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Artificial Neural Networks Based Dynamic Weight Estimation with Optical Arrangement

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Abstract. *In this essay, an optical arrangement for the measurement of dynamic weight, by means of conducting a thin ray of light through it, is designed in order to enhance the measuring accuracy in the weight-estimation device. In this arrangement, CCD is responsible for producing raw data for processing. An artificial neural network type, RBF, is also used to improve the quality and speed of the measurement. While the scale of the weight-estimation device is oscillating, by applying the weight on the scale, the neural network by sampling the proportionate wave-shape yields the weight of object with high accuracy and high speed.*

Keywords: *Optical arrangement; CCD (Charged Coupled Device); RBF neural network; Dynamic weight; Measurement.*

INTRODUCTION

In today's world, reaching high rate and high accuracy in all areas, especially weight measurement, is one of the most important challenges of researchers and scholars. The application of an object to a weighting platform results in a transient output waveform which can take a considerable amount of time to settle sufficiently in order to accurately indicate the weight of the object. In order to estimate applied mass, different methods are adopted, such as using an Artificial Neural Network (ANN) [1-4].

In this respect, we are unable to measure directly the parameter of weight, and for weight estimation we need a measurable variable that has a linear or nonlinear relation to the variations of the weight placed on the scale. Regarding the internal structure of the scales, various methods have been suggested to improve the quality of weight measurement, including accuracy and speed. In the structure of some ordinary scales, a Load Cell is used. The basis of a Load Cell is an electric magnet, which, as a result of the variations of weight placed on the scale, shows a certain change in electric current. Moreover, some other scales make use of Strain Gauges which contain a cord with electric resistance. The length of this cord is variable, and with the change of weight placed on the scale and thereby the cord length, its resistance changes. In the structure of some other scales, piezoelectricity is used. The variable used in this case is the pressure caused by placement of weight on the scale, and its basis is the vibration of the rope [5,6].

All methods used signify the behavior of the system on the basis of a variable other than weight, the best of which is a system which functions according to a variable with the highest rate, accuracy and power in confronting environmental noise.

In recent decades, in measurements, absolutely-mechanical methods are less approached. New technology produced alterations in measurement, based on the variable of a wavelength. In the structure of the majority of these systems, a Helium Laser is used for its high reliability and in this case the Zeeman Effect is employed [7]. In all aforementioned techniques, either the rate or the accuracy of the measurement is improved, and it is hard to find a system in which both qualities of speed and accuracy are jointly regarded.

In this paper, a new method is introduced for the weight estimation system, in which a new technique for jointly increasing both the accuracy and the rate of the measurement is represented. The introduced system includes an optical arrangement for improving the accuracy of the measurement. In this arrangement,

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after the passage of a thin ray of light through a couple of mirrors with different reflections to two CCDs, two pieces of raw data are produced. One is for the integer and the other for the fractional part of the weight value, which ultimately yields the weight of the applied mass. A variety of methods has also been suggested to improve the rate of the weight measurement in which transient effects diminish yet exist. In this paper, the use of an artificial neural network to predict the applied weight, by means of receiving data from the CCDs, is described. Applying this method will engender no residual transient effect. The results of the simulation demonstrate the high speed and accuracy of this system. Also, simply by properly covering the container of the system, its susceptibility to surrounding noises can be decreased to a considerable degree. The results of the simulation indicate the high accuracy of the designed system, along with its high rate of dynamic weight estimation.

MODEL OF DYNAMIC SYSTEM

A weight estimation system generally contains a dynamic scale vibrating like a dynamic spring that has one of the underdamped (u), critically damped (c), or overdamped (o) responses to the unit step input. The general equation for displacement of the scale caused by applying mass m on it, is in the form of Equation 1, in which C is the damping factor, K the spring constant and g the gravitational constant of the earth.

$$(m+m_p)y''(t)+Cy'(t)+Ky(t)=gm. \quad (1)$$

In this relation, $y(t)$ defines the deviation signal obtained, as compared with the initial position of the scale, and m_p is the weight of the pan. The deviation signal, obtained in addition to the explicit value also includes a transient expression, which can be underdamped (u), critically damped (c), or overdamped (o). Therefore, the solution of Equation 1 is:

$$y(t)=q_0+\{F_u(q_u,t) \text{ or } F_c(q_c,t) \text{ or } F_o(q_o,t)\}, \quad (2)$$

and the transient expression for under, critically, and overdamped is as follows:

$$F_u(q_u,t)=\exp(-q_{u1}t)*q_{u2}*\sin(q_{u3}t+q_{u4}),$$

$$F_c(q_c,t)=\exp(-q_{c1}t)*(q_{c2}+q_{c3}t),$$

$$F_o(q_o,t)=\exp(-q_{o1}t)*q_{o2}+\exp(-q_{o3}t)*q_{o4}.$$

In the above expressions, various q parameters are related to the initial platform displacement, b_0, initial velocity, b_1, the platform parameters, K, C, and m_p, and the applied mass, m, by the expression given in the Appendix.

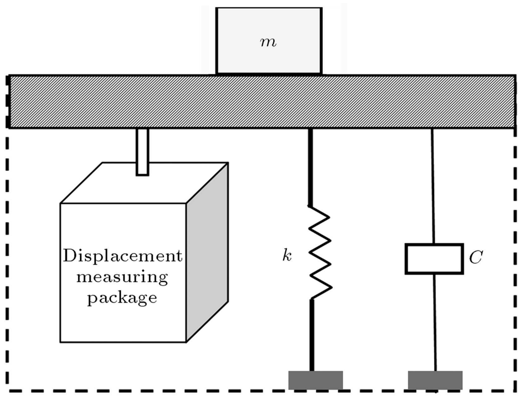

Figure 1. The model of the system; the general figure of the weight measurement system.

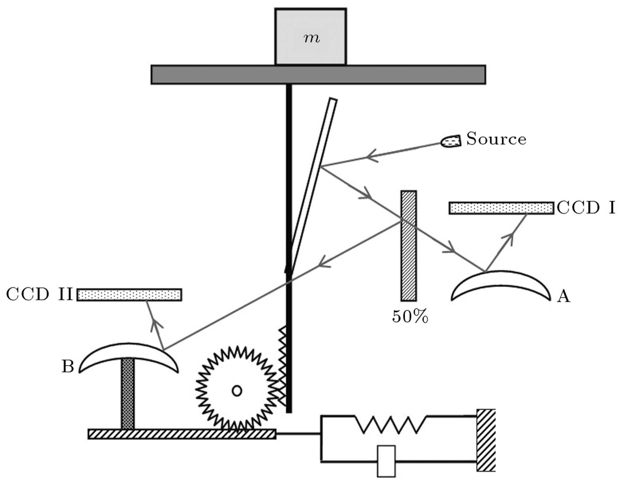

Figure 2. The optical arrangement for measuring the variations of the scale position.

Figure 1 illustrates the general schema of the dynamic weight estimation system, which in addition to having been modeled with a spring and damper includes a compartment for measuring the changes of the scale position by optical arrangement; this has been indicated with a box. In order to enhance measurement accuracy, this part has been designed with an optical element. To show entirely the elements of the optical architecture, some part of the modeled elements has been excluded and has been displayed in Figure 2.

OPTICAL ARRANGEMENT

Function of Optical Arrangement

To enhance measurement accuracy, the integer part of the weight value is taken from the output CCD I and its fractional part by eliminating the integer part and magnifying the partial variations of the physical position of the scale from the output CCD II according to Figure 2. In a CCD, the dimensions of pixels are approximately 5 microns whose measurement accuracy, due to the absence of diffraction, is significant. Some CCDs have nearly 4000 pixels with an approximate length of 2 inches [8,9].

In the optical arrangement, a ray of light with very thin radius and single-wavelength or nearly-single-wavelength, like the laser-diode or photodiode, after passing through an optical parallelizer, is reflected to the plane mirror, shown in Figure 2. The aforesaid mirror, which is attached to the device with a certain angle by a bar, is displaced by changes in the physical position of the scale. The ray of light reflected from the same mirror, in its path, reaches a two-way mirror. 50% of the light received passes through it and the other 50% is reflected from its surface. The light that has passed is reflected to convex mirror A, and after another reflection reaches the CCD I. With alterations in scale position, the path of the light reflected from the mirror attached to the scale also changes and, consequently, the ray of light reaches a different position on CCD I. The position of CCD I in relation to convex mirror A should be adjusted such that in case of zero displacement of the scale (applying zero weight on the scale), the first pixels and in case of maximum displacement (applying maximum weight on the scale), the last pixels receive the light. With this mechanism, the output CCD I is a value proportionate with the weight applied on the scale.

In order to enhance measurement accuracy, another CCD according to Figure 2, has been used. For measuring partial variations of the scale position, the variations on each 2 consecutive pixels of CCD I, which are not measurable by it, are magnified and reflected on the larger number of pixels of CCD II. In this regard, partial variations of the scale position, which are measured by CCD I, in the transition to CCD II must be eliminated from the sum of the general and partial variations, and only the partial ones should be transmitted to it. For this purpose, the set of mirror B and CCD II must be displaced in proportion with general variations of the scale in order that the ray of light reflected from the two-way mirror does not exit the range of CCD II owing to the magnification of partial variations of its path. As a method in this paper, a collection of separate rails and cogwheels is used. Furthermore, the step of the teeth of a cogwheel is chosen in such a way that for each step, the collection should be displaced to a degree where the integer part of the weight value is eliminated and only partial variations of the scale position are transferred to CCD II. A spring attached to this collection is also used for inhibiting its constant motion which in Figure 2 has been modeled along with a damper. Thus, the partial variations of the scale position are magnified and in the output CCD II a value proportionate to these variations is produced. The sum of the integer CCD I and the fraction CCD II yields the weight of the applied mass with satisfactory accuracy, which enters the designed artificial neural network that will be discussed in the next part. In the case of non-plane mirror B, a convex or elliptic mirror can be used, which depends on the resolution (the number of pixels per unit of length) of the CCD. If its resolution is low, a convex mirror is used. The relations pertaining to the position of the emitted ray of light, and the ensuing reflections from the external surface of each of the convex and elliptic mirrors for calibration of the device are included. As indicated in Figure 3, light with angle θ_i is reflected to the position with the coordinates (x_0, y_0) on the surface of the non-plane mirror and, after the reflection, reaches position x on the CCD which is at distance d from it [8,9].

θ_r in Equation 3 is the reflection angle from the surface of the mirror that is defined by Equation 4:

$$x = x_0 + (d - y_0)\cos\theta_r, \tag{3}$$

$$\theta_r = 2\alpha - \theta_i, \tag{4}$$

$$\alpha = \tan^{-1}\left(\frac{\partial y}{\partial x}(x_0, y_0)\right). \tag{5}$$

In Equation 5, $\frac{\partial y}{\partial x}$ is indicative of the ratio of the differential variations on the surface of the mirror, which, for the spherical mirror, equals $\frac{y}{x}$ and, for the elliptical mirror, is in the form of Equation 6:

$$\frac{\partial y}{\partial x} = \frac{-2x^4y+2y(-c^3+2c^2-4a^2)+(1+c^2)4x^2y}{8x(c^2+a^2)-4x^3y^2+(1+c^2)4xy^2}, \tag{6}$$

in which a is the major radius and c is the distance from the center to the focus of the ellipse.

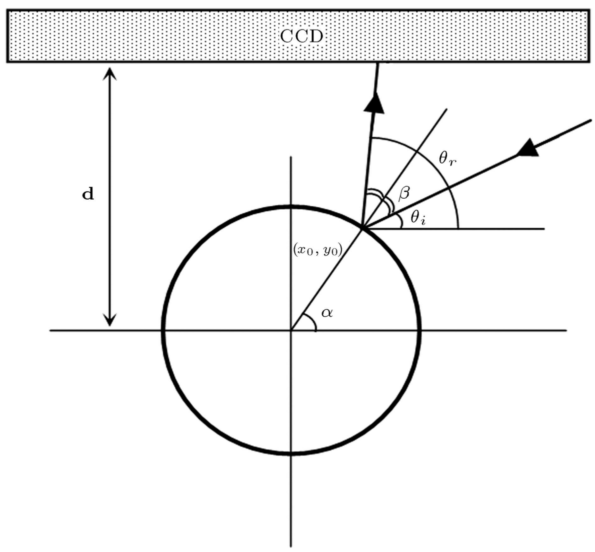

Figure 3. The reflection of the ray of light from the surface of the non-plane mirror.

Measurement Accuracy of the Optical Arrangement

In the previous section, the function of the system was explained. The integer part of the weight value is measured by CCD I; if CCD I has 4000 pixels, and for each pixel 5 gr is specified, the device will be able to measure the maximum weight of 20 kg with the accuracy of 5 gr by CCD I. Now, if the variations on each pixel of the CCD I are magnified on 5-10 pixels of CCD II, the measurement precision will reach $5 \times 10^{-4} - 10^{-4}$ kg for the maximum weight of 20 kg, which is a desirable result for system accuracy in accordance with the defined maximum weight. Of course, if the magnification on CCD II is performed on a larger number of pixels, the measurement precision will be within much better ranges around milligrams.

ARTIFICIAL NEURAL NETWORKS TECHNIQUE

As explained in the preceding section, the wave-shape of the variations of the scale position, according to the applied weight on the scale in relation to the time, is in the form of 3 responses; underdamped (u), critically damped (c), and overdamped (o) of which, in this work, only the underdamped circumstances are discussed. In Figure 4, some samples of the underdamped wave-shape for different applied masses are shown. In this regard, the goal is to estimate the final value of the produced wave-shape before the scale reaches steady state by the neural network, the result of which is an escalation of the rapidity of response of the system to input.

The neural network, MLP (Multi-Layer Preceptron), is regarded as one of the most popular artificial neural networks which, with nonlinear training, establishes the appropriateness between input and output. But, recently, the neural network, RBF, is being used in different applications, and this is due to some of its specific characteristics particularly its rapid functioning in training [4,10].

The neural network, RBF, is trained by means of a couple of signals produced by certain weights, and consists of an input layer, a hidden layer and an output layer. In the application for different inputs, it gives an appropriate response, both for those that entered the network as initial data for training and those that have not yet been experienced. According to Figure 5, by means of sampling in a limited number the signal entering into the network in a short time interval, the system, using its initial instructions, is able to give the appropriate output before the scale reaches steady state, and this significantly increases the rate of the system.

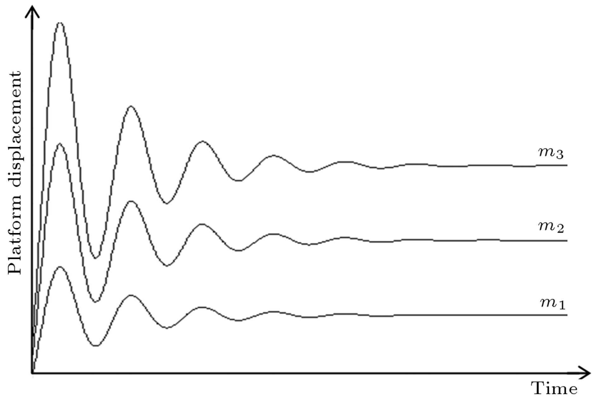

Figure 4. The unit step response of the dynamic weight estimation scale.

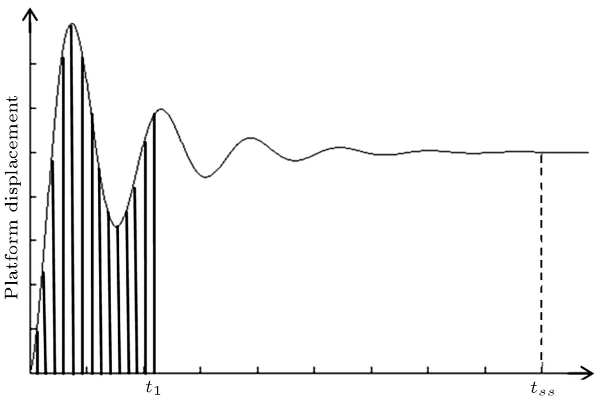

Figure 5. Sampling the unit step response of the scale, t_1, the length of the sampling, t_{ss}, the time taken for the scale to reach the steady state.

SIMULATED PERFORMANCE

In a simulation of the behavior of the system, artificial neural network (ANN) learning has been used. The number of samplings for every signal entering the network is assumed to be 100 samples in a time interval of 0.5 s. The number of layers in this system is 3: an input layer, 200 neurons in the hidden layer, and one neuron in the output layer. The signals produced by the application of the weights uniformly in the form of $m(t) = 0.1, 0.2, \ldots, 20$ kg are used for the learning of the network.

In order to simulate Equation 2, input patterns for learning and recalling, by means of MATLAB software, are used. Parameters of the scale estimation in all simulations are thus $g = 9.8$ m/s^2, m_p=0 kg, $c =$ 50 Ns/m, $k = 10000$ N/m, the initial displacement of the scale $b_0 = 0$ mm and the initial rate $b_1 =$ 0 mm/s. For the given parameters of the scale, only the underdamped expression is used.

An artificial neural network is trained by using noiseless samples. The function of the trained ANN in the recalling of data entered into the network for training is shown in Figure 6. In this figure, the simulation performance indicates a linear relation between the applied masses, $m(t)$, and the masses estimated by the neural network. Figure 7 signifies the error of the values recalled from the neural network and its input signals with a mean error of 2.7577×10^{-7} kg and $RMS = 2.9095 \times 10^{-8}$ kg. The results of this simulation show that ANN is able to model a nonlinear relation between the time series of the scale and the corresponding applied weight with very good precision. The act of recalling was also repeated for unobserved data, the error produced by which is shown in Figure 8. In order to test the function of the network under noisy circumstances, this time, the input patterns are combined with 2% of the noise and recalled by the network. This act was performed both for observed and unobserved signals, the error arising from which is included between the applied and evaluated data in Figure 9.

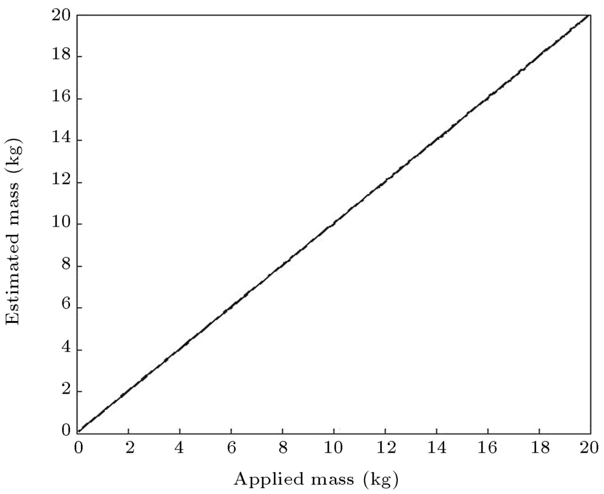

Figure 6. The function of ANN simulation for recalling noiseless patterns.

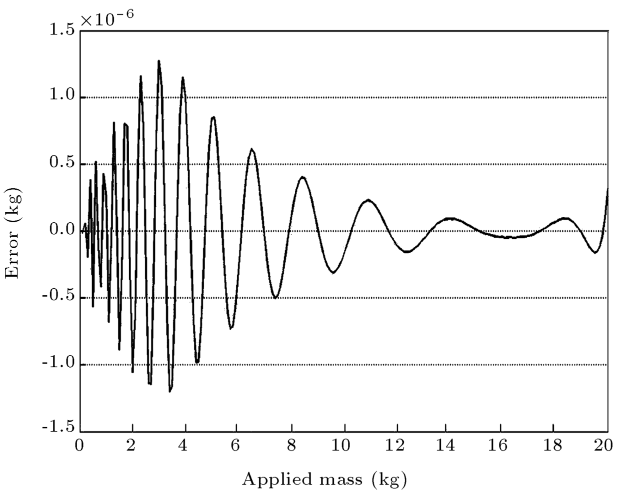

Figure 7. The error between applied weights and the estimated ones in Figure 6.

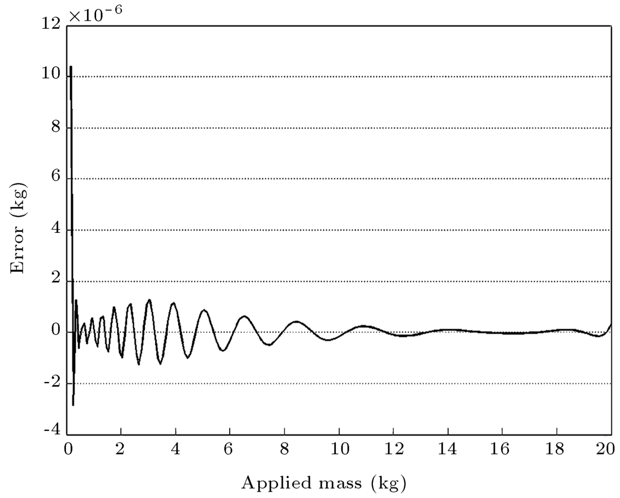

Figure 8. The error between the unseen applied weights and the estimated ones.

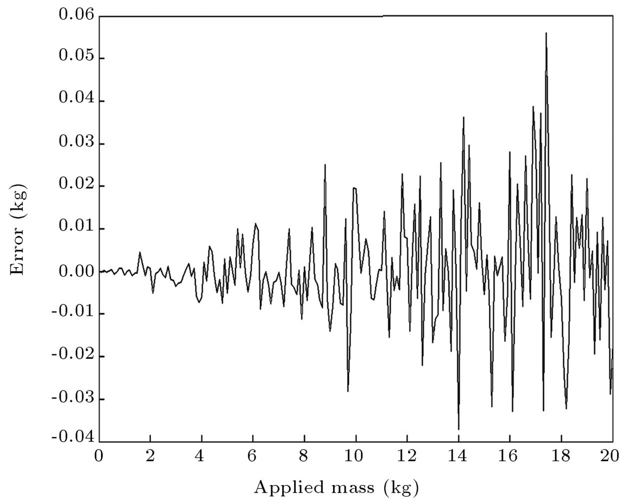

Figure 9a. The results of the simulation function with patterns with 2% of noise for the seen data.

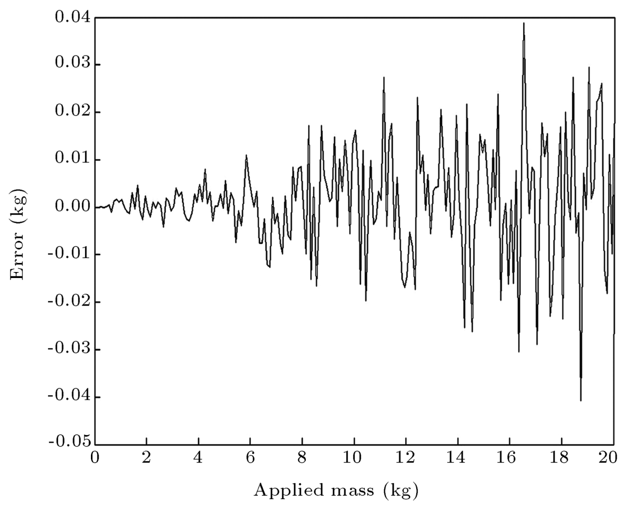

Figure 9b. The results of the simulation function with patterns with 2% of noise for the unseen data.

Table 1. The simulation errors for noiseless patterns and patterns with 2% of noise.

Patterns	Seen Patterns	Unseen Patterns
Noiseless	Error = 2.7577×10^{-7} kg RMS = 2.9095×10^{-8} kg	Error = 3.9644×10^{-7} kg RMS = 6.1664×10^{-8} kg
Rate of noise 2%	Error = 8.4000×10^{-3} kg RMS = 9.0690×10^{-4} kg	Error = 8.0000×10^{-3} kg RMS = 8.1390×10^{-4} kg

Table 1 represents the general results obtained from these observations, along with the mean value of the error and the related RMS, which singles out the consequences of the practicality of the artificial neural network in estimation of the weight applied on the scale, and the escalation of the rate of evaluation.

CONCLUSION

In this paper, a new model for a dynamic weight measurement device with an optical design has been presented. This method has resulted in an increase in estimation accuracy and less susceptibility to noise. Moreover, the technique of an artificial neural network has been adopted for rapid prediction of the value of the applied weight. The model of the neural network receives the data from two pieces of CCD and, then, speedily measures the dynamic weight. In this paper, the use of an optical arrangement in the application of CCDs with the aid of neural networks is a new and authentic method. The results of the simulation operations are indicative of application of the industrialization of dynamic weight estimation.

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APPENDIX

Relations concerning the calculation of underdamped (u), critically damped (c) and overdamped (o) case answers are as follows [1]:

Underdamped (u) case:

$$q_0 = (m(t) + m_p)g/K,$$

$$q_1 = 0.5\ C/(m(t) + m_p),$$

$$q_2 = \sqrt{B_1^2 + B_2^2},$$

$$q_3 = \omega_d = \sqrt{K(m(t) + m_p)^{-1} - q_1^2},$$

$$q_4 = \tan^{-1}(B_1/B_2),$$

where:

$$B_1 = q_0 - b_0, \qquad B_2 = b_1 + B_1 q_1/q_3,$$

and ω_d is the natural frequency.

Critically damped (c) case:

$$q_0 = (m(t) + m_p)g/K,$$

$$q_1 = 0.5\ C/(m(t) + m_p),$$

$$q_2 = q_0 - b_0,$$

$$q_3 = q_1 q_2 - b_1.$$

Overdamped (o) case:

$$q_0 = (m(t) + m_p)g/K,$$

$$q_1 = -0.5\ C/(m(t) + m_p) + \omega_d,$$

$$q_2 = -((q_0 - b_0)q_3 + b_1)/2\omega_d,$$

$$q_3 = -0.5\ C/(m(t) + m_p) - \omega_d,$$

$$q_4 = -((q_0 - b_0)q_1 + b_1)/2\omega_d.$$

BIOGRAPHIES

Hossein Balazadeh Bahar is Associate Professor of the Department of Electrical Engineering at the Faculty of Engineering of Tabriz University in Iran. He was awarded a M.S. degree in Electronic Engineering in 1980 and a Ph.D. in Digital Signal Processing in 1982 from The University of Wales in the UK. He was Dean of the Engineering Faculty and Chairman of Industrial Affairs at Tabriz University between 1983-94 where, from 1983-2008. He was also Director of the Department of Talented Students. His research interests include: Applied Research in Signal Processing, Interfacing Techniques and Artificial Intelligence (AI) Applications in Real-Time Industrial Systems. Besides scientific activities, he is currently involved in designing industrial AI based systems at Gostar Pazhouh Research Company (GPRCO).

Ebrahim Safari was born in Iran in 1966. He received a B.S. degree in Applied Physics from Tehran University, a M.S. degree in Solid-State Physics from Urumia University, Iran, and a Ph.D. in Experimental Physics (Laser) from Joseph Fourier University, France, in 1989, 1995 and 2002, respectively. He joined the Agricultural & Medical Research Center, AEOI, in Iran, and from 1991-1992 engaged in studies on Rotary X-ray Lamps and technical support for other sections. From 1995 to 1998, he joined the Spectroscopy Research Center, AEOI, in Tehran, where he was engaged in the research and development of Nd: YAG Laser and its Optical Devices. In 2002, he became an Assistant Professor at Bu-Ali Sina University in Hamadan, Iran, and then moved to Tabriz University in 2005, where he is Assistant Professor of Laser Physics.

Hamed Alizadeh Ghazijahani was born in Iran in 1988. His main research interests include: Mechatronics & Digital Signal Processing. He is at present collaborating with Gostar Pazhouh Research Company (GPRCO) and currently received two patents in Robotics and Electronics (2009) from the Industrial Possession Registrar Organization in Iran.