UniNeuro-HUDMOGA for advancing constrained optimization in double inverted pendulum

To cite this article: D H Al-Janan *et al* 2021 *IOP Conf. Ser.: Earth Environ. Sci.* **700** 012025

IOP Conf. Series: Earth and Environmental Science **700** (2021) 012025 doi:10.1088/1755-1315/700/1/012025

UniNeuro-HUDMOGA for advancing constrained optimization in double inverted pendulum

D H Al-Janan[1], T-K Liu[2], P-W Hsueh[2], H-c Chang[2], R D Widodo[1], Rusiyanto[1]

[1] Mechanical Engineering of Universitas Negeri Semarang
[2] Mechanical Engineering and Automation, National Kaohsiung University Science and Technology

aljanan@mail.unnes.ac.id

Abstract. This study aims for optimizing Double Inverted Pendulum (DIP) for swing then standing up within the stipulated time, and then can be stable even with any noise outside. The differences character outputs were applied to assess the robustness of proposed algorithm. This problem is worthy to examining, because in the controlling field, the stable position need in the matter of time; so then, the faster is the better sometime not necessary even dangerous. For example in comfortably of car's suspension controlling system, the smoother suspension does not mean the faster stability, unless the comfortably never occurs. The difficulty is happened due to unknown model to optimize; it becomes the more complexity problem. In the real problem, even the model sometime cannot represent the whole of controlling system, especially in the controlling system. Facing the problem above, this study was succeeding for solving the problem via Uniform Design (UD) NeuralNetwork-Hybrid Multi Objectives Uniform Design Genetic Algorithm (UniNeuro-HUDMOGA). This proposed algorithm begins with 40 experiments designed by Uniform Design for generating predicting model (metamodel). Then, the metamodel is using for cost function in Hybrid UD Multi-objective Genetic Algorithm (HUDMOGA) within UD, Pareto filtering and Euclidean distance together applies for enhancing the searching GA performance for search the best setting. Finally, the input setting recommendation is confirming using DIP equipment. As the result, the DIP can be controlled as correlated with the specification set. These results prove that the proposed algorithm can be applied to control a complex system that requires multi objectives.

1. Introduction

Optimization is the way to search the optimal performance of such a system; can be applied on the technical field or social field [1]. Meanwhile, performance optimizing such system requires such controlling mechanism, thus can be determined the optimal output due to particular input setting. In several cases the system or model of system unknown clearly, this condition caused by the idealization or simplification of system, or because the unpredicted noise in the system [2]. Therefore in the practical condition, the trial-error method is mostly used for optimizing the system, nevertheless this simply method has many lack such as waste time, high speculation, cost burning and requires expert person.

The complex system problems need the complex solutions as well. For controlling the complex actual system, the simplification called model or mathematical model is needed for increasing the solution probability. The mathematical model will propose the mathematical solution. On the other hand, this simplification has a drawback caused a limitation of the model doe to neglecting parameter of real system. This drawback occurs caused the miss election to eliminate the primary parameter [3]. So then, the solution model should be verified by real system for proofing the solution.

The procedure above is a series of sequences commonly performed to control a system. High cost couldn't be avoided because of the length of the procedure required. As another solution, experienced experts are used to control a system. Otherwise, the experts cannot immediately solve the problem, because of the different environmental conditions that interfere with it, and even this increase in funds is inevitable [3-6]. Therefore, various researchers have developed a data collection model so that the required amount can be efficient. Meanwhile, an optimization program is developed so that the control process can run more effectively and efficiently; starting from data retrieval to compiling the accuracy of the solution to setting the solution [7].

In an automated system, with high complexity and thus non-linearity cannot be avoided because of the complex component relationships. The complexity of the system can be found in various forms of the system, this is due to the complexity of the components that cannot be definitely connected, or the influence of interference outside the system that cannot be controlled surely. Inverted pendulum is a nonlinear complex system that has been used for a long time to analyse the effectiveness of a control method. In this system, each component has a very tight bond supported by external factors that are very difficult to control. The simplest thing is to try to set the input so that the inverted stands and can withstand outside interference. Inverted pendulum component of standing is only controlled by the only one motor which is influenced by several sensors which are used as a feedback signal to the motor [8-13]. The procedure controls the inverted pendulum starts from determining the input parameter to support signal of the motor for moving in a rotary manner, then it is converted into a translation in one line via belt to move the cart, and the reaction of this inertia force causes the swing motion (rotation), and causes the pendulum to stand. Despite inverted pendulum quit aged system model, but many researcher still using this system model to explore any objective such controlling model, balancing principle, metamodeling or optimizing parameters [8-16] .

Some researchers focus their studies in dynamic model; Xia et al. [17] studied on adaptive tracking without dynamic modeling, this method introduces a model formed with the Nussbaum function approach. While Chang et al. [13] controlled a sliding system with very varied conditions by using fuzzy logic. Some researchers use inverted pendulums. In this study predicts the control system on an inverted pendulum by using a linear model so that the pendulum can stand (Since the system has strong nonlinearity and inherent instability, a step of linearization is necessary to extract the linear state space model.) by using a variable speed cart motion on the track [18]. In their research, Fukushima et al. [12] discussed a robot car with a wheel-arm with the aim of adjusting the 4 wheel inverted pendulum to keep walking and standing using body modelling and tracking errors. In this study, stabilizing an inverted pendulum with 2 torsion by being able to stand, by controlling it while still standing using the predictive control (MPC) model, finally using stabilization [19]. The rotary inverted pendulum using a full state feedback controller based on modified particle swarm optimization with constraints on settling time, peak time and peak overshoot. The method paves way to advanced signal processing techniques for design and control of complex dynamic [16]. Mills (2009) A nonlinear model was created to predict inverted pendulums, using sequential quadratic programming on the modest hardware platform [10]. Two-Wheeled Inverted Pendulum (TWIP) robot is considered unstable and understated, influenced by the physical condition of the system and its environmental conditions. Robust Model Predictive Control (RMPC) based on linear matrix inequality (LMIs) is addressed to an optimization problem of the “worst-case” objective function over the infinite moving horizon, subject to input and output constraints [20]. Spring Loaded Inverted Pendulum (SLIP) is used to describe the motion behavior of animals and humans by using robots in dynamic locomotion. Uses torque using pumping energy using the controllable hip joint torque [21]. Trimpe et al. [15] in their study aims primarily to regulate feedback from the control dynamic system under control to make control decisions. However, the sensor in the inverted pendulum control is for sensory information in a stable system and the second is the data reveal with a large variation of disturbances by balancing. With a self-tuning algorithm, the explorer sensor data automatically adjusts.

Meanwhile, the development of the control, optimization method is carried out by; Bashiri et al. [23] used a method to approach a system using the one made with ANN to achieve optimum. Kazemi et al. [24] stated that Fuzzy Pareto is used to make it multi-objective of several multi-disciplinary objectives Li et al [25] found that Pareto dominance is used for reference in cluster distribution and PCI estimation. This is intended to evaluate convergence and diversity with a solution approach to the solution set. Reynoso et al. [4] analysed the performance suspension system makes maximum and at least based on multimodal-based techniques. Metamodel-based techniques are based on hardpoints and processed with adaptive metamodel-based optimization with hardness hardpoints using the kinematic performance of a McPherson suspension system approach.

The type of Inverted Pendulum used in this study has two pendulums arranged in series; thus called Double Inverted Pendulum (DIP). The five inputs used for controlling this DIP; with unknown function of each parameter on system performance because the system model was unknown yet. Therefore, the model in this study, training data is made directly from the system using a uniform design to make it more efficient, while the metamodel is built using a neural network and the results are optimized with the UD GA hybrid that has been previously studied, only in this study an additional constraint is given.

2. Problem Definition

DIP is used in this research; vast use equipment for modeling the nonlinear system which has strongly couple in its parameters. By the reason, this device used to checking the model is used for investigating the controlling system or design. These system categories to nonlinear, so then cause-effect correlation is hard to determine.

Figure 1 figures the part of the DIP mechanism. The mechanism is started with the user entering the five input values to CPU; the input signal is sent to the Digital Signal Processor (DSP) and is processed in the form of a signal to the servo motor which will use a single axis horizontal translation motion on the cart with a length of one meter of length. Meanwhile, the signal size controlled by the DSP is also influenced by the feedback signal from the three decoders. While the rotational motion of first pendulum and second pendulum is caused by the effect of the horizontal movement of the cart. When the cart starts moving, the pendulum movement can be detected on the CPU and can be seen on the monitor in the form of a graph signal. The physical specifications of DIP are described in table 1, while the input parameters that the user enters to the CPU are described in table 2 with minimal and maximal setting value. Although the five input parameters have clear names of parameters, their effect is not yet clear on the DIP motion character. Additionally, the input range is very narrow, resulting in very small changes in the behavior of DIP motion to very small changes in input configuration.

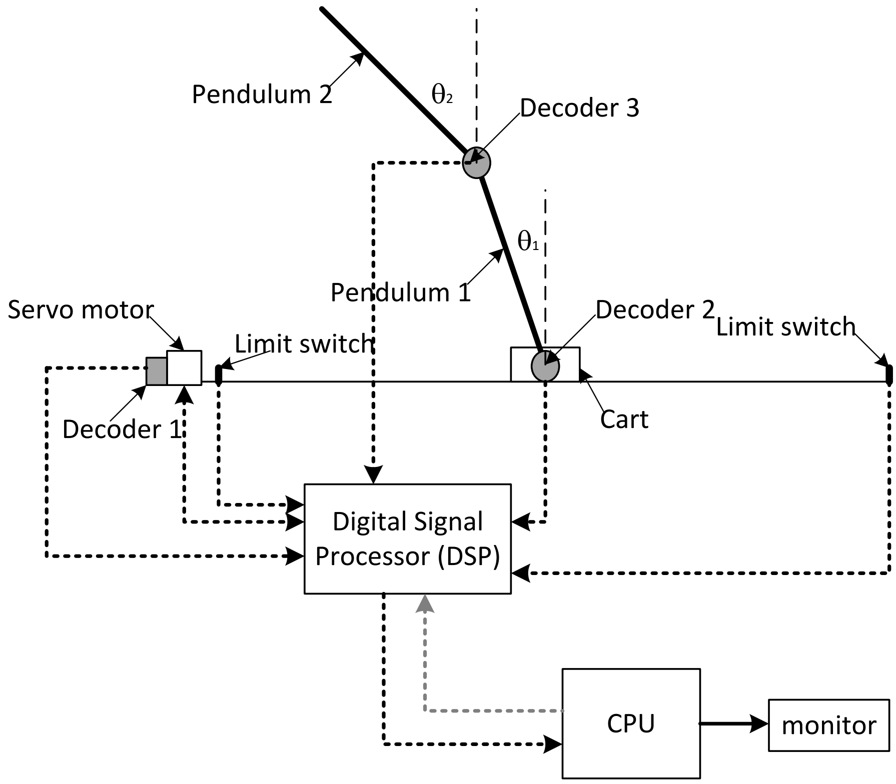

Figure 1. DIP Mechanism

Table 1. DIP specification

Parameters	Value
Mass of cart (M)	1.32kg
Mass of encoders (m_0)	0.208kg
Center length of each pendulums (l_1,l_2)	0.2m
Length of each pendulums (L)	0.4m
Displacement range of cart (x)	(-0.3,0.3) m
Mass of each pendulums (m_1 ,m_2)	0.108 kg
Friction coefficient of cart(f_o)	22.915 N.s/m
Friction coefficient of pendulums(f_1,f_2)	0.7756 N.s.m
Moment of inertia of pendulums(J_l,J_2)	0.00144 kg.m^2

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
E. Reverse acceleration	5.0	8.0

Uniform Design (UD) is a sampling method developed by Fang and Yang; which has been shown to be effective in reducing the number of experiments with results close to ideal. In this study, UD is used in the process of determining training data to form a model with a neural network, and to make GA performance effective during optimization. The use of UD can be easily accessed via its web [26-29].

Conceptually, this research is a development of previous research conducted by Al-Janan [30], duration of swing was added to evaluate the robustness of the algorithm. The swing duration was determined based on the minimum and maximum swing times that have never been obtained in the previous training data collection processes, thus ensuring that the specified time is truly unique. In this study, the set time for swing was limited to exactly eight seconds. Four objectives applied in this study as follows:

1. DIP can swing-than standing up during particular time (8 second, fix time).
2. No hard collision between cart and track boundary on the swing period.
3. The last harmonic swing angle of both of pendulum to 180^o (standing up position).
4. Could stable during standing position with some external disturbance (900 second).

Through the algorithm offered, the five inputs are arranged to produce 4 objectives for getting the minimum error.

Improved UniNeuro-HUDMOGA

Based on Al-janan [30], the procedure of this study was described below:

1. Compilation of data retrieval plans, using uniform design Kai-Tai Fang, 2001 [26-29]. With this data collection, the experimental number does not need to be a large number, only 40 times.
2. The process data created is used to become training data to create a meta model using the neural network (NN) method.
3. The model (equation) generated by NN is optimized using a hybrid genetic algorithm with a uniform design as the amount of child data.
4. In this study, UD was also added when collecting data, to evaluate the time constraints required for DIP to stand and be stable. To expand the solution, Euclidean distance is used; while preparing a multi-objective solution used Pareto front.

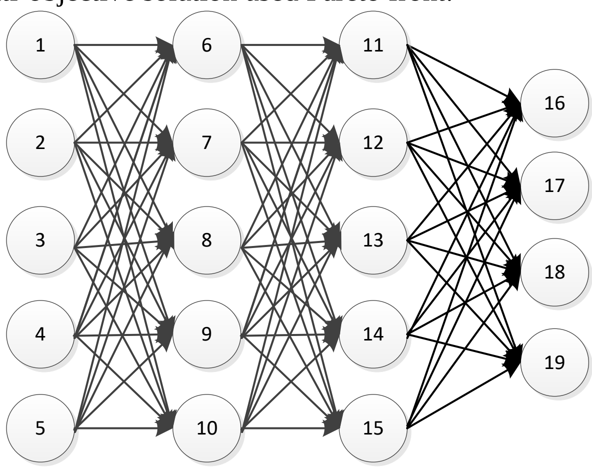

Figure 2. Neural Network structure

Figure 2 shows the structure used in this study. As the fitness function, NN structure has five inputs, two hidden layers within five neuron nodes in each layer, then finally for predict four objectives; so then totally 84 parameters will be search in HUDGA as the number of gene in each chromosome. Thus optimize the searching value of each weight the HUDGA is used as optimizer. The HUDGA is completely described in Al-Janan [30].

3. Result and discussion

After running UniNeuro-HUDMOGA for 20 times with a running time of only 300 seconds, the weighting of NN is deciding from the mean of each weighting. The problem is solved, the input setting parameters is found.

Table 3. Input setting solve

Setting	A	B	C	D	E	Swing (second)	Crash	ANGLE	STABLE (Second)
1	0.8873	2.0198	2.0233	5.0587	7.9574	8	0	180^o	900
2	0.8707	2.0110	2.0517	5.2466	7.9836	8	0	180^o	900
3	0.8770	2.0045	2.0123	5.3544	7.9930	8	0	180^o	900
4	0.8836	2.0001	2.0585	5.1684	7.9876	8	0	180^o	900

Table 3 shows the DIP input setting proposed by UniNeuro-HUDMOGA. A,B,C,D,E are the input parameters; Initial acceleration, Feedback coefficient direction, Negative feedback coefficient direction, Pull acceleration and Reverse acceleration. Input parameter is affecting each other within unknown correlation; therefore the slight number setting creates the huge effect of DIP motions. Meanwhile, the four output parameter are written on the right four columns; they are swing duration which was set 8 second, crash with boundary, angle between two pendulum, and lastly duration of stable.

While the signal output of DIP motions which are detected in decoders, curving on the three curve parameters are displacement, velocity and signal. The four output signals created from four input setting are figuring in figure 3 to 14 respectively.

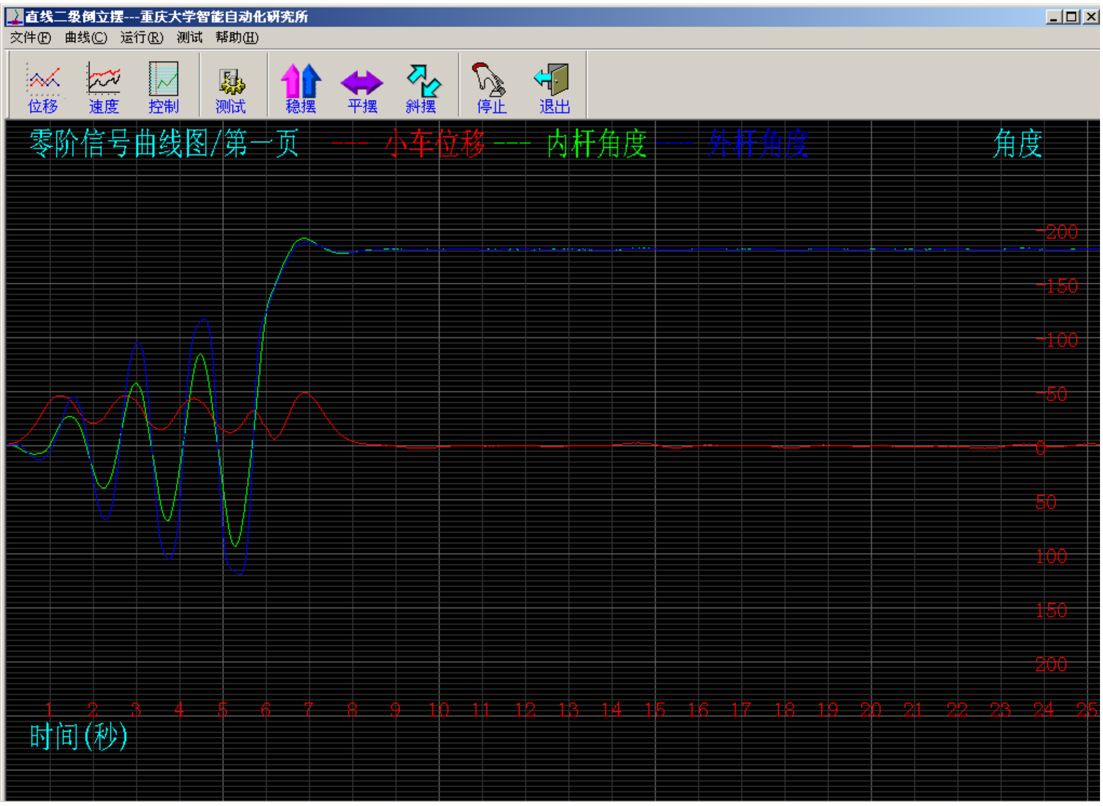

Figure 3. Output curve of displacement for input setting 1

Figure 4. Output curve of velocity for Input setting 1

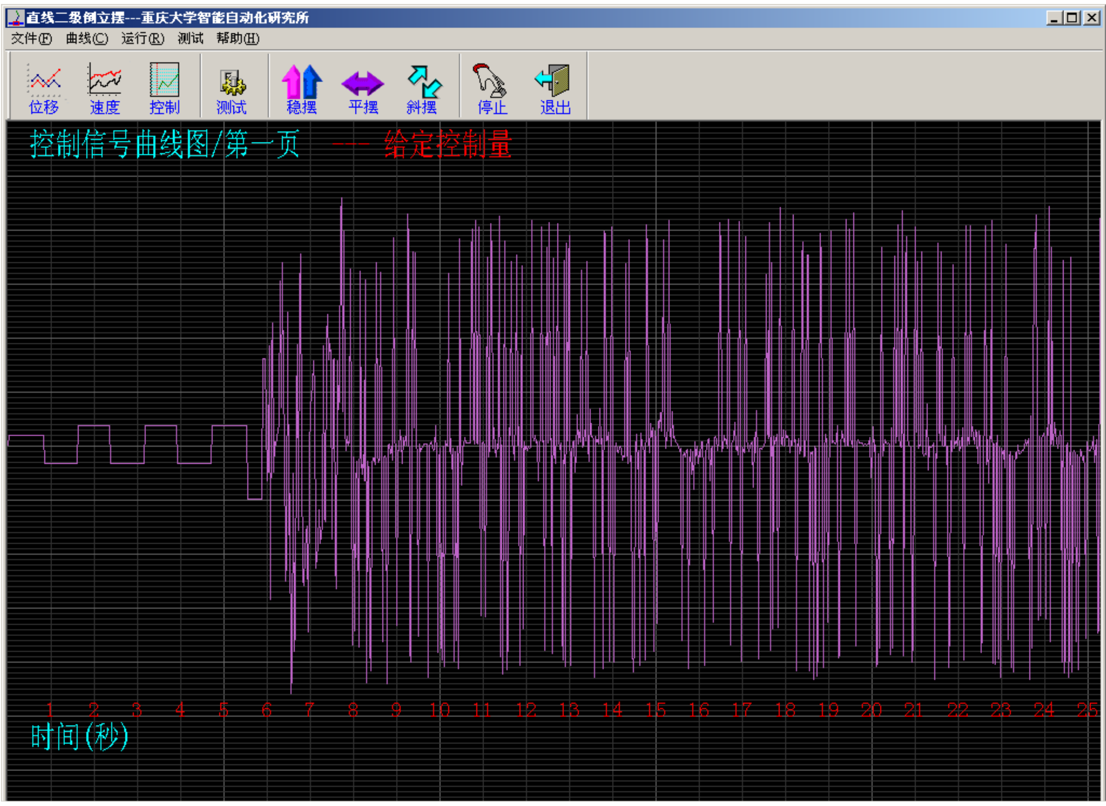

Figure 5. Output curve of signal for Input setting 1

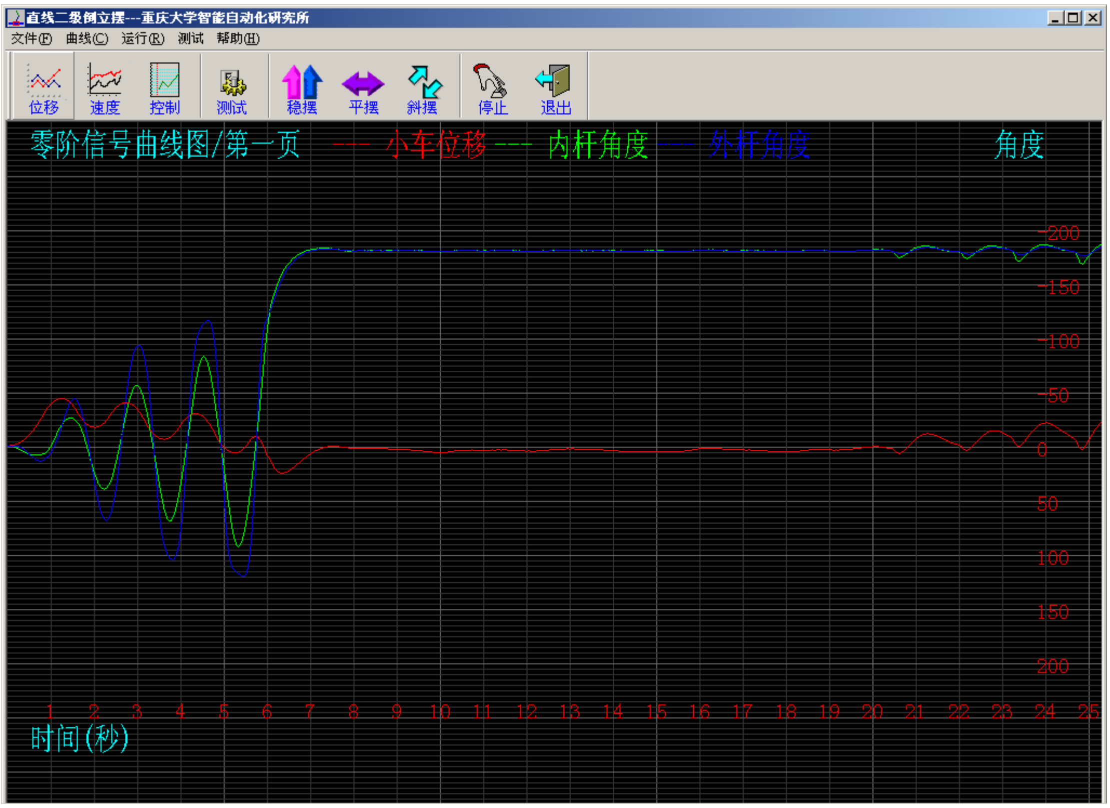

Figure 6. Output curve of displacement for input setting 2

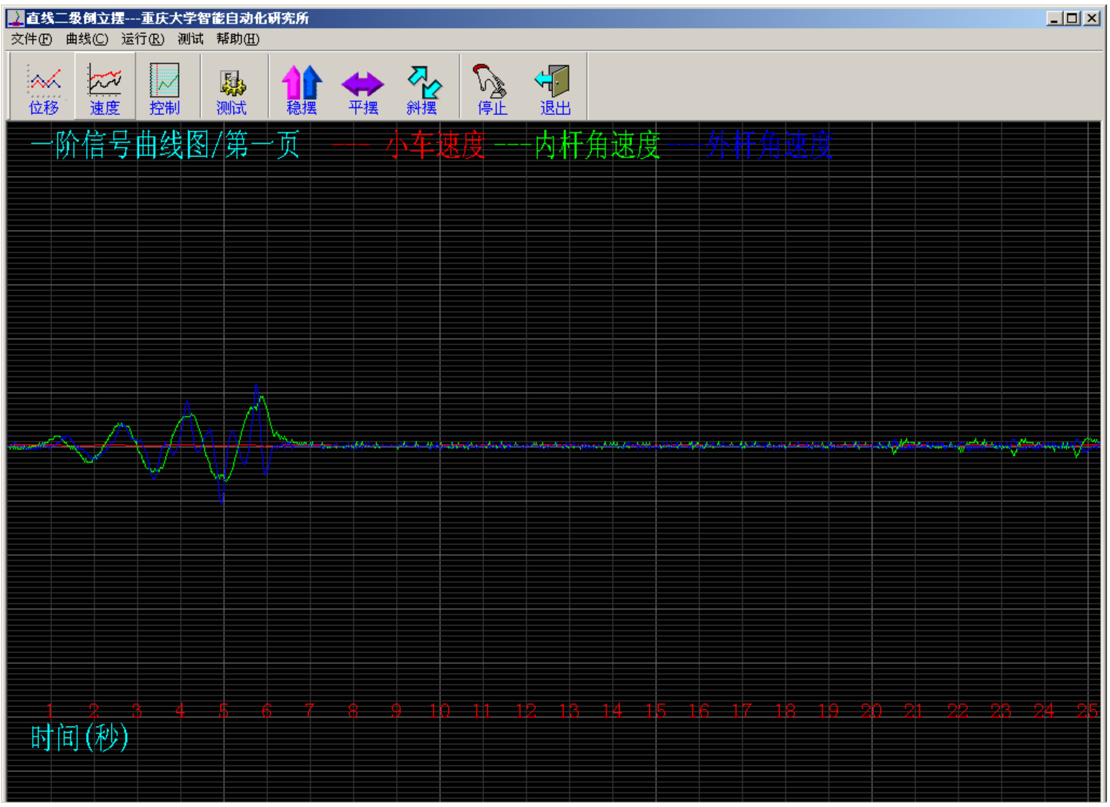

Figure 7. Output curve of velocity for Input setting 2

IOP Conf. Series: Earth and Environmental Science **700** (2021) 012025 doi:10.1088/1755-1315/700/1/012025

Figure 8. Output curve of signal for Input setting 2

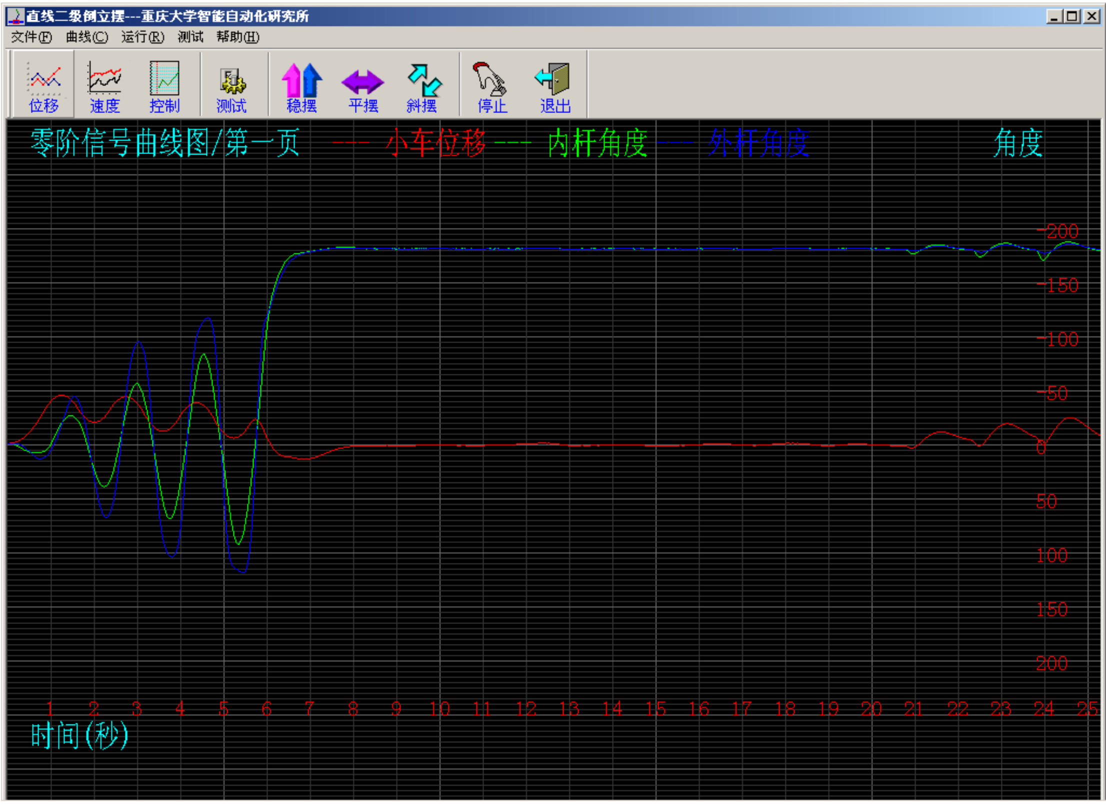

Figure 9. Output curve of displacement for input setting 3

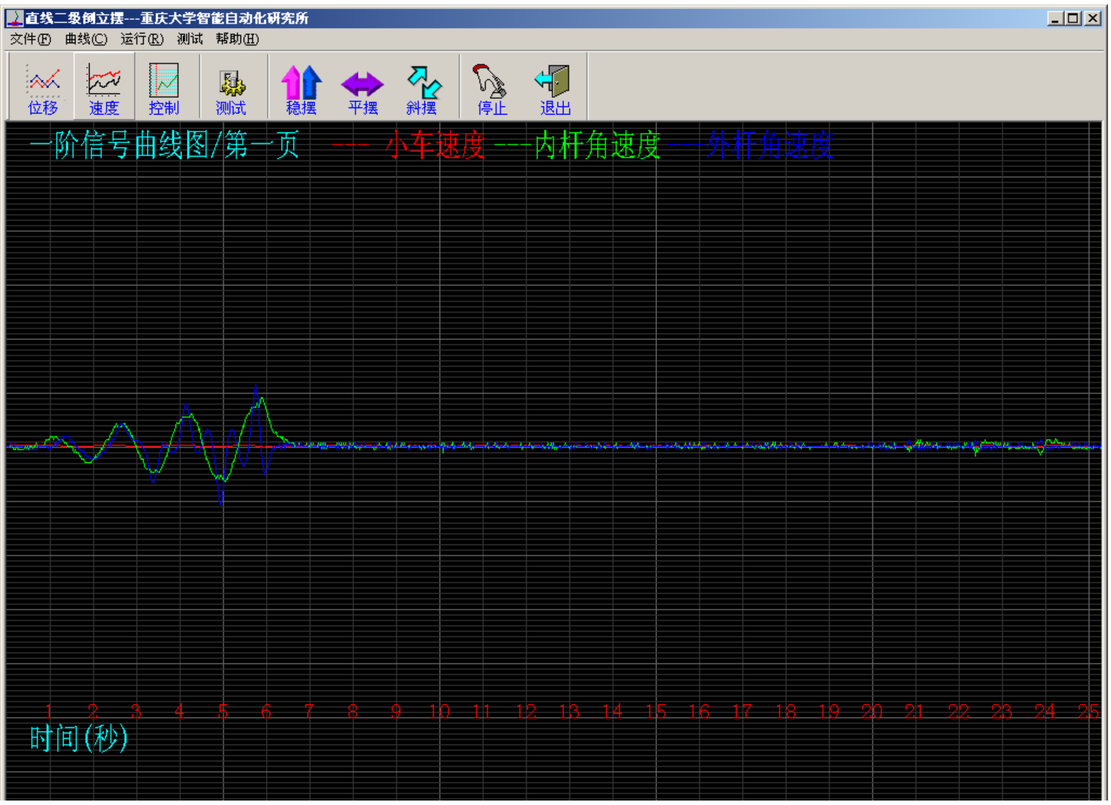

Figure 10. Output curve of velocity for Input setting 3

Figure 11. Output curve of signal for Input setting 3

IOP Conf. Series: Earth and Environmental Science **700** (2021) 012025 doi:10.1088/1755-1315/700/1/012025

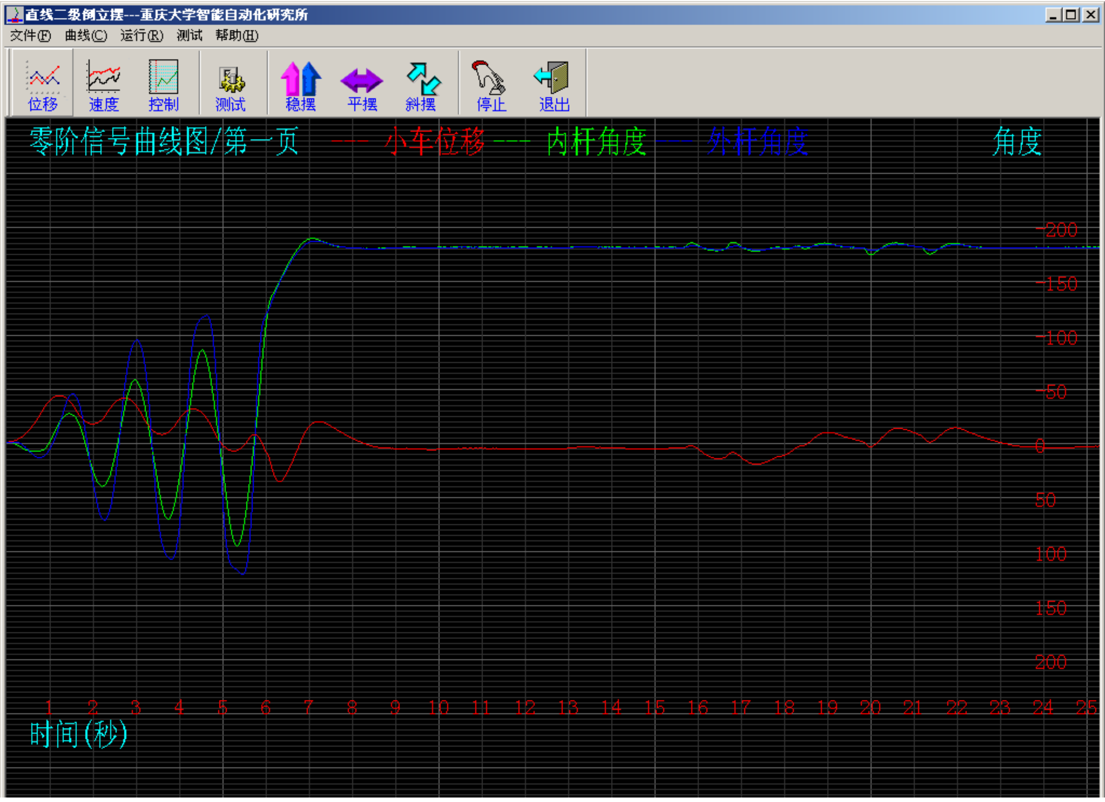

Figure 12. Output curve of displacement for input setting 4

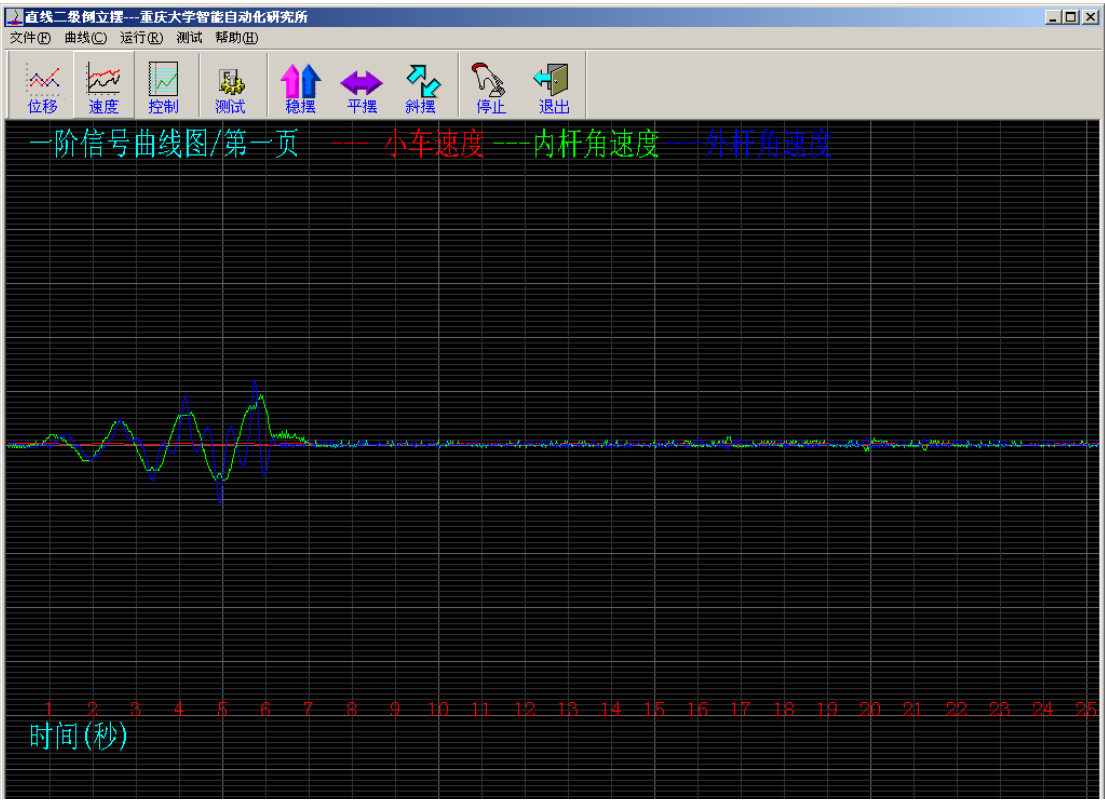

Figure 13. Output curve of velocity for Input setting 4

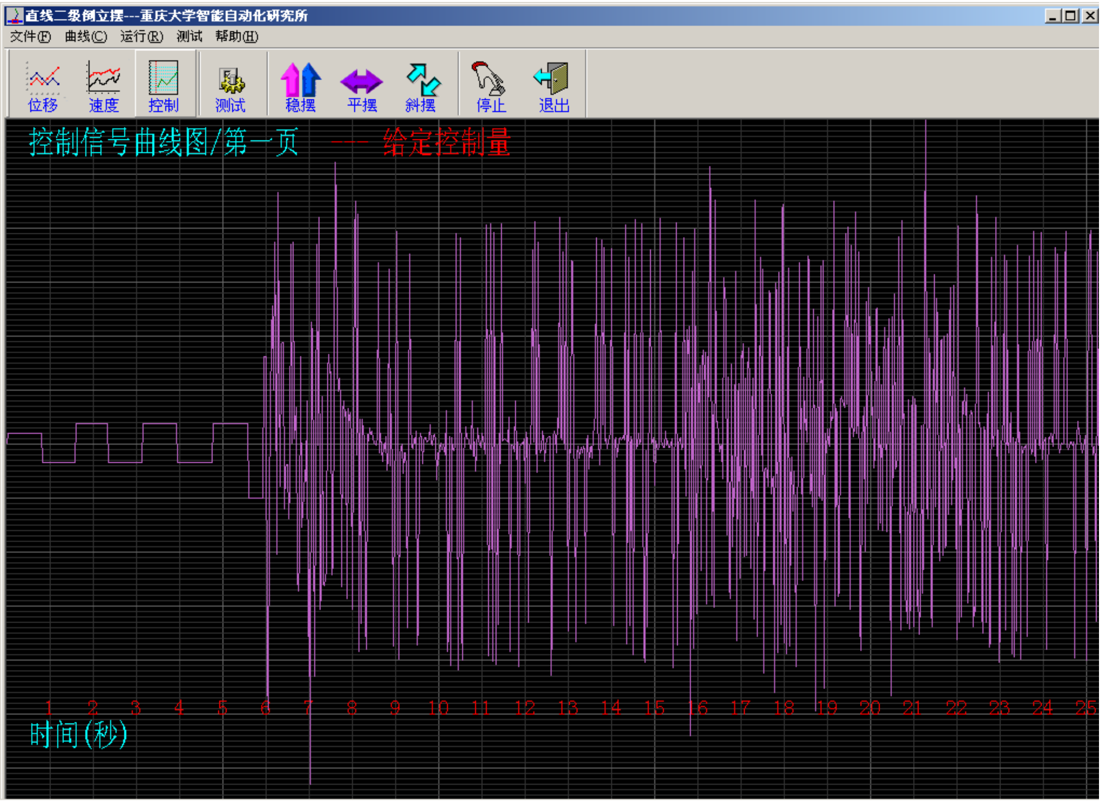

Figure 14. Output curve of signal for Input setting 4

Figure 3 to 14 shows that the horizontal line represents the time in seconds; then it can be seen clearly on the displacement curve, the pendulum stands at 8 seconds, and the next tends to be stable except when there is outside interference, - the system tries to re-balance its position. Meanwhile, the velocity and signal curves show the signal changes in the process of motion and DIP balancing. Figures 3 to 14 show the signal that works in DIP, and it shows the reaction in the form of DIP movement in real time, so that by looking at the curves that are formed, could describe the real conditions of the DIP. In the displacement and velocity curves, it can be seen that at the beginning of the swing movement, DIP requires a high range of motion, signal In the displacement and velocity curves, it can be seen that at the beginning of the swing movement, DIP requires a high range of motion, signal, while in the 8th seconds, when DIP starts to stand, the displacement and velocity only move very small because they only function to maintain the balance. Meanwhile, if the DIP is given excitation, then there will be a big change in the graph. Meanwhile, the signal graph shows that, during the swing process, the DIP requires a periodic input signal, while when the DIP starts to stand up, the signal given to equilibrium changes in dynamic.

These results indicate that the construction of a metamodel through a multi-objective neural network is quite effective in predicting a model that is still unclear (black system). Meanwhile, the use of a genetic algorithm combined with uniform design is reliable enough to find the optimal setting value.

The table is 4 different input data and can produce the desired output swing for 8 seconds and can last for 900 seconds with external interference. The four input settings are obtained from 20 runs of HUDGA, so then the optimal accuracy reaches 20%. Of course, it still requires effort; this is possible because the metamodel is not perfect and can be done by improving the Neuro methodology, as well as adding data.

4. Conclusion

In this research, DIP, which is a complex system model, is optimized to achieve various outputs, namely; Swing time 8 seconds, standing, without collision with limits and can bear to stand even if given outside disturbance for 900 seconds. To set up the input; starting with collected training data using uniform design to compile a metamodel on the neural network. Furthermore, to optimize the results to match the desired target, a hybrid Uniform Design-Genetic Algorithm (HUDGA)is used. To ensure chromosome diversification, the Euclidean distance is used. Meanwhile, Pareto filtering is used to select multi-objective results of single-objective.

This research generated four input settings that occur in specified output standards. These four settings are recommended from the 20 confirmed running times from HUDGA. This result only has 20% accuracy; the method of metamodel and its optimization still needs to be improved. However, this algorithm can increase the efficiency of setting up time, even though it was not composed by an expert.

References

[1] Simon D 2013 *Evolutionary Optimization Algorithms* (New Jersey: John Wiley & Sons)
[2] Ogata K and Yang Y 2002 *Modern Control Engineering* (New Jersey: Prentice Hall)
[3] Milovanović MB, Antić DS, Milojković MT, Nikolić SS, Perić SL, Spasić MD 2016 Adaptive PID control based on orthogonal endocrine neural networks *Neural Networks* **84** 80-90
[4] Yang Q, Huang J, Wang G, Karimi HR 2014 An adaptive metamodel-based optimization approach for vehicle suspension system design *Mathematical Problems in Engineering* **2014** 1-9
[5] Wong WK, Xia M and Chu W 2010 Adaptive neural network model for time-series forecasting *European Journal of Operational Research* **207** 807-816
[6] Zhang M, Ma X, Rong X, Tian X, and Li Y 2016 Adaptive tracking control for double-pendulum overhead cranes subject to tracking error limitation, parametric uncertainties and external disturbances *Mechanical Systems and Signal Processing* **76** 15-32.
[7] Hastie T and Tibshirani R 1986 Generalized Additive Models *Statistical Science* **1** 297-310.
[8] Woodyatt A, Middleton R, and Freudenberg J 1997 Fundamental Constraints For The Inverted Pendulum Problem *Proceedings of the IEEE Singapore International Symposium on Control Theory and Applications* (Singapore)
[9] Mahmoodabadi M and Jahanshahi H 2016 Multi-Objective Optimized Fuzzy-PID Controllers For Fourth Order Nonlinear Systems *Engineering Science and Technology, an International Journal* **19** 1084-1098
[10] Mills A, Wills A, and Ninness B 2009 Nonlinear Model Predictive Control of an Inverted Pendulum *American Control Conference* (Missouri: St. Louis) p 2335-2340
[11] Yi J and Yubazaki N 2000 Stabilization Fuzzy Control of Inverted Pendulum Systems *Artificial Intelligence in Engineering* **14** 153-163
[12] Fukushima H, Kakue M, Kon K et al. 2013 Transformation Control to an Inverted Pendulum For a Mobile Robot With Wheel-Arms Using Partial Linearization And Polytopic Model Set *IEEE Transactions on Robotics* **29** 774-783
[13] Chang WJ, Chen PH, and Ku CC 2016 Variance And Passivity Constrained Sliding Mode Fuzzy Control For Continuous Stochastic Non-Linear Systems *Neurocomputing* **201** 29-39
[14] Reynoso-Meza G, Blasco X, Sanchis J, Martínez M 2014 Controller Tuning Using Evolutionary Multi-Objective Optimisation: Current Trends And Applications *Control Engineering Practice* **28** 58-73
[15] Trimpe S, Millane A, Doessegger S, D'Andrea R, 2014 A Self-Tuning LQR Approach Demonstrated on an Inverted Pendulum *IFAC Proceedings Volume* **47** 11281-11287
[16] Kumar GN, Rao JS, and Srikanth K 2015 Stabilization at Upright Equilibrium Position of Rotary Inverted Pendulum Using Particle Swarms With Constrained Optimization *IEEE Workshop on Computational Intelligence: Theories, Applications and Future Directions (WCI)*

[17] Xia X, Zhang T, Yi Y, Shen Q, 2016 Adaptive Prescribed Performance Control of Output Feedback Systems Including Input Unmodeled Dynamics *Neurocomputing* **190** 226-236
[18] Boucherit MS, Hadjar R, and Zineb M. 2015 State Constrained Predictive Control of Cart With Inverted Pendulum *3rd International Conference on Control, Engineering & Information Technology (CEIT)*
[19] Kouchaki E and Sadigh MJ 2013 Constrained-Optimal Balance Regulation of a Biped With Toe-Joint Using Model Predictive Control *First RSI/ISM International Conference on Robotics and Mechatronics (ICRoM)*
[20] Minouchehr N, Hosseini-Sani SK, Vaezi N et al. 2015 LMI-Based Robust Constrained Model Predictive Control of Two-Wheeled Inverted Pendulum *International Congress on Technology, Communication and Knowledge (ICTCK)*
[21] Orhon HE, Odabas C, Uyanık I, ̇Morgul O, Saranlı U 2015 Extending The Lossy Spring-Loaded Inverted Pendulum Model With a Slider-Crank Mechanism *International Conference on Advanced Robotics (ICAR)*
[22] Zhang D, Han Q-L, and Jia X 2013 Network-Based H∞ Fuzzy Control For A Self-Balancing Two-Wheeled Inverted Pendulum *IEEE International Symposium on Industrial Electronics*
[23] Bashiri M and Geranmayeh AF 2011 Tuning the Parameters of an Artificial Neural Network Using Central Composite Design And Genetic Algorithm *Scientia Iranica* **18** 1600-1608
[24] Kazemi M, Wang G, Rahnamayan S, Gupta K, Metamodel-Based Optimization For Problems With Expensive Objective And Constraint Functions *Journal of Mechanical Design* **133** 014505.
[25] Li M, Yang S, and Liu X 2015 A Performance Comparison Indicator For Pareto Front Approximations In Many-Objective Optimization *Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation*
[26] Fang H-B, Fang K-T, and Kotz S 2002 The Meta-Elliptical Distributions With Given Marginals *Journal of Multivariate Analysis* **82** 1-16
[27] Fang KT, Li R, and Sudjianto A 2005 *Design And Modeling For Computer Experiments* (London: Chapman & Hall)
[28] Fang KT, Lin DKJ, Winker P and Zhang Y 2000 Uniform Design: Theory And Application *Technometrics* **42** 237-248
[29] Fang K-T and Ma C-X 2001 *Orthogonal and Uniform Experimental Design* (Beijing: Science and Technology Press)
[30] Al-Janan DH, Chang H-C, Chen Y-P and Liu T-K 2017 Optimizing the Double Inverted Pendulum's Performance Via the Uniform Neuro Multiobjective Genetic Algorithm *International Journal of Automation and Computing* **14** 686-695