 10. The pareto-optimal frontier marked with blue circle. Since the both objective function to find minimum value, the closest to origin indicates the most efficient value, represented by green triangle in the figure. Although the most efficient value predicted by RFBNN (5.417 for L2 and 6.744 for P2) is not same with real simulation, PSMA was able to give minimum coefficient parameter as in Table 5.

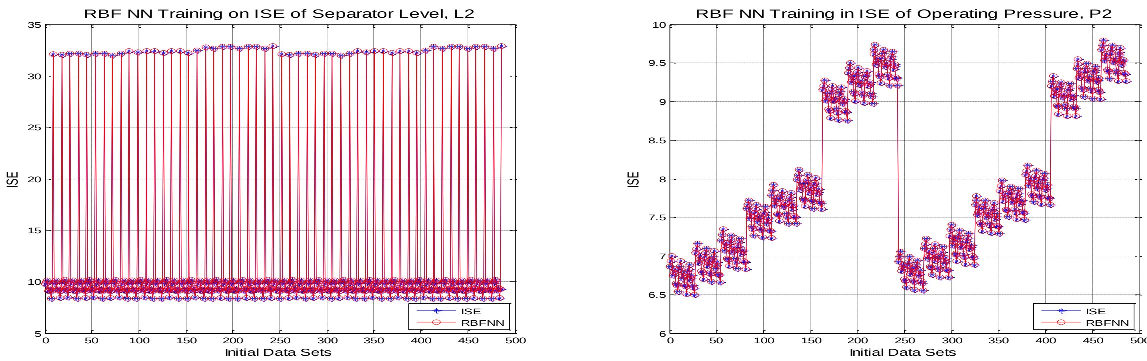


Figure 5. RBFNN training of ISE of initial data sets

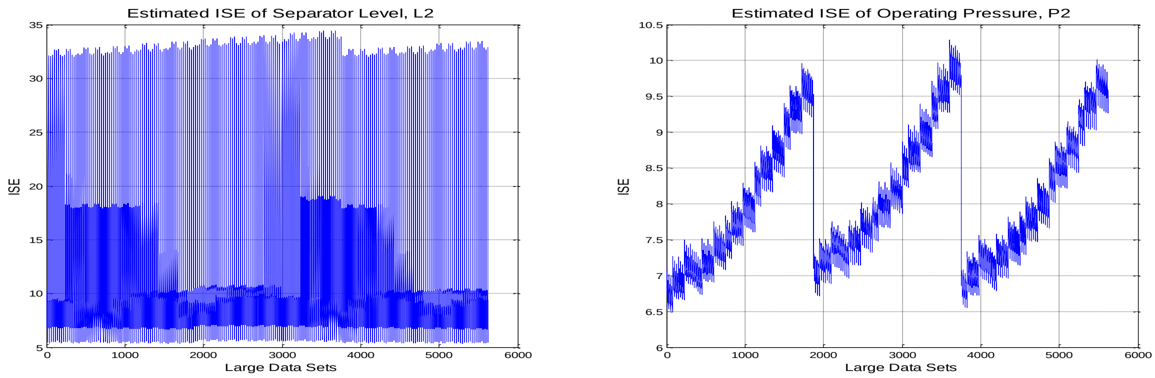


Figure 6. Surrogate modeling output for large data sets of L2 and P2

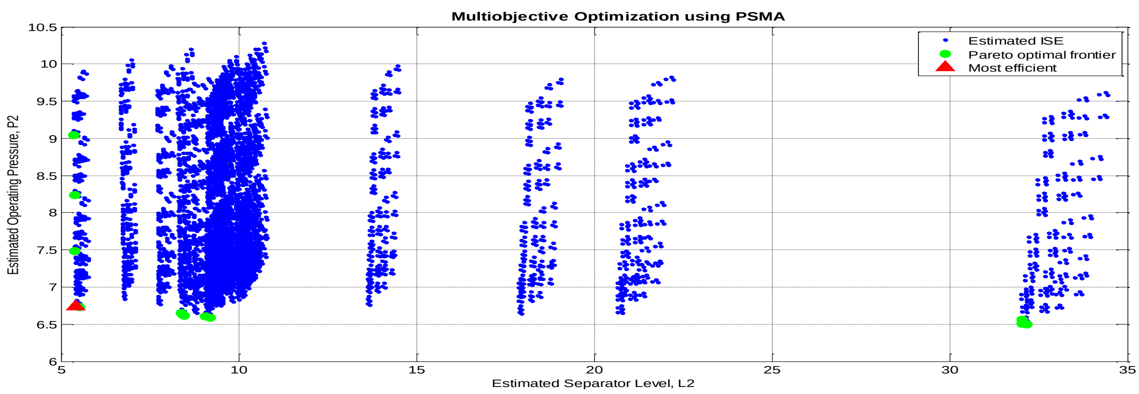


Figure 7. Plot of Pareto optimal frontier for L2 and P2 using PSMA

4.1. Simulation Result of NSGA-II

As comparison to PSMA, Figure 8 show the Pareto set of NSGA-II optimization. Most efficient value marked with green triangle.

Parameters of PID controller and their relevant cost values obtained by PSMA and NSGA-II approach are demonstrated in Table 7. From the simulation results in Table 8, the parameter controller obtained by PSMA clearly has better performance than NSGA-II. The ISE value obtained by PSMA for both outputs, L2 and P2 is lower than using NSGA-II. The PSMA simulation time took only 1.52 minutes compare to NSGA-II, 23.36 minutes. In general the controller obtained by PSMA has the best performance. The result in Table VIII shows the ability of PSMA in dealing with challenging optimization problems.

Figure 9 shows the response of controlled FCE to step input using different controllers obtained by PSMA and NSGA-II.

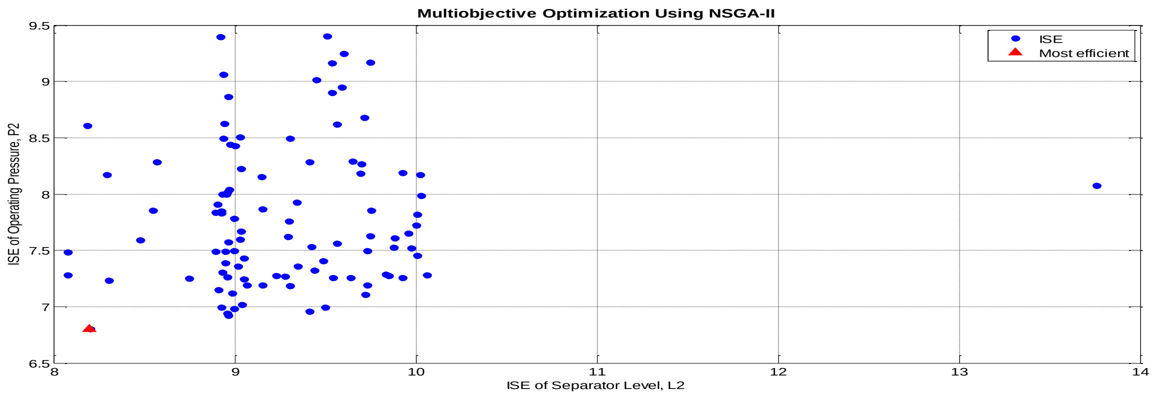


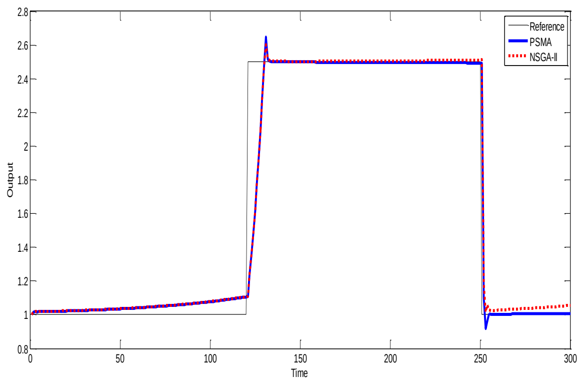
Figure 8 Plot of Pareto optimal frontiers for L2 and P2 using NSGA-II

Table 7. Parameter of PID controller obtained by PSMA and NSGA-II

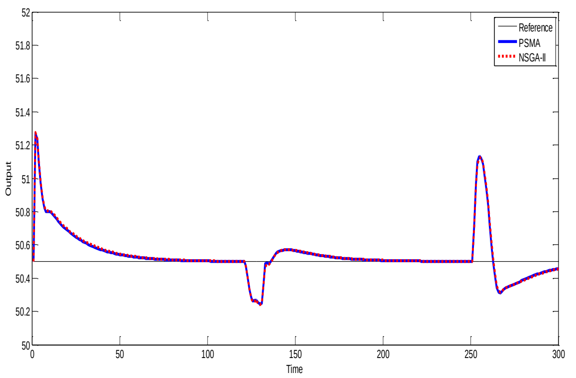
	Method	
PID Parameters	PSMA	NSGA-II
K_{p1}	-125	-119.66
K_{i1}	2	1.89
K_{d1}	-55	-59.05
K_{p2}	-410	-405.61
K_{i2}	-20	-19.14
K_{d2}	-10	-9.61

Table 8. ISE, Cost and simulation time by PSMA and NSGA-II

	Method	
Criteria	PSMA	NSGA-II
ISE for $L2$	8.041	8.187
ISE for $P2$	6.618	6.801
Cost	10.410	10.640
Simulation time (min)	1.520	23.360



(a)



(b)

Figure 9 (a) Response of separator level, L2. (b) Response of operating pressure, P2

The controllers gave a good response for separator Level, L2. In Figure 9(a) the settling time by using PSMA parameter is slightly better than NSGA-II. It can be seen at second 250 when step input changed to set point 1m, PSMA respond reach steady state until second 300. For operating pressure, P2, response obtained by NSGA-II and PSMA parameter almost identical. This condition occurs because the parameter gains, Kp2 Ki2 Kd2 of both optimization technique almost the same.

Similar to other optimization algorithm such as SPEA, NSGA, the discussed method in this paper, PSMA does not necessarily guarantee the real time requirements in exact applications. But as shown in this paper, PSMA was able to give fast computational time to obtain best value for the controller. In application of high computational complexity, the use of PSMA will be more preferable.

5. CONCLUSION

The purposed optimization method using PSMA offers advantages at especially reducing the cost and time by utilizing surrogate modeling for complex and expensive design. The genetic algorithm based optimization required large number of objective function evaluation to generate Pareto-optimal front. Therefore the evaluation of the required number of objective function values through a full model experiment. In this study NSGA-II took around 15 times simulation time to optimize the operating pressure and separator level of FCE whereas PSMA training and testing takes couple of minutes depending upon the user's experience and prediction through surrogate modeling. The PSMA approach us clearly a useful approach and this will become more significant for a larger D of for a more complicated problem.

Using FCE as a study case, PSMA used to optimize the parameter gain of PID controller. Surrogate modeling does provide the designer with a quick estimate for a good set of good parameter to begin with. Further simulation on the actual system can be done if better values are required. In this example, the data set D was created by choosing the input values like the grid fashion based on background knowledge of the problem. A more intuitive approach is to start with a small number of samples and then sequentially add more data samples intelligently employing Experimental Design techniques such as Worst Case Approach and Cross Validation technique. It is envisaged that a more strategic data location will allow the creation of a more accurate surrogate modeling using less data, therefore, less time required to estimate the best controller parameters.

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REFERENCES

[1] Obayashi S, Jeong S, Chiba K. *"Multi-Objective Design Exploration tor Aerodynamic Configurations"*. In 35th AIAA fluid dynamics conference and exhibit 2005 Jun (p. 4666).

[2] Zitzler E, Deb K, Thiele L. "Comparison of Multiobjective Evolutionary Algorithms: Empirical Results". *Evolutionary Computation*. 2000;8(2):173-95.

[3] Ma L, Xin K, Liu S. "Using Radial Basis Function Neural Networks to Calibrate Water Quality Model". World Academy of Science, Engineering and Technology, *International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering*. 2008 Feb 25;2(2):9-17.

[4] Santos IR, Santos PR. *"Simulation Metamodels for Modeling Output Distribution Parameters"*. In Winter Simulation Conference, 2007 Dec 9 (pp. 910-918). IEEE.

[5] Kleijnen JP, Sargent RG. "A Methodology for Fitting and Validating Metamodels in Simulation". *European Journal of Operational Research.* 2000 Jan 1;120(1):14-29.

[6] M.S. Mohamed Ali, SS Abdullah, Osman David C. "Controllers Optimization For A Fluid Mixing System Using Metamodelling Approach". *International Journal of Simulation Modelling*. 2009 Mar 1;8(1):48-59.

[7] M.S. Mohamed Ali, S.S. Abdullah, M.A. Ahmad and N. Hambali, *"Optimization of PID Controllers for Cartesian Coordinates Control of Hovercraft System Using Metamodeling Approach"*, Proceedings of the International Conference on Power Control and Optimization, Chiang Mai, Thailand, July 18-20, 2008.

[8] M. F. N. Shah, S. S. Abdullah, and Faruq, A., *"Multi-objective optimization of remotely operated vehicle control system using surrogate modeling"* in IEEE International Conference on Control System, Computing and Egineering (ICCSCE), 2011, pp. 138-143.

[9] Faruq A, Abdullah SS, Fauzi M, Nor S. *"Optimization Of Depth Control For Unmanned Underwater Vehicle Using Surrogate Modeling Technique"*. In Modeling, Simulation and Applied Optimization (ICMSAO), 2011 4th

International Conference on 2011 Apr 19 (pp. 1-7). IEEE.
[10] S. S. Abdullah & J. C. Allwright, "An Active Learning Approach For Radial Basis Function Neural Networks", *Jurnal Teknologi*, 45(D) Dec. 2006: 77–96, Universiti Teknologi Malaysia.
[11] Jin R, Chen W, Simpson TW. "Comparative Studies Of Metamodelling Techniques Under Multiple Modelling Criteria". *Structural And Multidisciplinary Optimization*. 2001 Dec 1;23(1):1-3.
[12] Broomhead, D. S. and Lowe D. "Multi-Variable Functional Interpolation And Adaptive Networks". *Complex Systems*.;2:321-55.
[13] M. F. N. Shah, Zainal MA, Faruq A, SS Abdullah. "Metamodeling Approach For PID Controller Optimization In An Evaporator Process". *IEEE In Modeling, Simulation and Applied Optimization (ICMSAO),* 2011 4th International Conference on 2011 Apr 19 (pp. 1-4).
[14] M. F. N. Shah, S. S. Abdullah, and Faruq, A., "Multi-objective optimization of an evaporator control system using surrogate modeling" in *IEEE International Conference on Control System, Computing and Egineering (ICCSCE)*, 2011, pp. 198–203.
[15] Newell, R. B. and Lee, P. L., "Applied Process Control: A Case Study", Process Control Group Department of Chemical Engineering University of Queensland, Australia, Prentice Hall, 1989.
[16] Deb K, Pratap A, Agarwal S, Meyarivan TA. "A Fast And Elitist Multiobjective Genetic Algorithm: NSGA-II". *IEEE Transactions On Evolutionary Computation*. 2002 Apr;6(2):182-97.

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