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# Optimizing the Double Inverted Pendulums Performance via the Uniform Neuro Multiobjective Genetic Algorithm

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**Abstract:** An inverted pendulum is a sensitive system of highly coupled parameters; in laboratories, it is popular for modelling nonlinear systems such as mechanisms and control systems, and also for optimizing programmes before those programmes are applied in real situations. This study aimed to find the optimum input setting for a double inverted pendulum (DIP), which requires the appropriate input to be able to stand and to achieve robust stability even when the system model is unknown. Such a DIP input could be widely applied in engineering fields for optimizing unclear systems on a limited budget. Previous studies have used various mathematical approaches to optimize settings for DIP, then have assigned control algorithms or physical mathematical models. This study did not adopt a mathematical approach for the DIP controller because our DIP has five input parameters within its nondeterministic system model. This paper proposes a novel algorithm, named UniNeuro, that integrates neural networks (NNs) and a uniform design (UD) in a model formed by input and response to the experimental data (metamodel). We employed a hybrid UD multiobjective genetic algorithm (HUDMOGA) for obtaining the optimized setting input parameters. The UD was also embedded in the HUDMOGA for enriching the solution set, whereas each chromosome used for crossover, mutation, and generation of the UD was determined through a selection procedure and derived individually. Subsequently, we combined the Euclidean distance and Pareto front to improve the performance of the algorithm. Finally, DIP equipment was used to confirm the settings. The proposed algorithm can produce 9 alternative configured input parameter values for standing and robust stability of the DIP from only 25 training data items and 20 optimized simulation results. In comparison to the full factorial design, this design can save considerable experiment time because the metamodel can be formed by only 25 experiments using the UD. Furthermore, the proposed algorithm can be applied in nonlinear systems with multiple constraints.

**Keywords:** Double Inverted Pendulum, UniNeuro-HUDMOGA, Uniform Design, Metamodel, Euclidean distance.

## 1 Introduction

In accordance with improvements in the industrial system, Industry-4.0 has recently exhibited rapid growth in industry, and has evolved from using traditional production technologies to integrating automation and data exchange, as well as mechanical, electronic, and manufacturing technologies, thereby bringing together cyber-physical systems and the Internet of services. For this reason, robotics and automation technologies continue to be developed to support these systems.

In addition to its complexity and because of the consequence of multiple connections between several components, a typical automation system has control properties that are nonlinear and cannot be neglected. Furthermore, simple individual systems are highly coupled with others. In the event that an intangible mechanism is also required to control a nonlinear system to satisfy the requirements of the situation, the output quality can be improved<sup>[1]</sup>. Nonlinear systems have been applied in various domains; for example, almost all robotic mechanisms use nonlinear control.

Solving nonlinear systems is a challenge, but sensitivity engendered by high-frequency pulse signals for use in mechatronic systems enables the adoption of a model with conditions similar to those of complex real problems within a utopian system, such as unlimited uncontrolled noise within the system itself. The predictive model has attracted attention. The model formed by the input and output of the experimental data (metamodel) in this study originated as a popular solver bridge used for unknown models or noise; it was adapted to become an adaptive optimization controller that can use a flexible model<sup>[2,3]</sup>.

Nonlinearity and physical phenomena are strongly connected; one can argue that nonlinearity is ubiquitous; for example, fluid phenomena, dynamism, elasticity, relativity, combustion, heat transfer, and thermodynamics are all approached by nonlinear equations, except for quantum mechanics. With this attention, research in this field has recently grown dramatically, mostly in the form of analysing all aspects, concepts, and applications of nonlinearity on both the micro and the macro scales. Understanding nonlinearity requires an understanding of the basic concept of linearity as the simplest point of access for an ideal system, even in purely theoretical terms. By contrast, when such a system is already known as a linear regime, it faces nonlinearity as a perturbation of itself<sup>[4]</sup>.

The inverted pendulum is a classic model that is typically strongly coupled, contains multiple variables, and has been

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used in many previous studies regarding nonlinear control systems to validate control theory. A consequence of the nonlinear system is that even if the model is determined, any controlled disturbance may modify the main model. The inverted pendulum system implies a highly nonlinear and unstable device because it is easily influenced by both elements within the system and by outside interference. The two types of inverted pendulum based on cart movement are the rotary and horizontal types. Moreover, single-link and multiple-link types exist. According to various preliminary stages, the inverted pendulum can be controlled in two states: swing-up, which uses the control energy in the pendulum to swing into an upward position; and balancing, which controls the stable position of the pendulum [5].

Some previous studies on DIP optimization have used a formulation control system as the fitness function. Liu *et al.* [6] optimized the parameters for evaluating preferences for the DIP using a genetic algorithm (EPGA). This approach adopts the traditional genetic algorithm (GA); however, search solutions are not improved by limited searches with Pareto dominance. The EPGA sensory-motor intelligent schema approach is used to control and optimize the DIP. A coded number is used as a chromosome that is optimized to find the most favourable setting for 16 parameters. In another study, Liu *et al.* [5] used simulation for the design of the DIP controller. A human-simulated intelligent control method was used as an approach controller that was applied in four-phase control positions. An inequalities-based multiobjective GA (MOGA) was used to determine the displacement over the rail boundary, the number of swings, settling time, overshoot of the total energy, and control effort (multiobjective). Finally, the chromosome was applied in the form of real number coding with 16 parameters. Other researchers have used MATLAB-Simulink for modelling the inverted pendulum [7], and as well as the dynamic web for presenting the inverted pendulum to model unstable systems [8].

A fuzzy GA with six weighted parameters and multiple inputsingle output was employed to optimize DIP parameters. Weighting decreased the number of parameters from six to two, thus reducing the degree of fuzzy logic [9]. A linear quadratic regulator was used to control the stabilisation of the DIP. Jacobian, Eulerian, and Lagrangian methods were used in the linearisation procedure. The mathematical modelling of the present study used Lagrangian decomposition of kinetic energy and potential energy to determine a feedback value composed of six parameters [10]. In Internet-based Java simulations, the DIP controlled a decoupled sliding mode controller with multiobjective particle swarm optimization [11]. Furthermore, a spherical inverted pendulum was studied [49] improve the solutions for standing up to control from the output regulation. The spherical inverted pendulum was employed by using an NN approach for forming the new model [12]. [41]

This study used the DIP of a horizontally-moving cart; the cart was driven by a servo motor that produced rotary movement that was converted to horizontal movement through a double link belt mechanism. Five-parameter input was processed in a signal controlling unit, which was affected by the control pulse input on a servo motor. That motor was influenced by 3 feedback signals from the de-

coder when the mathematical control system was unknown. This condition occurred when utilisation time had elapsed and the system configuration had changed from its initial condition. In accordance with this, the main objective of this study was to determine several new feasible optimal input settings for the DIP. Although this problem can be solved [17] by traditional methods; parameter input value settings were performed by time-consuming trial-and-error repetition, and were tuned on the basis of instinct and intuition. The present paper explains how UniNeuro-HUDMOGA can optimize the input DIP control settings automatically. In this case, the UD was employed to capture training data from the UD NN (UniNeuro), and the HUDMOGA was used to generate the optimized parameter settings. [34]

The remainder of this paper is organised as follows: Chapter 2 discusses the scope of the problem. The proposed method is described in detail in Chapter 3. The results and a discussion are presented in Chapter 4. A conclusion is offered in Chapter 5, and references are listed in the bibliography.

## 2 Problem definition

An inverted pendulum is an underactuated instrument with an unstable open loop within a highly dynamic nonlinear system; thus, it is a perfect system for arrangement [48] of both classical and advanced controls. This approach can be applied to a wide range of signal control processes such as robotic processes, or even rocket field processes. The system was initially proposed for modelling such nonlinear phenomena, because the condition of a linear controller is unstable. Because of highly coupled interactions, the nonlinear effect cannot be neglected within the systems response, thus it is useful for producing nonlinear modern control [14].

In an inverted pendulum, the objective equilibrium point is its straightening stability. This condition occurs through the control of such parameters that produce the cart movement of swinging the pendulum from a dead position into a standing position. Meanwhile, the cart movement is controlled in a particular position because of limitations of the rail length. All mentioned conditions are achieved through horizontal movement of the cart; hence [40] the inverted pendulum is classified as an underactuated mechanical system with fewer control inputs than degrees of freedom. This status proves that this classical system has the ability to evaluate all control strategies [14].

This paper explains the optimization of the five DIP input parameters that changed from the initial condition because of elapsed utilisation time. The initial model of the system changed in an undetermined fashion, causing difficulty in controlling the DIP using the standard equipment settings. This problem became more complex because a large amount of information within the product was lost; thus, conducting this study was similar to conducting blind optimization. In a real setting with a limited budget, engineers must optimize the frequency of an unclear model with similarly blind optimization.

The cart of the DIP system is driven horizontally by a servo motor that couples a frictionless link and a belt mechanism used for conversion from a rotary movement to a hor-

horizontal movement. The motors amplifier is used to amplify the input signal combined with signals from three encoders for controlling the rotation action of the motor; the motors action is processed by a digital signal processor (DSP). The three encoders serve to capture the reaction of the motor and the pendulum motion, and subsequently deliver the feedback signal to the DSP. Three decoders are placed at three points. The first point is in the motor; this decoder is used for detecting the reaction of the motor to its input. The second decoder is positioned on a joint between the cart and pendulum 1, and the third is mounted in a joint between pendulums 1 and 2. These two left decoder services serve to identify the movement of the pendulum in each joint.

The movement of the pendulum is a rotary swinging motion caused by inert horizontal relative movement of the cart coupled with the effect of the feedback signals from the aforementioned three decoders. The enumerated reaction to the decoder motion is displayed on three curves, called displacement, velocity, and output signal. Finally, for securing and limiting the motion of the cart, two limit switches are placed on each side. To visualise the principle of the DIP, Figs. 1 and 2 show the DIP controlling system and mechanism, respectively.

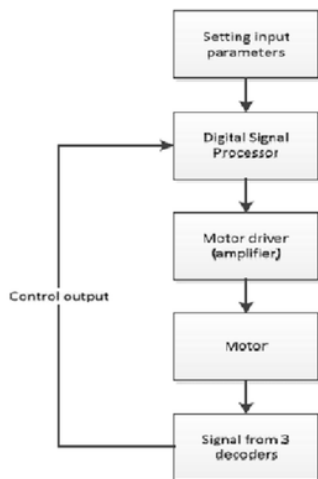


Fig. 1 DIP's controlling system

Table 1 shows the DIP specifications, including mass, dimensions, moving coefficient, and moment.

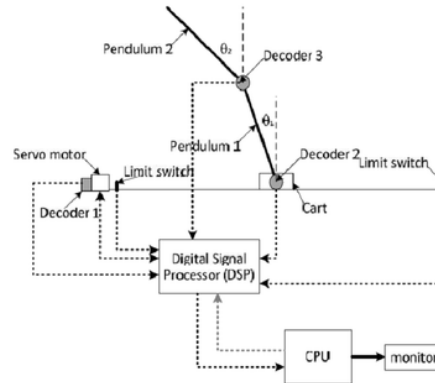


Fig. 2 DIP's mechanism

Table 1 DIP specification

Parameters	Value
17 parameters	
Mass of cart (M)	32kg
Mass of encoders ( $m_0$ )	0.208kg
Center length of each pendulums ( $l_1, l_2$ )	0.2m
Length of each pendulums (L)	0.8 m
Displacement range of cart (x)	(-0.3,0.3) m
M of each pendulums ( $m_1, m_2$ )	0.108 kg
Friction coefficient of cart ( $f_0$ )	22.915 N.s/m
Friction coefficient of pendulums ( $f_1, f_2$ )	0.7756N.s.m
Moment of inertia of pendulums ( $J_1, J_2$ )	0.00144 kg.m <sup>2</sup>

Five input parameters are employed to control the DIP system, which has a tiny step ( $10^{-4}$ ) numerical setting that affects its sensitivity (Table 2). Therefore, a powerful method is required to determine the feasible combination values.

Table 2 DIP's parameters input

Input parameters	Lower bound	Upper bound
A. Initial acceleration	0.4	0.9
B. Feedback coefficient direction	2.0	2.5
C. Negative feedback coefficient direction	2.0	2.5
D. Pull acceleration	5.0	7.0

In response to the aforementioned problem, this study aimed to determine suitable input parameter settings for the DIP for driving the pendulum to stand up and maintain stability for a certain period, during which the external pendulum may be subjected to disturbances while the relationship between the five input parameters is unknown. Thus, in this paper, the UniNeuro-HUDMOGA is proposed.

### 3 Uniform Neuro Multi-objective Genetic Algorithm

The proposed method combines the UD, NNs, and MOGA. Principally, the model for the fitness function of the MOGA programme is created by NNs using the UD

to manage the number of experiments for the developing model. The complete procedure is explained below:

### 3.1 Assemble data using UD

Various experimental designs have been developed to minimize the number of experiments for obtaining a result close to the optimal solution within the full factorial scope, or through a selected number of samples that represent the whole population [15, 16]. The number of experiments had to be reduced in consideration of the costs; for example, to examine  $s$  parameters with six levels,  $6^s$  experiments traditionally using the full factorial design are required. With the advancement of the experimental design method, the experiments can be reduced to  $6^2$  or even less; however, the result manages to come close to the most favourable result using the full factorial design. Some researchers have attempted to develop evolutionary experimental designs for reducing the number of samples by fractions of full factorials, such as the central composite design, hypercube, and orthogonal arrays that developed into Taguchi optimization and the UD [15, 17].

In this study, the UD was used for determining sample data for developing a model in an NN (UniNeuro) through the training data; the result was embedded in a GA to increase searching performance.

Using the UD, the number of experiments can be decreased considerably from the result of the complete full factorial design because the UD is a space filling design that seeks a point that can be randomly positioned in the domain. Furthermore, the UD can explore the relationships between the underlying model specifications. By using the UD to consider the patterns of the even data spread and uniform density, the training sample data represents the true model of the system.

The UD was developed by Fang and Yang. Following development, they published their research online, and made the UD open access and easily downloadable (<http://www.math.hkbu.edu.hk/UniformDesign/>) (UD-web) [17, 18]. The UD-web provides a high number of appraisals for a UD with three classifications for discrepancy of uniformity, as well as 2 – 29 parameters, enabling each design to be applied to an  $n+1$  parameter experiment. Optionally, if the UD-web is not appropriate to the problem, the UD can be developed flexibly using the uniformity of an experimental design with  $L_2$ -centered discrepancy (CD), which can be calculated using (1):

Where  $s$ : number of parameters,  $n$ : number of experiments,  $k$ : rows number,  $j$ : columns number,  $i$ : parameter's number. The better UD has the smaller CD value that concludes its uniformity quality.

Using CD criteria, we can develop a new suitable UD; for example, we can initially use a Latin square design as the base structure, and then optimize it through an optimization design with a smaller, more favourable CD as the fitness criterion [17, 18].

For a study that only requires five parameters, the UD website can be sufficient if the following steps are followed:

1. Determine the number of parameters by considering the level of each parameter. The experiment has a minimum number of parameters + 1 ( $n + 1$ ), and the

total level is equal to the number of experiments.

2. Select the appropriate table from UD-web for use in the experiment. In this case we selected  $5^2$  experiments.

Table 3 shows the UD table from UD-web for five parameters with six experiments. The number of rows represents the number of experiments performed, and the number of columns denotes the number of parameters (A, B, C, D, E).

Table 3 UD's table of five parameters

Run	A	B	C	D	E
1	3	1	6	5	4
2	5	2	2	2	5
3	6	5	3	6	3
4	4	4	5	1	1
5	2	6	4	3	6
6	1	3	1	4	2

This study used a UD table for five parameters, with 25 experiments researched. The UD table was used for data collection. Each parameter was evenly divided into a number of levels from the lowest level to the highest level. Subsequently, each parameter was used for data retrieval objectives for standing and stability while standing. Standing success offered a score of 0 to 1 through observation, and seconds were employed as the unit of duration for stability while standing. The standing measurement was performed with some external excitation from pendulum 2.

### 3.2 Uniform Design embedded in Neural Network

An NN uses interpolation of the input/output data layer through a neural mechanism for developing a model of the model (metamodel) as the approach model, and the amount of training data for determining the data distribution is one of the main factors of the NNs success. An NN that processes large quantities of data tends to yield an accurate prediction for gain time consumption; hence, several researchers have focused on the critical issue of determining the efficiency of training data [19]. Therefore, to enrich the quality of the model by conducting an appropriate number of experiments, in this study, the UD was used to determine the number of setting experiments for training data. Finally, the NN introduced the model by calculating the distribution of the weighted learning rate and the deviation for each point neuron using the sigmoid linear approach [19]. There is no fixed rule for building the connections in the NN or for determining the approach procedure. Moreover, as a prediction method, the NNs forecasting should be controlled to avoid overfitting or excessive confidence. Therefore, the UD was used in this study to distribute the collection of data uniformly with a small number of experiments; UD also generated the potential data that had primary effects for building a metamodel of the NN. This is named UniNeuro.

Before assignment into the NN, the data result from the experiment requires normalisation through (2):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

$$CD = \left(\frac{13}{12}\right)^2 - \frac{2}{n} \sum_{k=1}^n \prod_{j=1}^i \left[ 1 + \frac{1}{2} |x_k - 0.5| + \frac{1}{2} |x_j - 0.5| - \frac{1}{2} |x_k - x_j| \right] + \frac{1}{n^2} \sum_{k=1}^n \sum_{j=1}^i \prod_{l=1}^i \left[ 1 + \frac{1}{2} |x_k - 0.5| + \frac{1}{2} |x_j - 0.5| - \frac{1}{2} |x_k - x_j| \right] \dots (1)$$

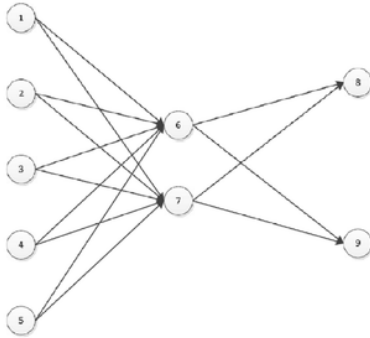


Fig. 3 Neuralnetwork schema

Where:  $x_{norm}$  is a value that has been normalized on this parameter.  $x$  is the value of data in each experimental run.  $x_{max}$  and  $x_{min}$  are the maximum and minimum values in each parameter [19]. Normalization generates a data value between 0 and 1. This procedure fairly compares all parameters that can be connected to each other without any differences in criteria or unit. The procedure is subsequently used to develop a metamodel in the NN (Fig. 3).

To build the metamodel, this research uses one hidden layer with two neurons. Fig. 3 shows points 15 as five input parameters determined in the UD Design of Experiments (DOE). Points 6 and 7 are two neurons in a single hidden layer, serving as prediction points derived from neuron information from the input, including weight information. Finally, points 8 and 9 are two objectives (multiobjective) based on the experimental results.

The NN is employed through the following steps:

- Step 1 : Determine the design of the NN, the number of neurons and hidden layers, the objective, learning rate ( $\alpha$ ), initial weight at each point neuron, and error criteria using the mean square error (MSE) for objectives 1 and 2. The MSE is used for constraining model overfitting. and 2; MSE is used for constraining the over fit of model.
- Step 2 : Arrange the normalised training data that are collected in the UD in the input and output of the NN.
- Step 3 : Calculate the weight factor, which in this case is calculated using the sigmoid linear approach.
- Step 4 : Build the linear metamodel for the two objectives; the linear metamodel consists of several specific weights implemented through parameters for constructing a value close to that of a real solution.

Step 5 : Check the MSE for the two fitness values of the two objectives in the metamodel using part of the training data. If the result is higher than the standard, return to step 3; otherwise, move on to step 6.

Step 6 : The metamodel is formed, and subsequently used as a fitness function in the HUDMOGA.

### 3.3 Hybrid Uniform Design Multi-objective Genetic Algorithm

After the metamodel is formed by the UniNeuro, the optimal parameter settings are achieved through the HUDMOGA, which is applied through the following steps:

Step 1 : Determine the parameters of the HUDMOGA, population number (PN), selection number (SN), generation number (GN), and Euclidean number (EN).

Step 2 : Initialisation is performed to generate a parent chromosome by initially using the UD for five parameters and 25 experiments obtained from the UD-web as real settings that have already been confirmed. Subsequently, the remainder of the population is generated randomly to accelerate the optimization procedure. Considering that the fitness function comes from the metamodel established by the UniNeuro, the value of the parameter is set between 0 and 1. Furthermore, the fitness value is calculated using the metamodel; the fitness value is the sum of the successful standing periods (the larger the better) and the steadiness duration (the larger the better). Finally, the sum of these outputs is evaluated (the smaller the better).

Step 3 : The selection process involves a roulette wheel. All the parent chromosomes occupy the roulette wheel based on probability for the whole result. The roulette wheel is then rotated to select chromosome pairs. Selection of the same chromosome pair more than once must be avoided to maximise the diversity of the solution set [20].

Step 4 : The crossover process is used to set the partition crossover that is applied to all the selected chromosome pairs. This method is initiated by determining a number for the genes position, which is subsequently used as the genes fixed position, finally replacing the unfixed gene with another gene from the paired chromosomes. The same procedure is then carried out for the remaining chromosomes [20].

- Step 5** : All chromosomes from step 3 are mutated in this step through a neighbour search. This method is applied to chromosomes individually by randomly determining two genes, then generating 4 permutations from these 2 genes, and using the permutation results to develop four new chromosomes in the same gene positions <sup>[20]</sup>.
- Step 6** : To increase variety among the children, the chromosomes from the crossover and mutation are combined, and two are selected randomly. Subsequently, the selected chromosomes are generated by experiments using a unique combination of a two-level UD for five parameters and 25 combinations <sup>[17, 18]</sup>; A total of 21 unique combinations are obtained. Because of its flexibility, the UD can be set according to the combination of the two levels and the number of available experiments <sup>[17, 18]</sup>. Principally, this procedure is similar to the hybrid Taguchi GA <sup>[20]</sup> but with the two levels of the Taguchi DOE replaced with the two levels of the unique UD.
- Step 7** : The chromosomes from steps 4–6 are combined in each child's chromosome, and the parents and children's chromosomes are combined. The chromosome with the shortest fitness value is stored as the most favourable chromosome and updated every generation. The remaining NP1 chromosomes are subjected to Darwinian selection (survival of the fittest).
- Step 8** : For maintaining diversity among the solution sets in each generation, the remaining chromosomes for the iteration described in step 7 are filtered using Euclidean distance and selected for NP1 chromosomes. The Euclidean distance method is used as a vector distance between each pair of chromosomes in sequence. Through this method, the various solution sets are proofed for their diversity based on the solution combination positions. In this case, because we have five solution sets, five solution dimensions are formed. The higher the Euclidean distance value, the higher the diversity among the solutions produced. An excessively high Euclidean distance only produces one single solution because of its distinct nature.

- Step 9** : Selected results from step 8 are ranked using the Pareto method. As a multiobjective problem, the two objectives trade off. In this case, we first chose the most feasible solution for each running programme, and then confirmed the solution with the automatic system. Alternative solutions were selected by Pareto front as the most favourable alternatives based on their abilities to update each generation <sup>[21, 22]</sup>.
- Step 10** : This study uses the number of iterations as a stopping criterion. If the iterations performed are lower than the GN, the process is repeated from step 3. If the iteration is met, continue to step 11.
- Step 11** : The most favourable result is displayed. This result is checked with the DIP equipment to verify its reliability.

The global procedure of the UniNeuro-HUDMOGA is shown in Fig. 4.

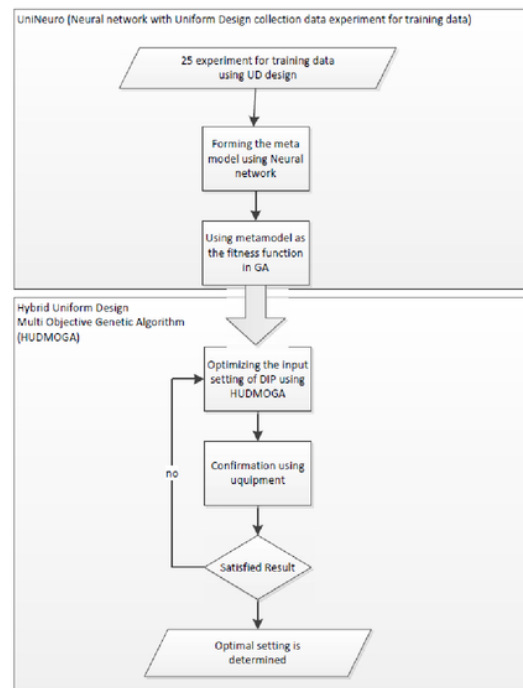


Fig. 4 UniNeuro-HUDMOGA design

## 4 Result and discussion

To examine the proposed algorithm, the UniNeuro-HUDMOGA was programmed in MATLAB and was run on an Intel Core i7-2630 QM CPU at 2.46 GHz. The UniNeuro used the following parameters: learning rate ( $\alpha$ )=0.1; mean square error (MSE) = 0.01; initial weight for  $w_{n=1-5, m=6,7} = -0.5$  to 0.5 (selected randomly); initial weight for  $w_{n=6-7, m=8,9} = -1$  to 1 (selected randomly);  $\theta$

$n=6-9=-0.5$  to 0.5 (selected randomly). The HUDMOGA parameters were set as follows: PN = 100, SN (selection number) = 0.8, GN = 1,000, and EN = 0.2. In addition, to confirm that this method could stably obtain the right solution, the algorithm was run 20 times.

In this study, data was retrieved by dividing the range of each parameter setting into 25 level sections, and then applying the settings on the UD table obtained from the UD-web. The data obtained served as training data for the UniNeuro to form the metamodel. Subsequently, the metamodel was used as a fitness function of the HUDMOGA. Finally, the settings results were confirmed by the DIP equipment (Table 4).

Table 4 Optimized Results by using UniNeuro-HUDMOGA

A	B	C	D	E	Swing time(s)	Steady time(s)
0.5904	2.1152	2.1152	5.4512	5.9648	8.0	900
0.7783	2.0217	2.0357	5.2500	5.2727	6.5	900
0.8863	2.0314	2.0375	5.1450	5.1236	7.0	900
0.9000	2.5000	2.4811	5.1250	5.8660	5.5	900
0.9000	2.4999	2.4782	5.1251	5.9209	5.0	900
0.9000	2.5000	2.4811	5.1250	5.8669	5.5	900
0.4385	2.0238	2.0200	5.1176	5.1667	11.0	900
0.9000	2.0264	2.0556	5.1250	6.3215	7.0	900
0.4395	2.0015	2.0202	5.1245	5.1820	11.0	120

Notes: A: Initial acceleration; B: Feedback coefficient direction; C: Negative feedback coefficient direction; D: Pull acceleration; E: Reverse acceleration.

Table 4 shows the DIP optimized result set obtained from running the UniNeuro-HUDMOGA 20 times. After running the algorithm, nine setting parameters were selected according to their success in confirming the DIP. Swing time denotes the time taken to swing followed by standing up; steady time denoted the time period for standing with interruptions from any excitations on the outside of pendulum 2. Steady time was judged for 900 seconds to conclude the optimized settings.

The proposed algorithm has nine setting values that can be chosen; previous studies have used only one setting, which can be determined as the optimization target caused by the rigid approach model [5, 6, 9–11, 21]. Moreover, the feasible solution may still only be available by running this programme, and subsequently updating the training data by using 20 confirmed settings. Hence, because of the artificial learning method, this development training data may increase the probability of obtaining the optimized result. The result of the optimization procedure can be rendered more precise if the model is closer to its real condition. Because of space limitations in this paper, only one parameter setting result is shown for each of displacement, velocity, and the output signal curve (Figs. 5 – 7).

The result proved that the UniNeuro is able to modify a metamodel that is used as a fitness function for the HUDMOGA. In other words, using the UD for determining the experiment training data set in the UniNeuro is extremely efficient for capturing or predicting the model of the DIP. Nine optimal settings can be produced from only 25 experiments. For future research, some modifications would be required to verify the robustness of the UniNeuro and

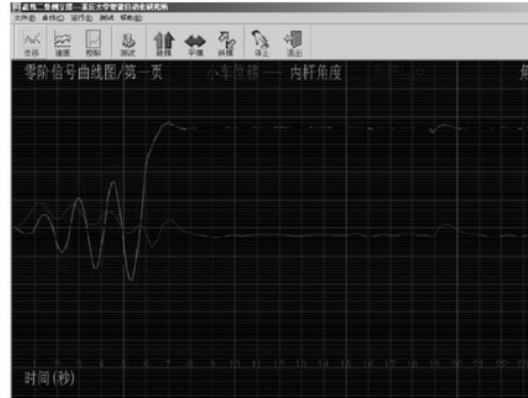


Fig. 5 DIP's displacement curve

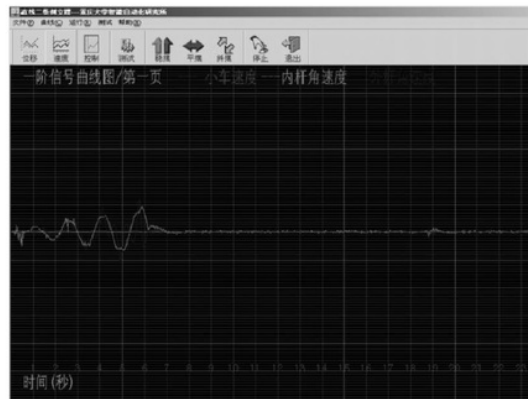


Fig. 6 DIP's velocity curve

improve its probability of success, similar to the adaptive fuzzy model used to obtain vital information for improving the autoerror correction model [3, 23, 24], and to a modified NN as a wavelet [25].

The optimization procedure was finalised using the metamodel from the UniNeuro as the fitness function of the HUDMOGA. In the optimization procedure, the HUDMOGA proved its performance by generating the true result for the optimal setting of the DIP, demonstrating this step as being able to obtain several true result settings, and also as being able to avoid being trapped in local optima. While the 11 failure settings from 20 simulations may have been caused by an incorrect metamodel produced by the UniNeuro as the prediction method, common sense suggests that it belonged to a limited amount of training data.

The results indicate that the proposed algorithm can solve this problem effectively and efficiently, if it is run 20 times using the 25 real data from the UD. It is evident that the proposed algorithm represents an outstanding trial-and-error method that makes the setting discovery process simple, and saves experimentation time. However, the reliability of the proposed algorithm must be improved to increase the performance of the optimization procedure.



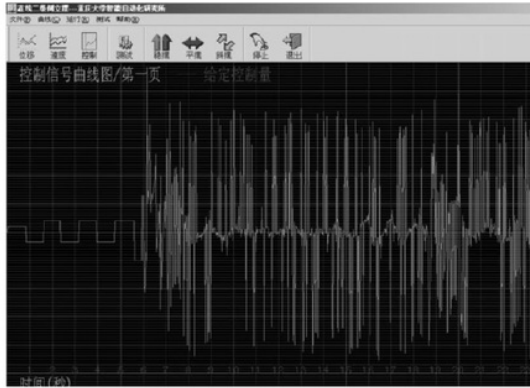


Fig. 7 DIP's signal curve

Furthermore, some particular aims such as standing time could be constrained.

Using the UD in assigning the experiment for training data is proven to be effective. In this case, information regarding the model could have been suggested even without the trend of the graphic result. Instead, the UD can promote a small sample that represents the entire feasible setting of the DIP. This is the intention of the UD: to be assigned to serve as the CD as the number of uniformity qualities. A lower CD denotes higher uniformity, which also implies that the UD is easy to use for solving any problem anywhere that requires capturing the whole system with limited data because of constraints such as limited time, manpower, and budget. The UD can be developed personally by the user, especially if the number of parameters is not available from the UD-web (maximum: 29 parameters). Through employing CD considerations as table criteria and then using this method for optimization designs such as cost functions or smaller-the-better targets, this solution can be highly popular in terms of DOE effectiveness and the corresponding optimization problems.

In comparison to a Taguchi design and an optimization design, the UD is more efficient in many parameters. Whereas a Taguchi design focuses on the level to determine the experiment, the UD does not. The UD can be easily developed by the user, whereas a Taguchi design cannot, because the aim of a Taguchi design is to propose robustness settings from the appropriate combinations shown by the signal-to-noise ratios, and to analyse the mean effect of each parameter [26].

## 5 Conclusions

This study intended to determine the most favourable settings for DIP input. The most favourable input setting for the DIP was for standing up, which proved to be robust against any outside interference. The model control system function was unknown, thus optimizing the parameters required an NN metamodel, which in turn was formed by training data retrieved by the UD, named UniNeuro. Furthermore, the HUDMOGA embedded in the UD was used to optimize the DIPs parameter settings based on the meta-

model as the fitness function. The HUDMOGA begins with initialisation by the UD, then does roulette wheel selection, then partition crossover, and finally neighbour search for mutation. The Euclidean distance used for maintaining diversity in the solution is filtered by the Pareto front.

The results of this study show the nine most favourable parameter settings that produce the DIPs ability to stand up robustly in a time period determined by outside interference. In comparison to using a trial-and-error method, this method proved to be considerably faster because it only requires 25 data as the training data for the UniNeuro to develop the metamodel. This method is a novel method that can be performed in more than one setting, as concluded in previous studies [6, 6, 9–11, 21]. Furthermore, it is more closely based on real situations than the simulation approach is [7, 8, 14]. The UD is highly efficient for generating UniNeuro training data in DOE, because this search can be spread uniformly on the solution search space, and can also obtain results close to those of a full factorial design with an extremely low number of experiments. The accuracy of the model requires improvement by adaptive arrangement of the structures of the metamodel [3]. Objective criteria could also be affected by multiple constraints and various disturbances.

This research is appropriately useful for optimizing a system undetermined by such model information. This method can achieve the advanced prediction of a metamodel that deals with input and response for forming the linear approach function. The DIP model is generally nonlinear, but this approach uses linear regression. Therefore, it makes sense that the proposed method is worthwhile for application in real situations. Sometimes the information of the system model is unknown, and the optimal solution is only close to itself, thus trial-and-error searches would be prohibitively expensive, but the proposed method can find a solution after a small number of experiments. For example, in this study, the method succeeded in optimizing and obtaining five DIP inputs of the undetermined model for the targets of standing and remaining stable in the upright position. Only 45 experiments were required for generating the advanced settings. If either the trial-and-error or full factorial design were used, the experiment time would increase dramatically because of the tiny level range in each parameter.

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## References

- [1] A. Shukla and H. Karki. Application of robotics in onshore oil and gas industry-A review Part I. Robotics and Autonomous Systems, vol. 75, pp. 490-507, 2016.
- [2] J. A. Anderson. An introduction to neural networks: MIT press, 1995.

[3] P. Palmes and S. Usui. Robustness, evolvability, and optimality of evolutionary neural networks. *Biosystems*, vol. 82, no. 2, pp. 168-188, 2005.

[4] A. Medio and M. Lines. *Nonlinear dynamics: A primer*. Cambridge University Press, 2001.

[5] T.-K. Liu, C.-H. Chen, Z.-S. Li and J.-H. Chou. Method of inequalities-based multiobjective genetic algorithm for optimizing a cart-double-pendulum system. *International Journal of Automation and Computing*, vol. 6, no. 1, pp. 37, 2009.

[6] T.-K. Liu, Y.-C. Shen and Z.-s. Li. An Application of Multi-objective Optimization Genetic Algorithm for Cart-Double-Pendulum-System Control. In *Systems, Man and Cybernetics*, 2006. SMC'06. IEEE International Conference on, IEEE, pp. 3292-3297, 2006.

[7] L. B. Prasad, B. Tyagi and H. O. Gupta. Optimal control of nonlinear inverted pendulum system using PID controller and LQR: performance analysis without and with disturbance input. *International Journal of Automation and Computing*, vol. 11, no. 6, pp. 661-670, 2014.

[8] F. Gazdo. Introducing a New Tool for Studying Unstable Systems. *International Journal of Automation and Computing*, vol. 11, no. 6, pp. 580-587, 2014.

[9] D. Cheng-Jun, D. Ping, Z. Ming-Lu and Z. Yan-Fang. Double inverted pendulum system control strategy based on fuzzy genetic algorithm. In *Automation and Logistics*, 2009. ICAL'09. IEEE International Conference on, IEEE, pp. 1318-1323, 2009.

[10] M. Nalavade, M. J. Bhagat and V. V. Patil. Balancing Double Inverted Pendulum on cart by Linearization Technique. *International Journal of Recent Technology and Engineering (IJRTE)*, ISSN, pp. 2277-3878, 2014.

[11] M. J. Mahmoodabadi, S. A. Mostaghim, A. Bagheri and N. Nariman-Zadeh. Pareto optimal design of the decoupled sliding mode controller for an inverted pendulum system and its stability simulation via Java programming. *Mathematical and Computer Modelling*, vol. 57, no. 5, pp. 1070-1082, 2013.

[12] Z. Ping and J. Huang. Approximate output regulation of spherical inverted pendulum by neural network control. *Neurocomputing*, vol. 85, pp. 38-44, 2012.

[13] Z. Ping. Tracking problems of a spherical inverted pendulum via neural network enhanced design. *Neurocomputing*, vol. 106, pp. 137-147, 2013.

[14] K. U. P. Lakshmi. Design of robust energy control for cart-inverted pendulum. *International Journal of Engineering and Technology*, vol. 4, no. 1, pp. 66-76, 2007.

[15] D. C. Montgomery. *Design and analysis of experiments*. John Wiley & Sons, 2008.

[16] K. Yang and B. S. El-Haik. *Design for six sigma*. McGraw-Hill, New York, 2003.

[17] K.-T. Fang, R. Li and A. Sudjianto. *Design and modeling computer experiments*. CRC Press, 2005.

[18] K.-T. Fang and D. K. Lin. Ch. 4. Uniform experimental designs and their applications in industry. *Handbook of statistics*, vol. 22, pp. 131-170, 2003.

[19] G. Dreyfus. *Neural networks: methodology and applications*. Springer Science and Business Media, 2005.

[20] D. H. Al-Janani and T.-K. Liu. Path optimization of CNC PCB drilling using hybrid Taguchi genetic algorithm. *Kybernetes*, vol. 45, no. 1, pp. 107-125, 2016.

[21] T.-K. Liu and T. Ishihara. Multi-objective genetic algorithms for the method of inequalities. *Control Systems Design*: Springer, pp. 231-248, 2005.

[22] A. Konak, D. W. Coit and A. E. Smith. Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering and System Safety*, vol. 91, no. 9, pp. 992-1007, 2006.

[23] X.-Q. Li, D. Wang and Z.-M. Fu. Adaptive NN dynamic surface control for a class of uncertain non-affine pure-feedback systems with unknown time-delay. *International Journal of Automation and Computing*, vol. 13, Issue 3, pp. 268-276, 2016.

[24] X.-J. Wu, X.-L. Wu and X.-Y. Luo. Adaptive neural network dynamic surface control for a class of nonlinear systems with uncertain time delays. *International Journal of Automation and Computing*, vol. 13, pp. 409-416, 2016.

[25] K. Owa, S. Sharma and R. Sutton. A wavelet neural network based non-linear model predictive controller for a multi-variable coupled tank system. *International Journal of Automation and Computing*, vol. 12, no. 2, pp. 156-170, 2015.

[26] W. Y. Fowlkes and C. M. Creveling. *Engineering methods for robust product design*. Addison-Wesley, 1995.



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---

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---

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---

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