Identification of Dynamic Models by Using Metaheuristic Algorithms

Author Notification
09 August 2021
Final Revised
20 August 2021
Published
23 August 2021

Mustafa Danaci[1], Fehim Koylu[2], Zaid A. B. Al-Sumaidaee[3]
Faculty of Engineering, Erciyes University
kayseri, Turkey[1,2,3]
e-mail: danaci@erciyes.edu.tr , fehimkoylu@erciyes.edu.tr , 4013032001@erciyes.edu.tr

To cite this document:
DANACI, M., KOYLU, F., & AL-SUMAIDAEE, Z. A. (2021). Identification of Dynamic Models by Using Metaheuristic Algorithms. *ADI Journal on Recent Innovation*, *3*(1), 36–48. Retrieved from https://adi-journal.org/index.php/ajri/article/view/492
DOI:
10.34306/ajri.v3i1.492
Hash : ABCa59RrcxBpfuwT05cdlZzHWt81MBF58aKkNE1uTIQtYCg6AiPcTslZZhKW0XCl

Abstract

A modified versions of metaheuristic algorithms are presented to compare their performance in identifying the structural dynamic systems. Genetic algorithm, biogeography based optimization algorithm, ant colony optimization algorithm and artificial bee colony algorithm are heuristic algorithms that have robustness and ease of implementation with simple structure. Different algorithms were selected some from evolution algorithms and other from swarm algorithms to boost the equilibrium of global searches and local searches, to compare the performance and investigate the applicability of proposed algorithms to system identification; three cases are suggested under different conditions concerning data availability, different noise rate and previous familiarity of parameters. Simulation results show these proposed algorithms produce excellent parameter estimation, even with little measurements and a high noise rate.

Keywords: Dynamic Weighing System(DWS),System Identification(SI),Parameters Predicted, Genetic Algorithm (GA), Biogeography-Based Optimization Algorithm (BBO), Ant Colony Optimization Algorithm (ACO), Artificial Bee Colony Algorithm (ABC).

1. Introduction

Identification of structural dynamic models is quite an important region of study in mechanical and civil engineering fields. So, they have been used for a lot of different purposes such as production lines, transfer companies and building bridges, highways, etc. also have widely used in monitor nondestructive, evaluation, quality control, overload detection and filing or sorting of products, etc. the objective of system identification is to determine a model of a system so that its predicted response to a given input is close enough to the measured response from the real system.

Looking at the previous works, the widely used methods for identifying dynamic systems are adaptive filtering, nonlinear regression techniques (NLR), artificial neural network (ANN) models, and some of the metaheuristic algorithms. Considerable efforts have been made to develop methods for parameter identification and state estimation of dynamical systems that consider either a complete or partial set of input as well as output measurements such as, W. J. Shi, have used an adaptive filtering technique to measure dynamic weight system [1], and W. Q. Shu, used a nonzero start of the dynamic weight system [2]. While, M. Danacı, et. al., had estimated dynamic weight applied on model of system using non-linear regression method (NLR) [3]. Another work by M. Hamilic, et. al., used "kalman filter" to offer a better solution for mass with a dynamic weight system measuring [4]. M. Danacı studied parameter identification dynamic weight measurement system by using (NLR) method [5]. Gary J. Grayand, et. al., used genetic programming identifies parts of nonlinear equations that describe a dynamic system with numerical parameters [6].M. Danacı, et. al., applied an estimated weight to noisy data for unknown starting conditions time by using modeling error method weight measurement system determined the model parameters at an early stage, then, they performed automatic prediction with (NLR) method treatment [7], and compared with adaptive filter technique [8]. M. Danacı, et. al., provided estimate by using the multi-layered architecture of artificial neural networks to find correct mass [9]. J. Li Zhou, et. al., prepared a prediction of dynamic weight measuring system overloaded masses by using Wavelet, Genetic algorithm and (ARX) [10]. C. Xiaoyan, et. al., used an artificial intelligence technique based on fuzzy logic, to eliminate the contradiction between accuracy rates and to improve the speed worked and organizing and self-learning skills [11]. H. Gao, et. al., made analysis errors and causes of the dynamic weight measurement system to make improvements on a neural network model [12]. Also, Q. Wu, et. al., prepared a signal processing platform for weight measuring system by building a hierarchical structure between Singular Spectrum Analysis and Learning Vector Quantization to noise-reducing and results showed significant improvement [13]. G. Liao, et. al., designed dynamic weight system measurement for an average mass of moving vehicles on roads, bridge and asphalt etc. to calculate damaged structures based on linear regression model by analyzing tools [14]. On the other side, W. Jeridi, et. al. studied the weight measurement process with filtering techniques to improve and develop security analysis team and security risk analysis [15]. P. Hu, et. al., proposed a new smart control strategy between the accuracy and speed in the dynamic numerical weight measurement system proportional integral derivative (PID) control theory and neural network to solve contradiction [16]. Last but not least, J. Sun, et. al. proposed a new initialization approach with a (PID) controller known as PID-neural network and direct heuristic dynamic programming then they tested the effectiveness of the initiation approach based on the wheelbarrow model [17]. Z. Ying, et. al. conducted a study on the data processing method that includes the filter design finite impulse response and infinite impulse response. These studies provide better results as observed [18]. A. D. Martin, et. al., examine simulate vertical force. In the process of filling to extract the ordered mass of a milk powder bag suspended used milk as a function of time, powder mass estimation process by using Kalman extensions such as augmented-state Unscented Kalman Filter (UKF), non-augmented UKF, and particle filter [19]. M. Niedźwiecki, et. al., applied finite impulse response (FIR) model to the weighing system [20]. López-Ibáñez, et. al., presented the (IRACE) package, implementing the iterated racing procedure for the configuration of automatic algorithm [21]. Furthermore, Dunbing Tang, et. al., proposed a method for addressing the dynamic scheduling issue by reducing energy consumption and makespan for a flexible flow [22]. Oliver Nelles, elucidated how equational and output errors are dealt with in the neural network terminology as series-parallel and parallel model structures [23].

This part including some of the metaheuristic algorithms literature-work's, are also used in identifying the models of dynamic systems. D. Sendrescu, et. al., used particle swarm optimization and genetic algorithms to search the nine parameters of Monod law and Haldane kinetic model which is used to define the mathematical model of bacteria growth process [24, 25]. M. Ulinowicz, et. al., used Genetic algorithm for ship model identification [26]. M. Kumar, et. al., applied a bat optimization algorithm to design an adaptive (IIR) system [27]. and, S. Ryzhikov, et. al., used evolutionary optimization techniques with a new restart mechanism to solve inverse mathematical modeling for dynamic systems [28]. Frumen Olivas, et. al., used interval type-2 fuzzy logic to improve the convergence and diversity of the particles in PSO algorithm [29]. Muhammad Rizwan Tanweer, et. al., used incorporated a dynamic mentoring scheme along with a self-regulation scheme in the standard Particle Swarm Optimization [30]. In 2017, Yali Wu, et al., suggested adapted chaos and Kalman filter based Particle Swarm Optimization algorithm (SCKF-PSO) which is proposed to solve economic dispatch (ED) problem while minimizing the cost with different equality and inequality constraints [31]. Feifei Zheng, et al., proposed an innovative parameter-adaptive strategy for Ant Colony Optimization (ACO) algorithms based on controlling the convergence trajectory in decision space to follow any prespecified path [32]. Qiang Yang, et al., extends ACO algorithm to deal with multimodal optimization [33]. A. E. Baktir used optimization algorithms to predict displacement information in dynamic weighing systems [34]. Jhang Jyun-yu., et al., assessed the performance of type-2 fuzzy neural controller with dynamic

p-ISSN : 2685-9106
e-ISSN : 2686-0384

group PSO on the wall following behavior of mobile robots' navigation control method in an unknown environment [35]. Ruwang Jiao, et al. proposed dynamic constrained multi-objective evolutionary algorithm to model the antenna design problem which is defined as a constrained optimization problem. Algorithm is applied on three different antenna class and promised good results [36]. It is also worthwhile to note that Qinghua Wu, et al., confirmed that improved PSO algorithm could markedly enhance inversion precision as well as rendering high correlation coefficients linked with elastic parameters [37].

In reviewing the literature, system identification can generally be divided into parametric identification and nonparametric identification, depending on the type of structural model used. When system identification is done with respect to an assumed model defined by a set of physical parameters, such as mass and stiffness, it is referred to as parametric identification, while nonparametric identification is used to categorize methods that use purely mathematical representations of the system. Since the proposed algorithms have been proven to cope with large optimization problems, it is natural to compare their performance with structural parameter identification, taking into account the problems associated with the limitations encountered in real applications, such as incomplete sets of measurements and noisy data.

2. Meta-Heuristic Algorithms (Research Method)

Meta-heuristic algorithms are procedures that can create solutions without slope knowledge. Moreover, the rate of using meta-heuristic algorithms is increasing day by day due to their fast response, high computational power and reusability for different problems [38]. In this part, general information about the algorithms proposed in this paper has been explained to identify a dynamic weight system.

2.1. Genetic Algorithm

In 1975 John Holland [39], presented developed algorithms proposing genetic algorithm as a stochastic global search method mimicking the natural evolution wherein functions on a population of potential solutions administering the survival principle with the aim of developing a better generation gives individuals can adjust better than parents. To illustrate, cell have chromosome as a string of bit namely A and B and the chromosome have strings of DNA where the crossover exchange genetic material between two chromosomes or parents.
Goldberg [40] describes the simple genetic algorithm (SGA) and uses it here for illustrating the basic components of the GA. A pseudo-code outline of the SGA is illustrated below. The population at time t is represented by the time-dependent variable P, with the initial population of random estimates being P (0). The most prominent variations are:

- GA searches a population of points in parallel rather than a single point.
- GA make use of probabilistic transition rules instead deterministic rules.

 p-ISSN : 2685-9106
e-ISSN : 2686-0384

- GA operates on an encoding of the parameter set except in where real-valued individuals are used.
- GA doesn't demand derivative or auxiliary information only the objective function and corresponding fitness levels affect the search directions.

Objective and Fitness Functions: The objective function is employed so that a measure of how individuals have performed in the problem domain could be provided. This raw measure of fitness is only benefited as an intermediate stage while determining the relative performance of individuals in a GA. Another function, namely, the fitness function, is, under normal circumstances, used so that the objective function value could be transformed into a measure of relative fitness [41].

Selection: is the process of how many times a particular individual is chosen for reproduction could be determined hence, the number of offspring that an individual is likely to generate. The selection of individuals could be seen as different processes:

- Determination of the number of trials an individual might take,
- Conversion of the anticipated number of trials into a discrete number of offspring.

The first part is related with the transforming raw fitness values into a real valued expectation of an individual's likelihood of reproducing and can be handled with in the previous subsection as fitness assignment. When it comes to the second part, it is the probabilistic selection of individuals for reproduction based on the fitness of individuals relative to each other and is also known as sampling. Many selection techniques make use such as roulette wheel selection methods, multi point crossover, uniform crossover, mutation and phenotypes[40- 43].

Genetic algorithm parameter's names and values that modified and used in this study are population size “30”, number of steps “100”, selection pressure “1”, crossover probability “1”, crossover inflation “0.1”, mutation probability “0.02” and mutation rate “0.1”.

2.2. Biogeography Based Optimization Algorithm

BBO is a nature-inspired algorithm which has roots in biogeography science it analyzes the distribution of species over time and space "research of the geographical distribution of biological organisms", in 2008, Dan Simon presented biogeography based optimization algorithm as an application of biogeography science to solve optimization issues [44, 45]. population based in which a population of candidate solutions " individuals " is employed to solve optimization issues, thus each possesses its own habitat suitability index (HSI) rather than fitness value to indicate the degree of its goodwill Whereas High-HSI habitat can represent a solid solution, low-HSI habitat may represent a weak solution, solution features range from high-HSI emigrating habitat to low-HSI immigrating habitat. it is Possesses operators namely migration "including emigration and immigration" in addition to mutation. One generation of the BBO approach could be described as:

- Find the fit test solution. Call this solution xi.
- Pick a random SIVs

- Choose the immigrating island xj from a uniform probability distribution
- xj(s) ← xi(s)

steps of the algorithm are explained below the first approach is based on migration, immigration rates for each island, and probabilistically determine if to immigrate each SIV " solution feature " independently or not. The simulation outcomes which have been given in the original BBO paper [44] have been attained using this approach. The second approach is to base migration on emigration rates for each island, and probabilistically determine if to immigrate each SIV independently or not.

Biogeography based optimization algorithm parameter's names and values that modified and used in this study are population size “30”, number of steps “100”, keep rate “0.1”, acceleration coefficient “0.5”and mutation probability “0.9”.

2.3. Ant Colony Optimization Algorithm

In 1991 Dorigo and Colorni suggest a new approach to distributed problem solving and optimization based on the result of low-level communications between a numbers of cooperating simple agents who do not notice their cooperative behavior [46]. In reality, ants take random tours around when they find food they go back to the colony and lay down pheromone trails they probably will not continue to travel randomly rather they will follow the trail left by the ants which first used that path returning and reinforcing it on condition that they detect food on the other side. Day by day, the pheromone trail begins to evaporate hence diminishing its attractiveness the more time it takes for ants to go all the way down the path and return the more time the pheromones have to evaporate by comparison, the short path gets marched over faster, hence allowing the pheromone density to remain high the paths selected by the first ants would be highly attractive to those which follow them.

ACO is based on several construction steps on a dynamic memory structure which contains information concerning the quality of old results [47, 48]. Therefore, each one of the ants may represent a probable solution to the issue ants find out solutions taking existing pheromone trails into consideration and heuristic information available a prior a pheromone table is updated accordingly wherein higher the solution quality are taked if the more pheromone is deposited main frameworks are evaporation based and population based [49 ,50] and the main distinction lies in the way pheromone is updated where the important variables of the framework are shown below. where probabilistic city selection and update pheromone explained in[51, 52]

- Trail intensity given by value of "τij" which indicates the intensity of pheromone on edge (i, j)
- Trail visibility is "μij= 1/dij"
- α Intensity in the probabilistic transition.
- β Importance of visibility of trail segment.
- ρ Trail persistence or evaporation rate.

- Q Constant and represents the amount of pheromone laid on a trail segment used by an ant.

Ant colony optimization algorithm parameter's names and values that modified and used in this study are population size “30”, number of steps “100”, sample size “40”, intensification factor “0.2” and deviation distance ratio “0.9”.

2.4. Artificial Bee Colony Algorithm

In 2005 D. Karaboga put forward Artificial Bee Colony algorithm (ABC) as a technical report for numerical optimization problems, ABC algorithm mimics the behaviour of real bees colonies [53]. Hence, ABC is a novel iterative improvement search paradigm, which is obviously an effective algorithm to solve combinatorial issues [54, 55]. Since its early days, various variations have been developed in parallel with last applications in many disciplines. It has been improved by simulating how honey bees behave while foraging.

A conventional ABC algorithm includes food sources each of which represents a possible solution to the issue. Types of bees which update food sources: Onlooker, Scout, and Employed bees. Each bee generates a new candidate food source position from the old one. In addition, ABC includes three control parameters:

- Population size (SN) is how many food sources exist (or solutions) in the population, SN is equavalent to the count of onlooker or employed bees.
- Maximum Cycle Number (MCN) refers to the highest number of generations.
- Limit is employed so that the search could be diversified. Moreover, limit is employed to determine the number of permitable generations for which every non-improved food source should be left.

Artificial bee colony algorithm parameter's names and values that modified and used in this study are population size “30”, number of steps “100”, onlooker bees count “30”, maximum acceleration coefficient “0.9”.

3. Findings

3.1. Identification Models

The identification models used in the process of system identification are classified according to the number of input/output parameters, time dependence, domain, linearity and confounding factors.

3.1.1. Number of input-output variables

These are models classified according to the number of input and output parameters. It is called models with one input and one output in return SISO(Single Input Single Output), models with multiple inputs and multiple outputs MIMO(Multiple Input Multiple Output), models with multiple inputs and one output MISO (Multiple Input Single Output). The most widely used model for dynamical systems is the MISO model, where one output corresponds to multiple inputs. The parameters are more difficult to determine than in the SISO model [56,57].

3.1.2. Time dependence

It is the classification of models according to time dependence. While the internal dynamics of some models are time dependent and some systems are not affected by time, most dynamic systems have time dependence. The responses that the system gives vary as a function of time. To simplify the computation, it is common to use time-independent models [57].

3.1.3. Domain

System models are studied in two domains, the time domain and the frequency domain. While time domain is used for identification with differential and difference equations, frequency domain models are used for identification of systems such as spectral density or Bode curves [57- 62].

3.1.4. The condition of linearity factors

It is the modeling of systems according to the mathematical relationship between input, output parameters and disturbance variables. When the relationship between signals can be expressed with linear equations, these models are called linear models. The relationship between signals can be differential, exponential, logarithmic, trigonometric, etc. When expressed with nonlinear equations, these systems are called nonlinear models [57].

3.1.5. Disruptive effects

Models where the input signal is known and the output signal can be calculated exactly are called deterministic models, while models with random values that cannot be calculated due to external effects are called stochastic models. Many systems are identified with the stochastic model [57].

3.2. Structural Dynamic Systems

Accurate and fast operation of weight measurement is an important requirement in the modern world. Therefore, a dynamic system model for a weight platform is used in this study as shown in Figure 1. The system of mass (M), damping (C) and spring (K) is a widely used shock absorption system in mechanical systems, There are three types of responses depending on applied mass at damping system responses are called under damped, critical damped, and over damped [63, 64]. The most general form of weight system is the "Under Damping" system as shown in Equation 1, [65, 66]. The measurement of a weight system was modeled using the second differential equation expressed below in Equation 2. The parameter

"M" refers to the applied mass, the parameter "C" refers to the damping constant, the parameter "K" refers to the spring constant.

$$Y= M(g/k)-Ae^{-(c/2m)t}sin(wdt+\phi)$$

$$F(t)=M(d^2y(t)/dt^2) + C(dy(t)/dt) + Ky(t)$$

$$F(t)= g^* (M/K)$$

$F(t) = g * \frac{M}{K}$ where, "g" parameter is gravitational acceleration.

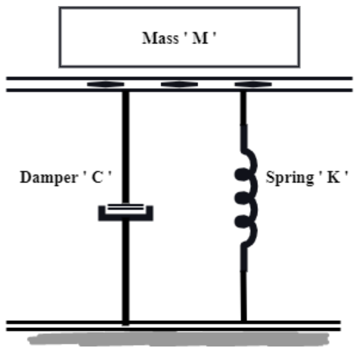


Figure 1. The model of the weight measuring system.

3.2.1. Preparation of System

GA, BBO, ACO, ABC algorithms are used to investigate the dynamic system and performance of the algorithms on predicting the parameters are compared on three parts of the nonlinear system with different parameter values and noise rates.

3.2.1.1. Identification System

The system response to the effect of data size on identification is studied; this part is for testing purposes and shows the identification performance of the algorithms.

In this section, the system response is performed to find the values of each 'M', 'C' and 'K'. The system parameters used for the response are mass(M) = 100 kg, damper constant(C) = 50 N/(m/s), spring constant(K) = 1000 N/m, number of samples(N) = 250. The system response is calculated for each 0.4 seconds and recorded for 10 seconds. The responses of the systems with 0, 1, 3, 5, and 10% are shown in Figure 2.

p-ISSN : 2685-9106
e-ISSN : 2686-0384

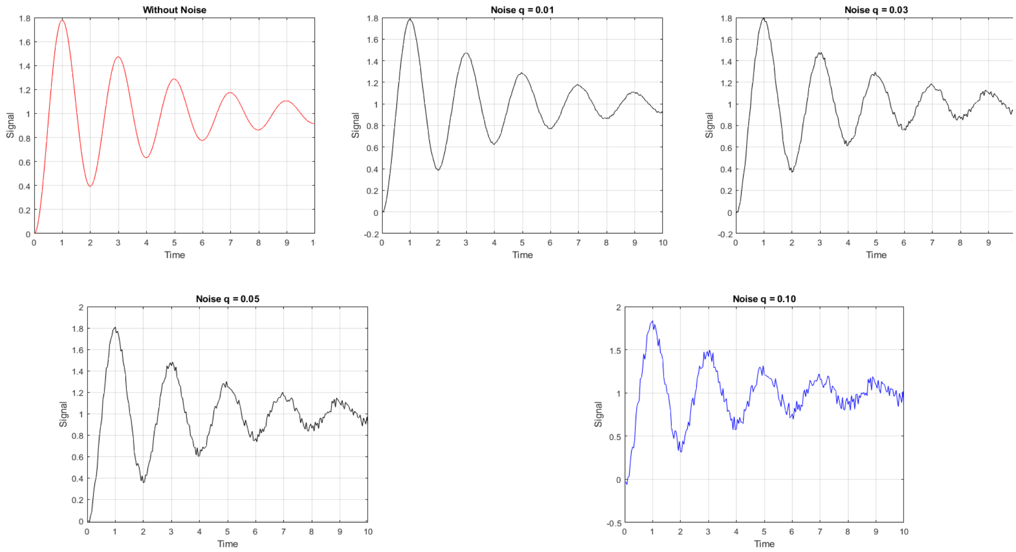
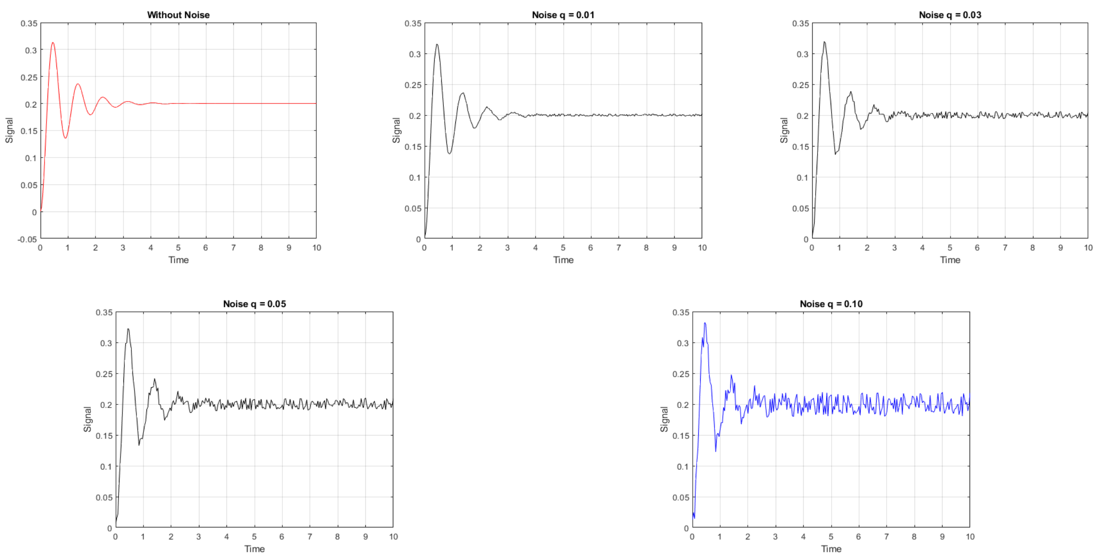


Figure 2. System response when mass =100, damper =50, spring =1000 with different noise rate(without noise, with 1% noise, with 3% noise, with noise and with 10% noise)

3.2.1.2. Prediction Damper (C) and Spring (K) System

In this experıments, Damper (C) and Spring (K) parameters are predicted as a function of Mass (M) within given bounds.

Mass datasets are prepared using different mass(M) values, such as 5, 20, 30, 45, 60, 70, and 90 Kg. The identified true values are 50 N/(m/s) for C, 1000 N/m for K, and 250 samples are collected. The system response is calculated for each 0.4 seconds and recorded for 10 seconds. The responses of the systems with 0, 1, 3, 5, and 10% are shown in Figure 3 and Fıgure 4.



p-ISSN : 2685-9106
e-ISSN : 2686-0384

Figure 3. Damping graph of scaling device with 20 kg mass; without noise, with 1% noise, with 3% noise, with noise and with 10% noise.

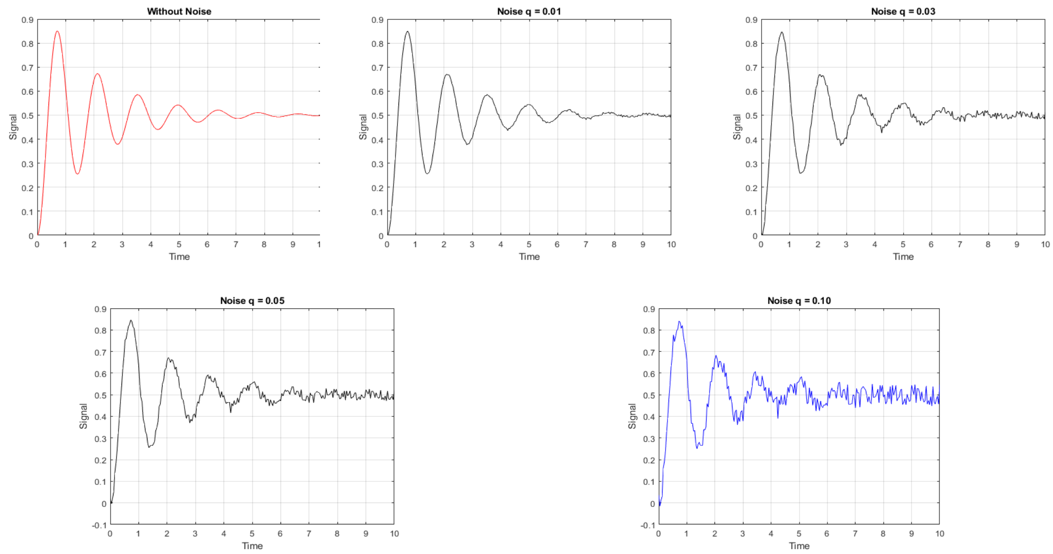


Figure 4. Damping graph of scaling device with 45 kg mass; without noise, with 1% noise, with 3% noise, with noise and with 10% noise.

3.2.1.3. Prediction Mass System

Prediction to determine Mass (M) of the range comparison of the system response part in which the pre-estimation process is performed with less data is done.

In this section, the mass constant (M) was predicted at an early stage, assuming that the values of the damper and the spring are known from the results of the identification in the second part (prediction of Damper Constant and Spring Constant). The determination process was completed by taking 10% of the system response, estimated min-max equal to 90%, the displacement of the system response t = 0 and 0, 1, 3, 5 and 10% noises.

Data generated in the simulation environment is used in the study. The system responses were obtained in the simulation environment by giving the model the parameter values known beforehand and called the reference system response. Using meta-heuristic algorithms, the found parameter values are designated as new system response by passing the data. These two outputs are compared with the sum of squares equation at each step to find the best parameter values up to the maximum number of steps. It is shown in following equation, [1, 63, 67-70].

- Here, the system is tested with different mass values.
- In each part of this study, "g = 10 m / s 2" , and "ms = 0".

$$\Delta y = \Sigma(y\text{-}y`)^2$$

p-ISSN : 2685-9106
e-ISSN : 2686-0384

3.3. Dynamic Weight Measurement

Identified dynamic weight systems using the algorithms GA, BBO, ACO and ABC then make predictions for parameters with 0%, 1%, 3%, 5% and 10% noise rates.

3.3.1. System Response Results

In this section, the system response performance of each algorithm is shown, where system response conducted to find the values of each 'M', 'C' and 'K' as shown below the results for each algorithm show separately in Figure 5; In this section, the results of the system responses for the performances of the proposed algorithms are recapitulated to find each "M", "C" and "K" value with the least sum squared error (SSE), see tables below, the best result of SSE obtained by using the system responses with 0% noise ratios founded by GA was equal to 1.7421e-11 and the ACO algorithm was equal to 6.1848e-07. And the best result of SSE obtained with system responses with 1% noise ratio founded by GA was equal to 2.4825e-10 and ABC algorithm was equal to 0.0080641, 3% and 5% noise ratio founded by BBO was equal to 0.071939, 0.20352 and 10% noise ratio founded by GA was equal to 0.84236 and ABC was equal to 0.80609. Comparing the obtained parameter values by using the proposed algorithms with the original system parameter values, we found that BBO and ABC have high performance and give better results, but in GA and ACO there are serious deviations for the original value in finding the damper caused by using a small amount of data, and the same algorithms have high performance and give good results in finding the mass, damper and spring, have very small deviations for the original value caused by using a large amount of data.

Noise	GA				BBO			
	Mass 100Kg.	*Damper 50N/ms*	*Spring 1000 N/m*	*SSE*	*Mass 100Kg.*	*Damper 50N/ms*	*Spring 1000 N/m*	*SSE*
0%	105.96	52.918	1009.7	1.7421e-11	100.33	50.48	1003.2	0.00043496
1%	101.07	50.537	1010.7	2.4825e-10	100.23	50.23	1002.3	0.0076896
3%	104.95	47.482	950.43	0.075814	110.18	56.256	1101.6	0.071939
5%	106.92	53.476	1071.1	0.21059	99.22	48.516	993.03	0.20352
10%	102.71	50.8895	1025.41	0.84236	114.16	57.082	1142.2	0.89527

Table 1. System Response of GA and BBO to identification Mass (M), Damper (C) and Spring (K) with the results of Summation Squared Error (SSE).

Noise	ACO				ABC			
	Mass 100Kg.	*Damper 50N/ms*	*Spring*	*SSE*	*Mass 100Kg.*	*Damper 50N/ms*	*Spring*	*SSE*

			1000 N/m				*1000 N/m*	
0%	100.94	50.458	1009.4	6.1848e-07	100.97	50.427	1009.8	2.4121e-05
1%	102.84	51.357	1028.5	0.0088596	99.473	49.735	994.71	0.0080641
3%	97.345	48.561	973.46	0.079767	99.469	49.694	994.83	0.072548
5%	97.216	48.43	972.33	0.22153	100.83	50.423	1008.5	0.20155
10%	104.15	52.052	1044.8	0.88593	95.474	47.628	955.18	0.80609

Table 2. System Response of ACO and ABC to identification Mass (M), Damper (C) and Spring (K) with the results of Summation Squared Error (SSE).

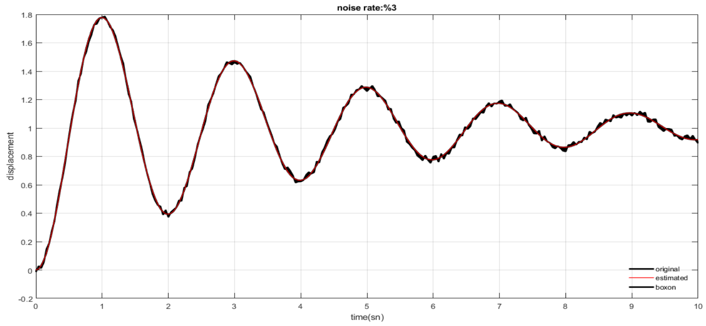


Figure 5. System response when mass =100, damper =50, spring =1000 with 3% noise rate.

3.3.2. Prediction Damper Constant and Spring Constant

In this part, the performance of the proposed algorithms for identifying the damper and spring values is shown by applying different values of mass, where the values of mass (M) are equal to 5 kg, 20 kg, 30 kg, 45 kg, 60 kg, 70 kg and 90 kg, the results of each algorithm are explained separately below.

Applied Mass	GA				BBO		
	Noise	*Damper C 50N/ms*	*Spring K 1000 N/m*	*SSE*	*Damper C 50N/ms*	*Spring K 1000 N/m*	*SSE*
5 Kg.	0%	49.999855	999.99996	2.0726e-14	48.390118	1000.217	2.5312e-06
	1%	49.786477	1000.1032	2.0196e-05	49.376407	999.86235	2.2317e-05
	3%	49.359871	1000.3084	0.00018176	49.831901	999.46719	0.00019893
	5%	48.933013	1000.5075	0.00050489	50.710647	999.13255	0.00055431
	10%	47.865495	1001.0151	0.0020195	48.319242	998.53407	0.0022098
20 Kg.	0%	49.997441	1000.0003	2.9481e-10	50.059334	1000.8689	8.4851e-06
	1%	50.093234	999.43696	0.00031343	50.031636	998.95862	0.00031918
	3%	50.288091	998.30894	0.0028208	50.962605	999.08292	0.0027837
	5%	50.486474	997.18016	0.0078351	51.831236	997.90506	0.0077383
	10%	51.026065	994.34652	0.031337	52.454183	996.95036	0.030965
30 Kg.	0%	50	1000	1.8985e-17	50.017286	999.99882	4.367e-08
	1%	49.933174	1000.1963	0.00079408	49.965364	1000.2725	0.000751

	3%	49.799004	1000.5871	0.0071467	50.01323	1000.7753	0.006761
	5%	49.664135	1000.9754	0.019852	50.702887	1003.8878	0.019068
	10%	49.32385	1001.9353	0.079408	49.699474	1002.2414	0.075104
45 Kg.	0%	49.999754	1000	2.9101e-11	49.90888	1000.0254	4.0356e-06
	1%	50.060663	999.89049	0.0017178	50.090689	998.81644	0.0017931
	3%	50.179664	999.76793	0.01546	49.859124	1001.2434	0.014735
	5%	50.301685	999.61695	0.042944	49.982525	1000.7681	0.040911
	10%	50.578621	999.25033	0.17178	49.08732	1003.2663	0.16365
60 Kg.	0%	52.366696	1003.4764	0.0077487	50.10165	1000.9646	0.0001605
	1%	50.040885	999.82236	0.0028513	49.81631	1000.9811	0.0033474
	3%	50.123434	999.46811	0.025661	50.834864	995.72167	0.034633
	5%	50.206817	999.11519	0.071282	48.282541	1015.321	0.11425
	10%	50.419303	998.23847	0.28513	49.634438	1002.9126	0.32554
70 Kg.	0%	49.99982	1000.0038	3.7844e-09	49.999252	1000.0045	6.0697e-09
	1%	49.978377	1000.0921	0.0042634	50.08091	1000.7095	0.0042631
	3%	49.935878	1000.2766	0.038371	50.806001	999.24606	0.036709
	5%	49.893249	1000.4622	0.10659	50.253417	998.99388	0.10005
	10%	49.794616	1000.9273	0.42634	49.600672	998.69952	0.40218
90 Kg.	0%	50.001479	1000	7.4903e-09	50.01418	1002.5333	0.003355
	1%	50.095384	999.97601	0.0066058	48.410358	990.11268	0.073142
	3%	50.285918	999.93234	0.059453	51.442259	1000.6134	0.059915
	5%	50.475786	999.89449	0.16515	50.841847	1000.4211	0.15959
	10%	50.950732	999.82538	0.66063	51.883219	1001.7712	0.63758

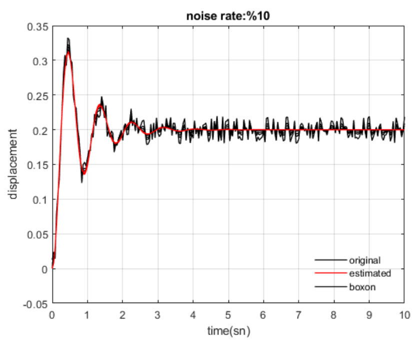
Table 3. Results of Prediction Damper (C) and Spring (K) by using GA, BBO with different Mass (M) and also different noise rate.

Applied Mass	ACO				ABC		
	Noise	*Damper C 50N/ms*	*Spring K 1000 N/m*	*SSE*	*Damper C 50N/ms*	*Spring K 1000 N/m*	*SSE*
5 Kg.	0%	50	1000	4.3333e-34	50.00012	1000.0005	1.7723e-13
	1%	49.496855	1000.6654	2.0262e-05	50.202405	1000.4958	1.8217e-05
	3%	48.503686	1001.9989	0.00018235	50.624659	1001.4995	0.00016395
	5%	47.526778	1003.3365	0.00050651	51.057885	1002.4974	0.00045541
	10%	45.145276	1006.7002	0.0020258	52.18623	1005.0092	0.0018215
20 Kg.	0%	50	1000	8.7052e-32	50.000553	999.99547	2.3655e-10
	1%	49.77266	999.30359	0.0003353	49.879053	1000.0806	0.00032533
	3%	49.316695	997.91301	0.0030175	49.634331	1000.2528	0.0029279
	5%	48.859144	996.52549	0.0083813	49.393144	1000.4199	0.0081332
	10%	47.709381	993.07063	0.033518	48.795694	1000.8899	0.032532
30 Kg.	0%	50	1000	0	50.000031	1000.0009	2.4054e-11
	1%	50.046888	999.94136	0.0007446	49.854536	999.88619	0.00078022
	3%	50.140308	999.82372	0.0067012	49.565402	999.66422	0.0070217
	5%	50.233259	999.70561	0.018615	49.26983	999.44508	0.019504
	10%	50.46363	999.40832	0.074459	48.529388	998.903	0.078011

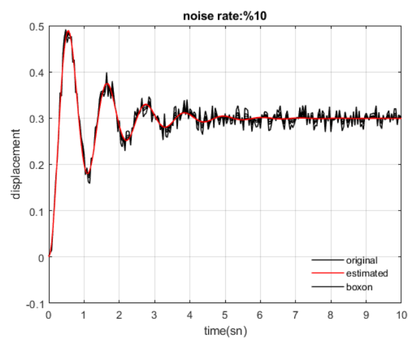
p-ISSN : 2685-9106
e-ISSN : 2686-0384

45 Kg.	0%	50	1000	0	49.999852	1000.0002	1.3565e-11
	1%	50.103451	1000.3424	0.0016703	50.089971	999.87108	0.0016993
	3%	50.310326	1001.0293	0.015033	50.270334	999.60126	0.015293
	5%	50.51711	1001.7192	0.041758	50.451029	999.3305	0.042481
	10%	51.033254	1003.4567	0.16704	50.907104	998.64691	0.16992
60 Kg.	0%	50	1000	3.5314e-30	50.000668	999.99606	2.9615e-09
	1%	49.849704	1000.0578	0.0028016	50.073272	1000.3753	0.0031431
	3%	49.551379	1000.177	0.025215	50.218351	1001.131	0.028287
	5%	49.255998	1000.3014	0.070041	50.368172	1001.8962	0.078574
	10%	48.529842	1000.6343	0.28016	50.748679	1003.8251	0.31427
70 Kg.	0%	50	1000	3.6793e-30	49.999113	1000.0011	1.6436e-09
	1%	50.007325	999.70261	0.0037797	49.991115	1000.0481	0.0038159
	3%	50.022479	999.10598	0.034017	49.974146	1000.1451	0.034343
	5%	50.038284	998.50686	0.094489	49.9563	1000.244	0.095398
	10%	50.080505	996.99803	0.37794	49.908413	1000.4871	0.38159
90 Kg.	0%	50	1000	0	50.001972	999.99896	1.3877e-08
	1%	49.868261	1000.1087	0.0064954	49.89527	999.88091	0.0063895
	3%	49.605428	1000.3236	0.058458	49.688649	999.64365	0.057506
	5%	49.343461	1000.5351	0.16238	49.480796	999.40329	0.15974
	10%	48.692378	1001.0498	0.64951	48.97645	998.78067	0.63896

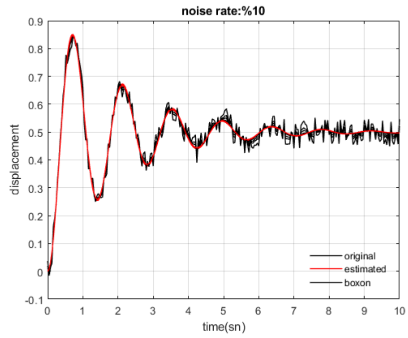
Table 4. Results of Prediction Damper (C) and Spring (K) by using ACO, ABC with different Mass (M) and also different noise rate.



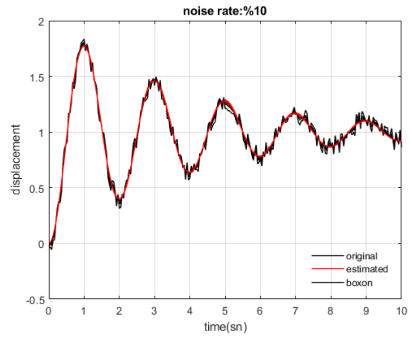
a) Mass 20 Kg.



b) Mass 30 Kg.



b) Mass 45 Kg.



b) Mass 90 Kg.

Figure 6. Response of Prediction Damper (C) and Spring (K) when mass =20,30,45 and 90 Kg.,with 10% noise rate.

The summary of the results for the proposed algorithms in this study to identification of the constants ' C' and 'K' to be assigned by taking the mean values of the found values when applying different mass values to the dynamic weight measurement system model separately within certain limits. The results of identifying the parameters 'C' and 'K' are shown in "Table V". Considering the values of GA and BBO it is found that the identification performance of the constants performed using the system response with a noise ratio of 0% is 50 for C, 1000 for K and 1.8985e-17 for SSE in GA when m = 30 kg. Whereas 49.999252 for C, 1000.0045 for K and 6.0697e-09 for SSE in BBO when m = 70 kg. The results of ACO and ABC are shown in "Table VI" respectively. The performance of identification with system response even at 0% noise ratio is 50 for C, 1000 for K and 0 for SSE in ACO when m = 30 kg, 45 kg and 90 kg respectively. Where 50.00012 for C, 1000.0005 for K and 1.7723e-13 for SSE in ABC; the results of GA and BBO as shown in the tables above, it can also be seen that the average performance of identification study with system response with %1,%3,%5 and %10 noise ratio, 49.99571054 for C, 999.6948975 for K and 0.07987367 for SSE in GA, while 50.17161807 for C, 1000.238145 for K and 0.082813005 for SSE in BBO. and 49.42941946 for C, 1000.087197 for K and 0.076403386 for SSE in ACO, while 49.99966457 for C, 1000.441206 for K and 0.077968008 for SSE in ABC. As (Swarm Intelligence Algorithm) it is seen that ACO has the best SSE values in %0 noise ratio followed by ABC with very little difference and as (Evaluation Algorithm) it is seen that GA has the best SSE values in %0 noise ratio. When the noise ratio equal to %1, %3, %5 and %10, it also seen that ACO has the best SSE values in noise ratio followed by ABC and GA.

3.3.3. Prediction to Determine Mass

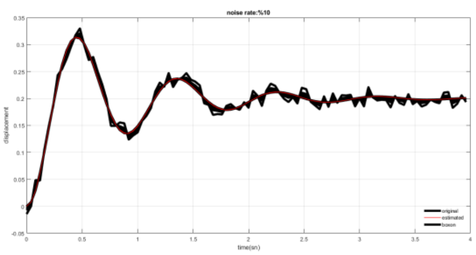
In this section, the mass constant "M" was predicted at an early stage, assuming that the values of the damper and the spring are known from the results of the identification in part (B. Identification Damper Constant and Spring Constant prediction). The determination process was completed by taking 10% of the system response, estimated min-max equal to 90%, the displacement of the system response t = 0 and 0%, 1%, 3%, 5% and 10% noises. The results are shown below in the tables as for all algorithms.

Original Mass	Comparison of Algorithms Results				
	Noise	*GA*	*BBO*	*ACO*	*ABC*
M=20 Kg.	0%	19.996	20.020	20.003	19.992
	1%	20.008	19.986	20.003	19.999
	3%	20.031	21.436	20.002	20.020
	5%	20.054	19.929	20.000	20.038

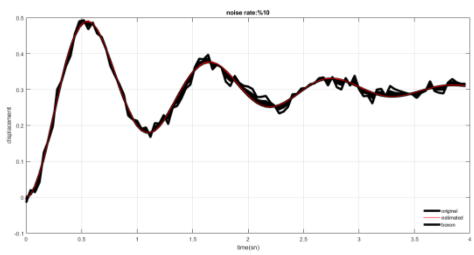
	10%	20.150	19.923	19.997	20.083
M=30 Kg.	0%	29.993	30.027	30.006	29.985
	1%	30.015	30.147	29.992	29.993
	3%	30.059	29.748	29.965	30.001
	5%	30.104	30.059	29.938	30.012
	10%	30.270	30.111	29.870	30.036
M=50 Kg.	0%	49.987	50.030	50.011	49.976
	1%	49.995	49.983	50.010	49.970
	3%	50.012	49.977	50.009	49.952
	5%	50.029	49.482	50.009	49.934
	10%	50.160	49.953	50.009	49.892
M=100 Kg.	0%	99.993	100.152	100.011	99.954
	1%	100.025	100.234	99.976	99.988
	3%	100.059	100.056	99.906	100.060
	5%	100.102	100.112	99.835	100.132
	10%	100.417	100.181	99.656	100.310

Table 5. Results of Prediction to Determine Mass (M) by using GA, BBO, ACO and ABC Algorıthms

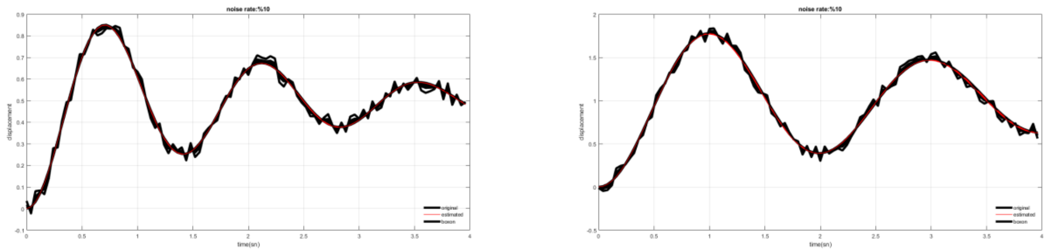
A summary of the results on the preliminary estimation answer for the determination of the mass and the performance of the proposed algorithms are explained. By looking at the tables, it can be seen that the performance of GA algorithm had good response values when the noise rate was equal to 0%, 1%, 3% and 5%, while the BBO algorithm had good response values when the noise rate was equal to 0%, 1%, 5% and 10%, with ABC and ACO algorithms having the best values at all noise rates equal to 0%, 1%, 3%, 5% and 10%. In the mass estimation studies, it was observed that the results of GA, ABC and ACO were very good at different noise rates to find different mass values, in the second class BBO gave successful results at different noise rates.



a) original mass =20 Kg.



b) original mass =30 Kg.



c) original mass =50 Kg. d) original mass =100 Kg.

Figure 7. Response of Prediction Mass (M) when original mass =20,30,50 and 100 Kg.,with 10% noise rate.

4. Conclusion

A modified version of the GA, BBO, ACO and ABC algorithms has been presented in the context of structural systems identification. In order to investigate the applicability of these proposed techniques for the identification of systems with estimation parameters, nonlinear systems were studied under different conditions, taking into accounts such as the number of measurements used for the identification, noise signals and knowledge of the mass. In all the cases considered, the simulation results show that the proposed algorithms are successfully applied to identification system and estimate the mass, When the found parameter values are compared with the original parameter values, it was found that very successful results are obtained. Considering obtained results, in the mass estimation part, it has been observed that the GA and ACO have good parameter values with the system response with different noise ratio, and BBO, ABC yielded successful results at different mass values. The presented methods is effective, robust and efficient even with reduced partial measurements and high noise.

Meta-heuristic algorithms can be used as an alternative solution in parameter estimation procedures, especially in system identification procedures. If the algorithms used in the study are improved in terms of their response times, they can be used for online applications. For future studies, hybrid algorithms, parallel signal processing techniques can be used to improve the response times.

References

[1] Shi, W.J., White, N.M., Brignell, J.E., 1993, Adaptive filters in load cell response correction, Sensors & Actuators A, 37:280-285.

[2] Shu, W.Q., 1993, Dynamic weighing under non-zero initial conditions, IEEE Transactions on Inst. & Meas., 42(4): 806-811

[3] Danaci, M. and Horrocks, D.H., 1995, High speed modelling by non-linear auto regression, Cardiff School of Engineering, University of Wales PO Box 917, Cardiff, CF2 1XH, UK.

[4] Hamilic M., Balacharhan W., 1995, Kalman filter for dynamic weighing system, industrial electronics, pp. 786-791, ISIE '95, Proceedings of the IEEE International Symposium on, 10-14 July, Dubrovnik, Croatia.

[5] Danaci, M. 1996, Non-Linear Regression Techniques For Dynamic Weighing Systems Ph.D. Thesis. Cardiff University of Wales, UK.

[6] Gray J.G., Murray-Smith, D.J., Li Y.,Sharman K.C., Weinbrenner T., 1998, Nonlinear model structure identification using genetic programming, Control Engineering Practice, 6(11): 1341-1352.

[7] Danaci M. Kalınlı A., 1999, Detection of the starting of the newly applied mass for successive weighing, Mathematical & Computational Applications, 4(1):53-59.

[8] Danaci M., Yaz M., 1999, New approaches to successıve contınuous weighing, pp. 584-591, Proceedings of the IASTED International Conference Control And Applıcatıons Banff, July 25-30, Canada.

[9] Danaci, M., 2000, Platform parameters ıdentification by non-linear regression method, pp. 811-818, 14th European Simulation Multiconference, ESM’2000, 23 – 26 May, Ghent, Belgium.

[10] Li J. Zhou L. Wang Q., 2007, Study on dynamic weighing system base on intelligent algorithm, 765-768, IEEE International Conference on Control and Automation WeDP-17 Guangzhou, 30 May-1 June, Guangzhou, China.

[11] Xiaoyan C., Zhenliang, L., 2008, An ıntelligent dynamic weighing controller, pp. 1609-1612, Proceedings of the IEEE International Conference on Automation and Logistics Qingdao, 1-3 Sept.,Qingdao, China.

[12] Gao H., Pang W., 2009, A high-accuracy dynamic weighing system based on singleidler conveyor belt, pp. 2483-2487, Proceeding of the Eighth International Conference on Machine Learning and Cybernetics, 2-15 July, Hebei, China.

[13] Wu Q., Pan R., Luo X., Li Y., 2009, A signal processing method for dynamic weighing system by ssa-lvq network, pp. 4-403 - 4-407, The 9th International Conference on Electronic Measurement & Instruments, 6-19 Aug., 87 Beijing, China.

[14] Liao G. and Xi J., 2010, Design and ımplement of vehicle dynamic weighing system, pp. 1131-1134 International Conference on Intelligent Computation Technology and Automation, 11-12 May, Changsha, China.

[15] Jeridi W., Benabdallah S., Hamdi M., Boudriga N., 2010, Dynamic expert weighing for security risk analysis team synergy, pp. 1 - 8, Engineering Systems Management and Its Applications (ICESMA), Second International Conference on, 30 March-1 April, 2010.

[16] Hu P., Liang L., Hu J., 2010, The control strategy and application for dynamic quantitative weighing system based on embedded linux pan, pp. 4917-4921, Proceedings of the 8th World Congress on Intelligent Control and Automation, , Jinan, China.

[17] Sun J., Liu F., Si J., Mei S., 2010, Direct heuristic dynamic programming based on 86 an improved pid neural network and initial weighs choosing method, 7-9 July, 2010 Critical Infrastructure (CRIS), 5th International Conference on, 1-6, China.

[18] Ying Z., Yunbin H., Min L., 2011, The research on data processing for dynamic batching-weighing system, pp. 888-890, The 6th International Conference on Computer Science & Education, 3-5 Aug., 2011, Singapore, Singapore.

[19] Martin A. D., Molteno T. C. A., 2015, Automated weighing by sequential inference in dynamic environments, pp. 274-278, Proceedings of the 6th International Conference on Automation, Robotics and Applications, 17-19 Feb. 2015, Queenstown, New Zealand.

[20] Niedźwiecki M., Pietrzak P., 2016, High-precision fir-model-based dynamic weighing system, IEEE Transactions on Instrumentation and Measurement, 65(10): 2349 – 2359.

[21] López-Ibáñez M, Dubois-Lacoste J, Cáceres LP, Birattari M, Stützle T. , 2016, The irace package: iterated racing for automatic algorithm configuration. Oper Res Perspect 3:43–58.

[22] Tang D, Dai M, Salido MA, Giret A 2016, Energy-efficient dynamic scheduling for a flexible flow shop using an improved particle swarm optimization. Comput Ind 81:82–95. https://doi.org/10.1016/j.compind.2015.10.001

[23] Oliver Nelles, 2020, Nonlinear Dynamic System Identification, University of Siegen Netphen Germany, book.

[24] Sendrescu D., Roman M., 2013,Parameter Identification of Bacterial Growth Bioprocesses using Particle Swarm Optimization, 9th Asian Control Conference (ASCC), 23-26 June , Istanbul, Turkey.

[25] Sendrescu D., Bobasu E., 2013, Parameter Identification of Bacterial Growth Bioprocesses using Heuristics for Global Optimization, pp. 485-490, 17th International Conference on System Theory, Control and Computing (ICSTCC), 11-13 Oct., Sinaia, Romania

[26] Ulinowicz M., Andrzejczak M., 2014, An Heuristic Approach to a Ship Nonlinear Model Identification, pp. 239-244, European Modelling Symposium, 21- 23 Oct., Pisa, Italy.

[27] Kumar M., Aggarwal A. Rawat T.K., 2016, Bat Algorithm: Application to Adaptive Infinite Impulse Response System Identification, Arabian Journal for Science and Engineering, 41(9):3587-3604.

[28] Ryzhikov S. and Semenkin E.S., 2016, Restart Operator Meta-heuristics for a Problem Oriented Evolutionary Strategies Algorithm in Inverse Mathematical MISO Modelling Problem Solving, pp. 1-11, V International Workshop on Mathematical Models and their Applications, 7–9 November, Krasnoyarsk, Russia.

[29] Olivas F, Valdez F, Castillo O, Melin P. , 2016, Dynamic parameter adaptation in particle swarm optimization using interval type-2 fuzzy logic. Soft Comput 20(3):1057–1070

[30] Tanweer M, Suresh S, Sundararajan N 2016, Dynamic mentoring and self-regulation based particle swarm optimization algorithm for solving complex real-world optimization problems. Inf Sci 326:1–24. https://doi.org/ 10.1016/j.ins.2015.07.035.

[31] Wu Y, Liu G, Guo X, Shi Y, Xie L 2017, A self-adaptive chaos and kalman filter-based particle swarm optimization for economic dispatch problem. Soft Comput 21(12):3353–3365.

[32] Zheng F, Zecchin A, Newman J, Maier H, Dandy G 2017, An adaptive convergence-trajectory controlled ant colony optimization algorithm with application to water distribution system design problems. IEEE Trans Evol Comput 21(5):773–791.

[33] Yang Q, Chen WN, Yu Z, Gu T, Li Y, Zhang H, Zhang J 2017, Adaptive multimodal continuous ant colony optimization. IEEE Trans Evol Comput 21(2):191–205.

[34] Baktir A.E., 2018, System Identification Of Dynamic Weighing System With Heuristic Algorithm, M.Sc. Thesis, Erciyes University, Turkey.

[35] Jhang JY, Lin CJ, Lin CT, Young KY 2018, Navigation control of mobile robots using an interval type-2 fuzzy controller based on dynamic-group particle swarm optimization. Int J Control Autom Syst 16(5):2446–2457.

[36] Jiao R, Sun Y, Sun J, Jiang Y, Zeng S 2018, Antenna design using dynamic multi-objective evolutionary algorithm. IET Microw Antennas Propag 12(13):2065–2072.

[37] Wu Q, Zhu Z, Yan X, Gong W., 2018, An improved particle swarm optimization algorithm for avo elastic parameter inversion problem. Concurr Comput Pract Exp, p e4987.

[38] Alataş, B., 2007, Kaotik Haritalı Parçacık Sürü Optimizasyon Algoritmaları Geliştirme, Doktora Tezi, Fırat Üniversitesi, Fen Bilimleri Enstitüsü, Elazığ.

[39] J. H. Holland, 1975, Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. University of Michigan.

[40] D. E. Goldberg,1989, Genetic Algorithms in Search, Optimization and Machine Learning. Addison Wesley.

[41] K. A. De Jong, 1975, Analysis of the Behaviour of a Class of Genetic Adaptive Systems, PhD Thesis, Dept. of Computer and Communication Sciences, University of Michigan, Ann Arbor.

[42] Booker L., 1987, “Improving search in genetic algorithms,” In Genetic Algorithms and Simulated Annealing, L. Davis (Ed.), pp. 61-73, Morgan Kaufmann Publishers.

[43] G. Syswerda,1989, “Uniform crossover in genetic algorithms”, Proc. ICGA 3, pp. 2-9.

[44] D. Simon, 2008, Biogeography-based optimization, IEEE Transactions on Evolutionary Computation (12) pp. 702-713.

[45] Simon D 2009, "A probabilistic analysis of a simplified biogeography basedoptimizationalgorithm".http://academic.csuohio.edu/simond/bbo/simplified/bbosimplified.pdf

[46] A. Colorni, M. Dorigo, V. Maniezzo, 1991, Distributed optimization by ant colonies, in: F. Vaerla, P. Bourgine (Eds.), Proceedings of the European Conference on Artificial Life, Elsevier Publishing, Paris, pp. 134–142.

[47] Dorigo, M., & Stutzle, T. 2004, Ant colony optimization. Cambrige MA: MIT Press.

[48] M. Dorigo, V. Maniezzo, 1996, A. Colorni, Ant system: optimization by a colony of cooperating agents, IEEE Trans. Syst. Man Cybern. Part B: Cybern. 26 (1) 29–41.

[49] T. St ¨utzle, H. Hoos, 1997, MAX–MIN ant system and local search for the traveling salesman problem, in: IEEE International Conference on Evolutionary Computation, pp. 309–314.

[50] M. Guntsch, M. Middendorf, 2002, Applying population based ACO to dynamic optimization problems, in: M. Dorigo, G. Di Caro, M. Sampels (Eds.), Ant Algorithms, Vol. 2463 of Lecture Notes in Computer Science, Springer Berlin Heidelberg, pp. 111–122.

[51] T. Stützle, 2004, Ant Colony Optimization, MIT Press.

[52] L. Rutkowski, 2005, Computational Intelligence, Methods and Techniques "Springer Verlag Germany.

[53] D. Karaboga, 2005, An idea based on honey bee swarm for numerical optimization, Technical Report TR06, Erciyes University, Turkey.

[54] Bansal, J.C., Sharma, H., Jadon, S.S. 2013, Artificial bee colony algorithm: a survey. Int. J. Adv. Intell. Parad. 5(1–2), 123–159.

[55] Karaboga, D., Basturk, B. 2008, On the performance of artificial bee colony (ABC) algorithm. Appl. Soft Comput. 8(1), 687–697.

[56] Perrot, M. H., Cohen , R. J., 1996. An efficient approach to arma modelling of biolagical systems with multiple ınputs and delays, IEEE Transactions on Biomedical Engineering, 43(1), 1-14

[57] Özçelik Y., 2007 Farksal Evrim Algoritması Kullanarak Sistem Kimliklendirme, Yüksek Lisans Tezi, Erciyes Üniversitesi, Fen Bilimleri Enstitüsü, Kayseri.

[58] Eykhoff, P., 1974. System Identification, Parameter & State Estimation, John Wiley & Sons University of Southampton, UK

[59] Close, C.M., Frederick, D.K., 1978. Modelling & Analysis of Dynamic Systems, Houghton Mifflin Co., London

[60] Schwarzenbach, J., Gill, K.F., 1988. System Modelling & Control, Chapman & Hall, 2nd Ed., NY 88

[61] Ogata, K., 1990. Modern Control Engineering, Prentice-Hall, 2nd Ed.

[62] Golden, J., Verwer, A., 1991. Control System Design & Simulation, McGraw-Hill Book Co., UK

[63] Kupper, W.E., 1990, High accuracy mass measurement from micrograms to tons, ISA Transactions, 29(4):11-20.

[64] Shi, W.J., Brignell, J.E., 1991, On-line optimisation in sensors frequency response, Sensors & Actuators A, 25:37-41.

[65] Haberman, R., 1977, Mathematical Models, Mechanical Vibrations, Population Dynamics & Traffic Flow, Prentice-Hall Inc., Englewood Cliffs, London

[66] Spriet, J.A., Vansteenkiste, G.C., 1982, Computer Aided Modeling And Simulation, Academic Press, London.

[67] Danaci, M. and Horrocks, D.H., 1995, A non-linear regression technique for improved dynamic weighing, pp. 507-510, Proc. Euro. Conf. on Circuit Theory and Design, Aug., Istanbul, Turkey.

[68] Close, C.M., Frederick, D.K., 1978, Modelling & Analysis of Dynamic Systems, Houghton Mifflin Co. London.

[69] Norden, K.E., Kersten, 1984, Electronic Weighing İn Industrial Processes, Granada Technical Books, London.

[70] King (Fellow), A., 1987, An introduction to weighing systems, Electronic Technology, 21:25-29.