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Adaptive spiral dynamics metaheuristic algorithm for global optimisation with application to modelling of a flexible system

A.N.K. Nasir[a,*], R.M.T. Raja Ismail[a], M.O. Tokhi[b]

[a] Faculty of Electrical & Electronics Engineering, Universiti Malaysia Pahang, Pekan Pahang 26600, Malaysia
[b] Department of Automatic Control and Systems Engineering, University of Sheffield, S1 3JD, UK

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ABSTRACT

This paper presents a nature-inspired metaheuristic algorithm namely linear adaptive spiral dynamics algorithm (LASDA) and its application to modelling of a flexible system. The performance of spiral dynamics algorithm (SDA) is in general not satisfactory due to the incorporation of a single radius and single angular displacement values during the whole search process. LASDA is proposed as an improved version of SDA where the spiral radius and angular displacement are dynamically varied by employing novel mathematical equation based on linear function, which establishes a relationship between fitness value, spiral radius and angular displacement. The proposed algorithm is tested with various types of multimodal and unimodal benchmark functions and its performance in terms of fitness accuracy is discussed. A linear parametric modelling approach is utilised with an autoregressive model with exogenous inputs (ARX) structure for a flexible system. The proposed algorithm is then used to optimise parameters of the ARX structure. The performances of the LASDA in terms of convergence speed to the optimum value, fitness accuracy, time-domain and frequency-domain responses of acquired model is presented in comparison to SDA, BFA and IBFA. The results show that the proposed algorithm achieves better performance in finding an optimal solution for the benchmark functions as well as for the modelling of the flexible system.

1. Introduction

1.1. Dynamic modelling of a system

In science and engineering, the mathematical model of a physical system is an important area to study because it provides essential information about the physical behaviour of a system or a process. In fact, the information contained in the acquired model can be used by scientists or engineers to make further analysis on the system stability and system characteristics under different operating conditions, or as a principal knowledge for designing a control system. The derivation of a mathematical model of a system or process can be divided into modelling and identification. Modelling normally

* Corresponding author. Tel.: +60 94246000; fax: +60 94246111.
E-mail addresses: kasruddin@ump.edu.my, anq_qass1@yahoo.com (A.N.K. Nasir), rajamohd@ump.edu.my (R.M.T. Raja Ismail), o.tokhi@sheffield.ac.uk (M.O. Tokhi).

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refers to the determination of the mathematical equation of a system or process based on the fundamental law of science. On the other hand, identification usually refers to acquiring the mathematical model of a dynamic system based on real experimental data [1].

System identification is extensively used in various applications such as in the field of medicine [2], biomedicine [3], chemical process [4], power system [5], communication [6], signal processing [7], aeronautics [8], and robotics [9]. The advantage of system identification compared to conventional modelling approach is that a system can be modelled accurately without prior knowledge or physical information of the system. One of the well-known identification approaches used by researchers is linear parametric modelling. It is an identification method, which determines predefined set of parameters in a linear mathematical function of a dynamics system based on the captured real experimental inputs and outputs data.

In general, the parametric modelling approach can be divided into information processing, model structure determination, parameter estimation and model validation. Information processing involves the collection of experimental input and output data from a real physical system. The data collected will determine the accuracy of the estimated dynamic model, which consist of dynamic behaviour and characteristics of the system under study. The dynamic model can be represented by a transfer function or differential equation or difference equation of a certain order based on suitable model structure. A model structure with high order may represent good dynamic behaviour but can result in a very complex model with many unknown parameters. On the contrary, a structure with low order may represent a simple model with insufficient information about the dynamic behaviour of the system with few unknown parameters. In order for the model structure to represent the dynamic model of a system, the unknown parameters must be determined via a suitable estimation or optimisation algorithm, such as recursive estimation algorithm [10,11], and bio-inspired algorithm [12]. Therefore, the selection of an optimisation algorithm in predicting the parameters must be properly chosen. Algorithm that can produce more accurate solution is more favourable in determining the best parameters. All these three steps are counted as modelling phase, and they must be critically considered in parametric modelling approach since improper conduct may lead to a large error or an unsatisfactory result of the predicted model. The estimated model of the system is finally tested or validated through certain method to check whether it adequately and accurately represents the dynamic behaviour of the system under study. This step is also called as validation phase. In the field of engineering, linear parametric modelling has been used to predict solar radiation [13], to forecast the tuple of wind speed and direction [14], to model ceiling radiant cooling [15], to forecast aero-engine rotate speed signal [16] and to identify thermal behaviour of a building [17].

Modelling and control of flexible systems are increasingly attracting the attention of researchers worldwide. The unique features possessed by flexible systems include oscillatory response behaviour, making modelling of the system more difficult and more challenging. Flexible systems have been extensively used in several applications such as in robotics [18,19], spacecraft and space exploration [20], radar antennae [21], and waste material handling [22]. Flexible robot manipulator is a commonly used real-world example of a flexible system which is considered in this study. The flexible manipulator system exhibits the behaviour of both flexible and rigid bodies. In general, its rigid behaviour originates from a rigid electromechanical actuator while the flexible behaviour is due to the flexible beam joining the actuator and payload. Flexible manipulators are light in weight, less bulky design and operate at higher speed with consumption of low energy as compared to their rigid counterparts. High payload-to-weight ratio, better manoeuvrability and transportability are other advantages of the flexible manipulator, which lead to higher productivity and efficiency [23]. Moreover, due to reduced actuator and low inertia, the operation of the flexible robot is viewed to be safer. These features of flexible manipulator have motivated many researchers to explore modelling of the system, which can be done through the application of laws of physics or the application of system identification approaches. The most commonly used techniques in modelling of flexible manipulator based on laws of physics are assumed-mode method and finite-element method [24], Lagrange-mechanic and assume-mode [25], Euler–Lagrange and assume-mode [26] and Lagrange method [27]. However, derivation of the mathematical model through these methods involves dynamics/kinematic equations and requires a lot of prior knowledge of physical parameters of the system. Moreover, when dealing with complex and nonlinear systems, certain assumptions have to be made, and thus reduce the accuracy of the derived model.

1.2. Metaheuristic algorithm

Metaheuristic optimisation algorithms have gained a lot of interest among researchers worldwide. These algorithms are inspired by biological phenomena or natural phenomena. Some of the newly introduced algorithms include biogeography-based optimisation [28], artificial bee colony [29], firefly optimisation algorithm [30], galaxy-based search algorithm [31], and spiral dynamics inspired optimisation (SDA) [32]. All these algorithms have gained attention due to their simplicity to program, short computing time, easy to implement, and the possibility to apply to various applications. There are a lot of possibilities to improve the algorithms from various aspects. Many attempts have been made to improve performances of the algorithms such as hybridizing two or more algorithms and mostly developing adaptive approaches or incorporating powerful mathematical functions into the algorithms.

The SDA is a metaheuristic algorithm adopted from spiral phenomena in nature. This simple and effective strategy retains the diversification and intensification at the early phase and later phase of the trajectory as diversification and intensification are important features of an optimisation algorithm. At the early stage, the spiral trajectory explores a wider search space and it continuously converges with a smaller radius and angular displacement providing dynamic step size when approaching the final point, which is the best solution, located at the centre. The distance between a point in a