Development of system identification from traditional concepts to real-time soft computing based

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Abstract. Advancement in computer and data acquisition technology gave the system identification a push forward, especially in the speed of the process and parallel calculation techniques. This article reviews the progress of system identification methods and techniques from traditional to modern methods and from offline to fast on-line analysis through previous years till these days. It takes into account part of artificial intelligence techniques (soft computing techniques), primarily artificial neural networks methods, for off-line system data analysis and real-time system identification, including the linear and non-linear issues. This study will provide a very concise survey for researchers about the development of system identification, its implementations, and techniques that have been used.

1. Introduction
System Identification is steps of logical operation which are followed to build a mathematical model that describes features of a dynamic system (or a process) depending on existing relations among its parameters and variables or between the input and corresponding measured output data [1]. Each system has parameters and variables that interconnected together to form its behavior. Sometimes, these parameters and variables could be seen clearly [2], hence it could build a mathematical model to describe a system with small error margin (although the mathematical model is involved, it cannot adequately describe a real system), and that what is named in some references as a white box [3]. In contrast, a black box [4] is a system that has unknown variables, parameter values, and their relations. All that can be seen are the input (to the system) and output (from the system); so, the system is evaluated by observing the output-input relationship. Finally, there is a gray box system [3], which is mixed from white box and black box systems; there are some features known and others unknown. It is crucial to select appropriate variables from the principle equations and tune the parameters by using regression methods to minimize the variation between the derived mathematical model and the measured data [1]. Most modeling operations are done after the data have been collected (off-line), but there is another type of modeling is done within real-time to estimate the parameters of a specific system, which is named on-line system identification [5,6]. The main equipment in the system identification are: measured data, derived model, selected cost function, and the numerical method used to minimize the cost function (it must be fast to convoy on-line system identification [7,8]).

Nowadays, researchers trend to use the Artificial Intelligence technique to solve many system problems like non-linearity, time-varying, and ambiguity or inaccessibility [9,10]. This technique based
on the learning concept, where weights that belong to a specific perception start with random values, then these weights are tuned up to be suitable amounts. Whenever the learning increased (till a specific limit), it makes weights close from appropriate value. Artificial intelligence techniques can be divided into two types relative to teaching manner; supervised learning and unsupervised learning. Where the first type compares the output of the network with the desired output (that means the desired output is known), while the second type is learning without teacher, also it is can be divided into two kinds relative to the size of network; single layer and multi-layer networks [11,12], and there are other classifications according to training methods and used function.

The following sections will explain the off-line and online system identification, what is the difference between them, and how the soft-computing algorithms were used in these two types instead of the traditional methods.

2. Off-line System Identification

Off-line system identification is the analysis of the pairs of input-output data (with older information for current pairs in the dynamic system) to find the internal mathematical structure of the system (model of the system) and assess the parameters of that structure one step ahead, after collecting the data via sensors. The steps of off-line identification can be summarized by:

1- Finding the mathematical model for the system from the principle physical rules, if the system is a white or gray box. The black box has no known structure, so this step ignored.
2- Stimulating the system with a controlled input to get on system response.
3- Sensing the input and output signals and accumulating them in pairs form.
4- Implementing the system identification operation on the input/output data (in some cases, the data needs to be treated before the identification operation) to estimate the value of the parameter in the defined model.
5- After completing the identification operation, the model now ready to be compared to part of the data through operation named model validation. If the output of the model is convergent from the original output, it can consider the model represent the system relatively, if not the step (4) must be returned.

Soft computing methods can substitute the traditional methods in creating Identifying a mathematical model for either known (white box) or partially known (gray box) system’s properties, and unknown system’s properties (black box).

De la Sen et al. [13] designed an expert network that had been created to estimate a discrete transfer function for a linear time-invariant system with impulses sampling. They ran different methods for system identification. One of these methods relied on recursive least squares (RLS);

\[
A(q^{-1})y_l = B(q^{-1})x_l + v_l
\]

\[
V_M = \sum_{l=1}^{M} y_l
\]

\[
\hat{\theta}_l = \hat{\theta}_{l-1} + k_l(y_l - \hat{y}_l)
\]

Where \(v_l\) represent the calculated error, \(M\) is the amount of the samples, \(\hat{\theta}_l\) are the expected parameters at time \(t = l\), \(y_l\) is the measured output at the same time \(t\), and \(\hat{y}_l\) is the predicted output. Another method relies on Leverrier’s algorithm;
where, $q$ represents a shift time in the dynamic system $q \ y_t = y_{t+1}$ and $q^{-1} y_t = y_{t-1}$.

Artificial Intelligence is one of the best choices to solve the non-linearity problem; it has some attributes that make it more adaptable. The soft robot was used for the motion of some parts of a body during radiotherapy was used as a case study, using supervised deep learning for multilayers recurrent neural networks [14]. de Canete et al. [15] indicated how to benefit from the Labview, which is a graphical language for the data acquisition and the automation control, to Identify the distillation column process. The nonlinearity of the system was solved by neural networks tactic.

Shamsudin and Chen [16] developed an off-line dynamics system identification approach for unmanned copter depend on neural networks (NN). The Levenberg-Marquardt model form was applied to teach the NNs with autoregressive exogenous (AXR). A combination of correlation analysis, cross-validation, weights regulation, and Lipschitz criterion was used to enhance the form of the network.

Hanafi et al. [17] developed a mathematical model that relied on the physical principle laws, that ruled the system, and the attributes of the parameters. The case study was a suspension system of a car with nonlinearity in the damper and spring elements. The SI was based on the multilayers NNs to solve the complex relations between the inlet and the outlet of the system. The car was examined using the artificial bump on the road, the data were handled off-lined, and the NNs were taught by the weighted least squares (WLS) method.

Mills and Zomaya [18] examined an off-line dynamic system identification with the assist of neural networks. They utilized a backpropagation procedure for training the networks based on the linear estimator of the algorithmic least-squares for the nonlinear system. Besides NNs, the Fuzzy Logic with Gaussian member shape was used to be a six-layer fuzzy neural for improving the weights with pre-optimization step using the genetic algorithm (GA) optimization method [19].

Cong et al. [20] followed a parametric system identification, which is one of the identification approaches, to construct a nonlinear dynamic mathematical model representing a DC motor with the nonlinear effect of the Coulomb friction. The suggested approach utilized GA, which is one of heuristic and evolutionary methods, with the simplex method to solve the global optimization problems for estimating the model. The validation, which was utilized to compare between the model and the DC motor, was comparing the output of the motor with the output of the model (from the simulation).

Conforming to Herreros et al. [21], a straightforward model was employed to identify the suspension system of a car applying non-interfering input signals. The amplitude difference between the real and the estimated power magnitude of the system output for spectral density was taken as the main objective to be reduced and to reduce a discrepancy of estimation due to distorted input (because of the noise and ignoring the presence of dynamics), the GA was implemented as an optimizer tactic.

Jizhen et al. [22] suggested a model based on the gray-box principle for identifying an online parametric model of wind turbine generation system (WTGS) in a closed-loop system. The system as an aerodynamic system and a generation core of the WTGS entirely were modeled all together to obtain a total identification model relied on a nonlinear state-space model. GA was implemented to assist in identifying the system and assess the parameters of the suggested model.
As stated by Cen et al. [23], a gray-box multilayers perceptron neural networks and integrator was established for identifying a nonlinear dynamic system and estimating fault scheme. The model was formed from simple rules of the neural networks, the essential criterion is the deviation between the actual system output and the derived model output, which represents the error offset value for various fault values.

The article [24] proposed a process to find the cross-section of neutron-induced reaction in a specific condition, used weighted least squares method to regress the error and to update the neural network weights and backpropagation technique for training the network off-line.

Kurita [25] examined the teaching procedures of multilayers NNs from the maximum likelihood estimation (MLE) viewpoint. It was shown that Fisher information (FI) of the network, with subtraction expectancy values of Hessian matrix (H), was gained from a weighted covariant tensor of input variables. The training approach utilized Fisher’s scoring concept, which applied FI instead of H, that can be symbolized by the weighted least squares technique for multilayers (with single hidden layer) neural networks.

Puscasu and Codres [26] proposed a non-linear system identification and system control tactic supported by structured NNs. To decrease the degree of computation complexity for whole the system, in the research, splitting the system into subsystems by separating algorithm, was offered. Thus, each nonlinear subsystem module has a nonlinear controller built from neural networks, and it was switched among the networks of controllers by a dynamic switch which was done also by neural networks.

Narendra and Parthasarathy [26] presented the principles of model representation to identify and control a non-linear dynamic system by utilizing NNs ability. The research tried to solve some problems with applying the neural networks for higher-order multi-variable nonlinear systems, and the effects of applying simpler models for identification and control. Quiroga et al. [27] explained utilizing neural networks for identifying a permanent magnet synchronous motor (PMSM). The recurrent neural network pattern used for maintenance to perform fault detection or integrity assessment. It was used Matlab/Simulink with other techniques to implement and validate the model.

Sierra and Santos [28] examined implementing alternative tactics for identifying an unmanned quadcopter system; artificial neural networks approach, parametric model estimation methods, neuro-fuzzy structure, and a hybrid of some previous methods. The comparison among these methods revealed that the hybrid method was retaining an appropriate balance between precision and computation time.

Ismeal et al. [29] investigated a permanent magnet DC motor identification using artificial neural networks. Input-output data (armature voltage-current and angular speed, respectively) were taken to use in building a non-parametric black-box model for identifying a dynamic system of motor. The neural networks with hidden three-layers depended on a non-linear autoregressive network with exogenous (NARX) input was applied. NARX network was taught by parallel constructions and scaled gradient algorithm using the error derivative (first and second order derivatives) to decrease the error. Whereas, Rahim et al. [30] examined utilizing a non-linear autoregressive moving average for exogenous input (NARMAX) method with multilayers neural networks to identify a non-linear system for the DC motor. The off-line learning of neural networks was improved by implementing the regularization method.

Lu et al. [31] built a semi on-line, locally linear model for an unmanned drone system. Angles of attack and sideslip are measured as output for the system. The observer/Kalman filter identification algorithm is used for identifying a fixed-wing unmanned aerodynamic system, built on the state-space method, which developed from both lengthways and side force-components.

Pislaru and Shebani [32] utilized the feed-forward neural network established on radial basis function, which is a function with real values that relies on the distance from the origin only, what is known as (RBFNN) technique for identifying a nonlinear system. That technique was validated by applying it on a DC motor, tank system, double tank system, and two lab’s models. The clustering algorithm of K–means used to choose the RBFNN centers.
3. Real-time System Identification

Real-time (online) system identification is estimating the model parameters at the current moment depending on the pairs of input/output data (with older information for the current pairs in the dynamic system) to find the internal mathematical structure of the system (model of the system) one step ahead. The steps of real-time identification can be summarized by:

1- Finding the mathematical model for the system from the principle physical rules, if the system is a white or gray box. The black box has no known structure, so this step ignored.
2- Stimulating the system with a controlled input to get on system response.
3- Sensing the input and output signals and accumulating them in pairs form. The input signal for the system is the same input for the model, and the subtraction of the model from the real system output represents the current error.
4- Implementing the system identification operation recursively on the input/output data (in some cases, the data needs to be treated before the identification operation), to estimate the parameter’s value in the defined model.
5- Using the calculating error to update the parameters’ value instantaneously.
6- After completing the identification operation, the model now ready to evaluate the model. If the output of the model was convergent from the original output, it could consider the model represent the system relatively; if not, it may return the whole process or start from the step (2).

The recursive methods are dominant in real-time system identification.

An approach inspired by Takagi-Sugeno model for real-time training was proposed by Angelov and Filev [33], it was constructed on supervised and unsupervised teaching algorithm that updated the model parameters and structure repetitively. It was implemented to the data obtained from airconditioning equipment operating in a certain construction.

Qian et al. [34] proposed a system identification scheme adopted a parametric online identification method to get parameters of an actuator for a range of loads using hybrid simulation. A GA was built on experimental data, which was loaded the input part to the actuator and the output used to assess the convergence of estimated values for the model’s parameters from the original system behavior.

Al Seyab and Cao [35] developed an identification process based on recurrent neural networks (RNN) for nonlinear predictive and control models. The process based on neural networks was derived from a nonlinear state-space form to be a real-time process using a developed automatic differentiation.

Figure 1. RBFNN [32].
algorithm. The technique was used for online optimization and predictive controller, as well. Wang et al. [36] offered an unconventional motion-mode energy method to identify moving shapes of a vehicle body (roll, bounce, and pitch motion modes) with a minimum error ratio by applying neural networks.

Pairan and Shamsudin [37] introduced experimental results based on the RBFNNs trained by minimal resource allocating network approach (MRAN) for identifying the quad-chopper system in real-time. The activity of the MRAN tactic was compared to the RBFNN tactic with a constant trace (CT) process for 2500 pairs of input-output data samples. It was found that using MRAN appending or eliminating hidden layer neuron tactic to optimize RBFNN improve weights estimation precision and minimize the time of teaching.

![System identifier based on NN](image)

**Figure 2. System identifier based on NN [37].**

Kirkpatrick et al. [38] proposed a linear system identifier by using neural networks for airplane system, the identifier function was derived from state-space equations and the data used for training the neural networks, to get matrices of the state space, were obtained from previous flight operation, the same data had already been utilized for identifying the dynamic airplane system by Observer/Kalman filtering approach. The suggested identifier compared with (O/K) filter method [39], which was locally linear, for airplane dynamic nonlinear system identification in real-time.

Hussein et al. [40] introduced a model for identifying and controlling a DC motor speed; the input voltage was provided from the solar power system through a DC-DC converter utilized two universal learning networks (ULNs). The feed-forward NNs were applied to control, evaluate and update the parameters of the nonlinear model in real-time. The essence of Rubaai and Kotaru [41] research was how to deal with controlling a DC motor speed through utilized from feed-forward NNs to represent the nonlinear system of the DC motor in an on-line system identification with on-line learning for neural networks were done.

Griñó et al. [42] proposed a tactic depended on NNs structure for identifying a dynamic system which has an unknown dynamical behavior; an adjustable NNs were added to take the place of unknown dynamic part of the system. The model of NNs has linear parameters with updating weights synchronously. Two techniques were used; the first technique adopted the gradient method and analysis of the model’s output attitudes against calculated parameters, the second one used variant calculation, which was leading to an offline statement and the invariant embedded way that converts it to an online solution.
Guo et al. [43] proposed a method based on (RNN) with shared and specialized memories (ShM and SpM) or (SSMs) tactic for chaotic adaptable filtering to improve a simultaneous estimation. The SpM involved weights of the last layer with linear specifications, whereas ShM designed for nonlinear weights, which was pre-learned in off-line to a particular value, then implemented as fixed weights in on-line, while the SpM is trained on-line. The method based on recursive least-squares teaching. Ibrahim [44] suggested an approach for identifying the system depended on neural networks as the auto-adjusting regulator. A real-time identification is implemented by RNNs to estimate parameters of discrete PID control, which inspired by the Zeigler-Nichole method. It was tested in simulation software and compared to the traditional PID controller.

Sadeghi and Farrokhi [45] presented a model for Identifying a nonlinear dynamic system in real-time based on Wiener oriented blocks. The Levenberg-Marquardt algorithm with multilayer NNs were used for the nonlinear static part in the Wiener model, the identifier of subspace with the multi-variable approach was used for the linear dynamic part. The proposed model was simulated on the supposed system and Lyapunov method utilized to improve the steadiness of model convergence.

Axial Idea of PIVOŇKA et al. [46] studied the impacts on the identification procedure in high-speed sampling and compared among three techniques of real-time identification: recursive least-squares, gradient, and system identification approach based on neural networks with damped least-squares minimizing method, then showed that the neural networks getting the better of the others. The structure of neural networks was upgraded from [47] and [48], which utilized to identify a black-box system in real-time updating parameters according to the stability of Lyapunov.

Chen et al. and Purwar et al. [51,52] utilized a model of neural networks for identifying ambiguous, dynamic, nonlinear systems in discrete time. Purwar et al. [49] applied only one layer of neural networks instead of multilayers and substituted that by distributing the input by Chebyshev-polynomials, and it used the iterative least-squares technique with forgetting factor as real-time teaching algorithm to update parameter. While, Chen et al. [50] adopted a multi-layer NNs (with a single hidden layer), and used a developed algorithm derived from prediction error formulation.

Jafari et al., and Salahshoor and Jafari [51,52] produced an approach using the consecutive growth and trimming radial basis function (RBF) to identify a nonlinear system online. It was a newly proposed method for the growing and pruning neurons criteria to be proper for identifying online with modified

![Figure 3. Suggested online identification [45].](image-url)
teaching tactic based on unscented Kalman filter (UKF) for neural networks, the method implied using a changeable forgetting factor technique embedded in UKF form to stimulate parameter assessment in nonlinear dynamic systems.

Rocha Filho and de Oliveira Serra [53] presented an identification algorithm for a black-box stochastic system in real-time built on neuro-fuzzy approach with impressive variables to model a dynamic system. A continuous online neuro-fuzzy technique with Takagi-Sugeno developed structure, which applies the maximum likelihood with iterative parameter estimation, was adopted as a procedure. Copter with two degrees of freedom was used as a case study.

Aeronautics is a rich area for applying online system identification since it needs a quick reaction and moving. By utilizing three layers unmanned airborne vehicle with fixed wings as a plant; Puttige and Anavatti [54] found the differences and similarities between the real-time identification and off-line identification using three layers of neural networks with a multiple input\output system that has a six-output, where ARX was applied to minimize the error. The same previous strategy was implemented on Eagle helicopter six degrees of freedom [55].

Feng et al. [56] determined a non-straight scientific model for the electro-water driven stage, including the impact of Stribeck friction, where the friction dissipated power was determined from a deliberate weight of pressure-driven chambers at different speeds extend. There are a few upgrades were made on GA method, like the fitness, crossover, and mutation assumption. In real-time, a noticed speed utilized to assess the actual velocity, and dynamic feed-forward remuneration for friction impact was configured.

4. Conclusion
Identifying a dynamic system allows scientists and engineers to understand the nature of the system and, as a result, gives them the ability to control that system or to gain full knowledge of the system and improve it. Conventional linear analyses for identifying systems are developed to include some systems with nonlinear behavior (using linearity assumption). The majority of the dynamic systems are not linear, and implementing linearity presumptions lead to a false mathematical model. Determining a precise nonlinear model is not a simple mission (to reach the genuine physical model), and evaluating the parameters of that condition will be somewhat hard, so utilizing artificial intelligence can deal with non-linearity and uncertainty issues. Estimating the value of parameters in the off-line analysis is a little bit different from the on-line analysis, where the first leads to get fixed values, which have a considered error in specific points, while the on-line analysis has flexible and adaptable parameters.

5. Future Work
Based on the previous, the soft-computing features could be employed in the system identification, either off-line and online mode. The noted effectiveness in dealing with nonlinear systems makes the soft-computing aspects be nominated as a perfect solver for the complexity of the system so that future work will be using this approach from developing the system algorithm for gray-box, not only representing the black-box system depending on the input-output data.

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