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

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Article Info

Article history:
Received Jun 5, 2017
Revised Oct 24, 2017
Accepted Nov 8, 2017

Keyword:
MIMO evaporator
Multi-objective Optimization
PID controller
Surrogate modeling

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.

Journal homepage: http://iaescore.com/journals/index.php/IJECE
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](image)

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

\[ \eta(x, w) = \sum_{k=1}^{S_1} W_{1k} \phi(||x - c_k||) \]

(1)

Where \( x \in \mathbb{R}^{R\times1} \) is an input vector, \( \phi(\cdot) \) is a basis function, \( ||\cdot||_2 \) denotes the Euclidean norm, \( W_{1k} \) are the weights in the output layer, \( S_1 \) is the number of neurons (and centers) in the hidden layer and \( c_k \in \mathbb{R}^{R\times1} \) are the RBF centers in the input vector space. Equation (1) can also be written as Equation (2)
\[ \eta(x, w) = \phi^T(x)w \]  \hspace{1cm} (2)

Where basis function in Equation (3)

\[ \phi^T(x) = \left[ \phi_1 \left( \|x - c_1\| \right) \ldots \phi_{S_1} \left( \|x - c_{S_1}\| \right) \right] \]  \hspace{1cm} (3)

And weight layer in Equation (4)

\[ w^T = [w_{i1} \ w_{i2} \ldots \ w_{iS_1}] \]  \hspace{1cm} (4)

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

\[ \phi(x) = e^{-x^2/\beta^2} \]  \hspace{1cm} (5)

Where \( \beta \) 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 \( X_1 \), temperature \( T_1 \) and flow rate \( F_1 \). It will mix with recirculation liquor, which is pumped through the evaporator at flow rate \( F_3 \). The evaporator itself is a heat exchanger, which is heated by steam flowing at a rate \( F_{100} \), with temperature \( T_{100} \) and pressure \( P_{100} \). 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 \( L_2 \). The operating pressure inside the evaporator is \( P_2 \). Some portion of liquid from separator drawn out as product with concentration \( X_2 \), with flow rate \( F_2 \) and temperature \( T_2 \); most of it becomes the recirculation liquor with flow rate \( F_3 \). The vapor from the separator flow to a condenser at flow rate \( F_4 \) and temperature \( T_3 \), where it is condensed by cooled water flowing at flow rate \( F_{200} \), with entry temperature \( T_{200} \) and exit temperature \( T_{201} \).

![Figure 2. Forced Circulation Evaporator](image-url)
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  |
|----------|--------------------------------------------------|-------|--------|
| $\rho_A$ | Liquid density and cross-sectional area of separator | 20    | kg/m   |
| $M$      | Amount of liquid in the evaporator                | 20    | kg     |
| $C_p$, $C_p'$ | Heat capacity of the liquor                     | 4     | kg/kPa |
| $A$      | Latent heat of vaporization of the liquor         | 38.5  | kg/min |
| $\lambda_s$ | Latent heat of steam at the saturated conditions | 36.6  | kg/min |
| $U_{as}$ | 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   |
| $T_2$   | vapor temperature            | 84.6  | deg C   |
| $T_3$   | separator level              | 1.0   | metres  |
| $P_1$   | operating pressure           | 50.5  | kPa     |
| $F_{200}$ | steam flow rate             | 9.3   | kg/min  |
| $T_{100}$ | steam temperature           | 119.9 | deg C   |
| $P_{100}$ | steam pressure               | 194.7 | kPa     |
| $Q_{200}$ | 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      |

### Table 3 PID variables and design space

| Variables | Lower limit | Upper limit |
|-----------|-------------|-------------|
| $K_{p1}$, $K_{i1}$, $K_{d1}$ | -130 | 0  |
| $K_{p2}$, $K_{i2}$, $K_{d2}$ | -10 | 50 |

### Table 4 Variable constraints

| Variable | Lower limit | Upper limit |
|----------|-------------|-------------|
| $F_1$   | 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:

\[
ISE = \int (y_d(t) - y(t))^2 \, dt
\]  

(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:

\[
Cost = \sqrt{\sum_{i=1}^{n} (ISE)^2}
\]  

(7)

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

![PID Forced Circulation Evaporator](image)

3.1. Pareto based Surrogate Modeling Algorithm

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

| Objective function | PID Parameter | Initial data sets (D) | Large data sets (D’) |
|--------------------|---------------|-----------------------|----------------------|
| F2                 | \( K_{p1} \)  | \([-130, -120, -110]\) | \([-130, -125, ..., -110]\) |
|                    | \( K_{i1} \)  | \([-2, 0, 2]\)        | \([-2, -1, ..., 2]\)       |
|                    | \( K_{d1} \)  | \([-66, -55, -50]\)  | \([-60, -55, -50]\)      |
| P2                 | \( K_{p2} \)  | \([-410, -400, -390]\) | \([-410, -405, ..., -390]\) |
|                    | \( K_{i2} \)  | \([-20, -15, -10]\)  | \([-20, -17.5, ..., -10]\) |
|                    | \( K_{d2} \)  | \([-10, -5]\)        | \([-10, -7.5, 5]\)       |

Total number of data configurations: 486

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 | Real values |
|--------------------------------------|-------------|
| 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 ANALYSIS
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.](image)
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.
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](image)

![Table 7. Parameter of PID controller obtained by PSMA and NSGA-II](table)

![Table 8. ISE, Cost and simulation time by PSMA and NSGA-II](table)

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

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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.

ACKNOWLEDGEMENTS

This project is supporting by Ministry of Science, Technology and Innovation (MOSTI) e-Science Fund Research Grant. Special thanks to Faculty of Electrical Engineering, Universiti Teknologi Malaysia (UTM), also Electrical Department University Muhammadiyah of Malang (UMM) for giving full support and cooperation. Also warmest thanks to research and development centre of UTM. Their supports are gratefully acknowledged.

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