

A Comparison of Control Design Methods for Philips Glass Furnace using Experimental Data

Magdi S. Mahmoud⁺

Abstract— This paper describes a comparison of control system design to Philips glass furnace. The first stage considers the application of system identification techniques to obtain models using experimental data. Several models were identified, wherein the one picked up for control design has the largest level of fitness. In the second stage a set of improved control methods are implemented to design controllers based on non-adaptive (including LQR, LQGR, H_2 , H_{∞}) and adaptive (including MRAC, L_1) methods. Simulation studies were performed and evaluated.

Keywords— Philips glass furnace, identification, control design, adaptive methods, non-adaptive methods.

I. Introduction

A Philips glass furnace considered as a chemical reactor, where the raw materials are burnt in a confined space surrounded by refractory, at high temperatures of 1400 - 1600 degree C to produce molten glass, see Fig. 1. The melting area of a glass furnace consists of a molten glass bath and a combustion chamber. The walls, floor and the roof of the melting area are made up of refractory (which is capable of handling high temperatures). The furnace operation involves combustion, heat transfer, batch melting, glass flow patterns. [1] – [4]. In the literature, there are several methods for identification and/or control of different types of glass furnace [8]–[20]. The combined identification and control design based on empirical data for glass furnace has received little attention.

In this paper, we develop a two-stage approach to the control design of Philips glass furnace. In the first stage, a mathematical model of is identified using empirical data. This model is then fed to the control design pool of methods, which consist of non-adaptive (including LQR, LQGR, H_2 , H_{∞}) and adaptive (including MRAC, L_1) methods. By extensive Matlab-based simulation studies, the performance of the design methods is compared and evaluated.

II. Identification Stage

Using the DaISy (Database for the Identification of Systems; SISTA's Identification Database), a data set consists of 1247 samples of three inputs and six outputs. The inputs represent the heating and cooling inputs to the furnace and, all the six outputs represent the outputs from temperature sensors in a cross section of the furnace. There are two types of modeling techniques that are

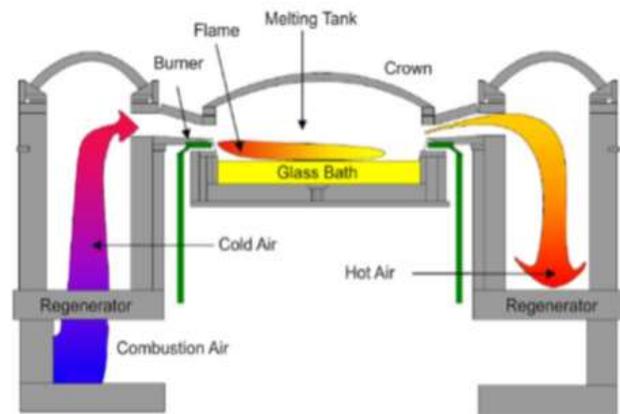


Fig. 1. Schematic of a glass furnace

currently applied for modeling of glass manufacturing processes: Black-box method and First-principles-based method. In the first method, a mathematical model of the process is obtained from the experimental input-output data of the process by applying identification techniques. Process identification techniques result in models that allow very fast simulation of process dynamics [2], [3]. In the second method, a mathematical model is derived from basic physical laws utilizing computational fluid dynamics (CFD) techniques. In this paper, we follow the first method using the data in Figs 2–4.

Using parametric identification techniques, we obtain state-space models that represent dynamical models of the glass furnace from the on-line data. The basic state-space model in innovations form can be written as:

$$\begin{aligned} x(t + T_s) &= Ax(t) + Bu(t) + Ke(t) \\ y(t) &= Cx(t) + Du(t) + e(t) \end{aligned} \quad (1)$$

Where $x(t)$ is the state vector, $u(t)$ is the input vector, $e(t)$ is the noise vector and $y(t)$ is the output vector. In addition, A is the state matrix, B is the input matrix, C is the output matrix, D is the feedthrough matrix, and K is the matrix representing the noise/disturbance characteristics of state space models: Subspace method (N4SID and Prediction Error Method (PEM) [7]. The numerical values of matrices are omitted for space limitation. A comparison between the n4sid model and the pem model obtained using one data set is depicted in Fig. 5, whereas a comparison of the fitness of n4sid models and pem models using different sets of data for output y_1 is presented in Fig. 6.

⁺ Distributed Control Research Lab,
Systems Engineering Department, KFUPM,
P. O. Box 5067, Dhahran 31261, Saudi Arabia

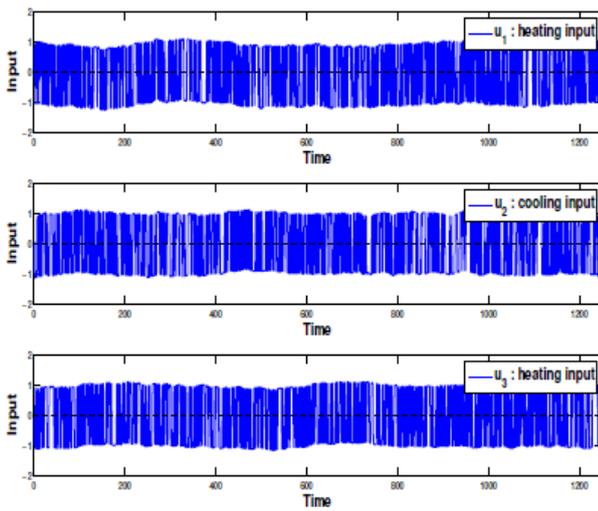


Fig 2. Input data

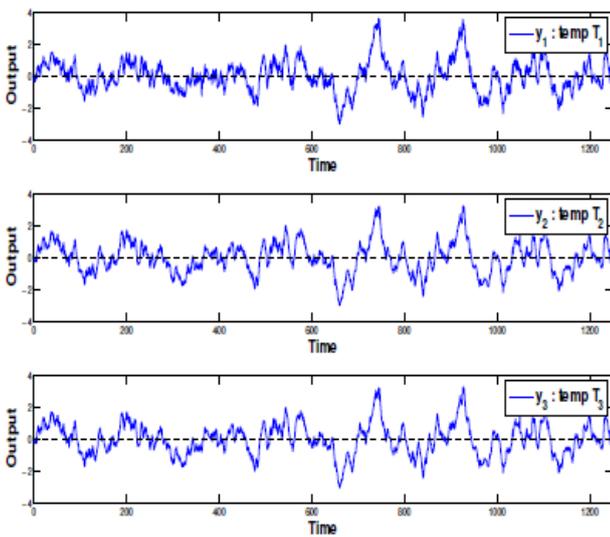


Fig 3. Output data I

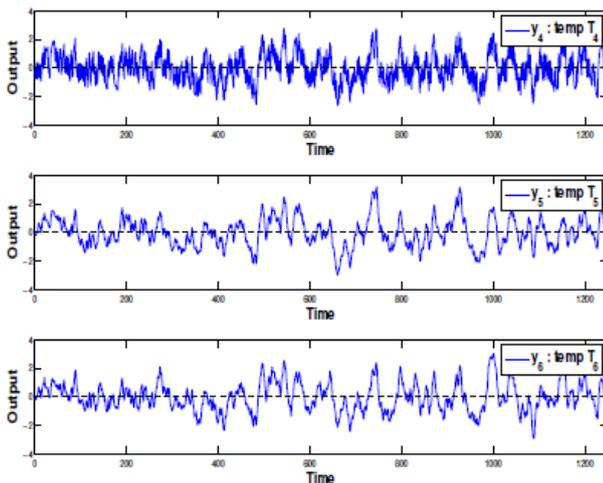


Fig 4. Output data II

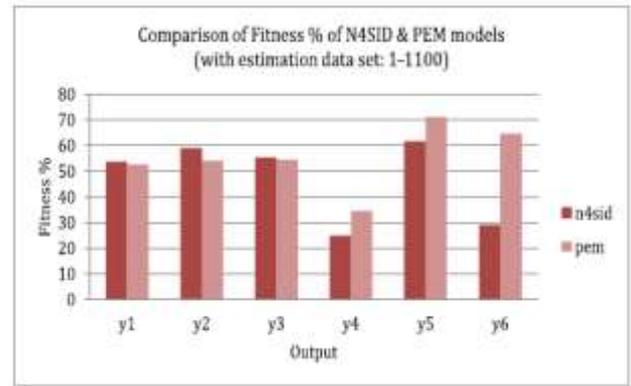


Fig 5. Fitness comparison of n4sid model and pem model obtained from the estimation data 1-1100

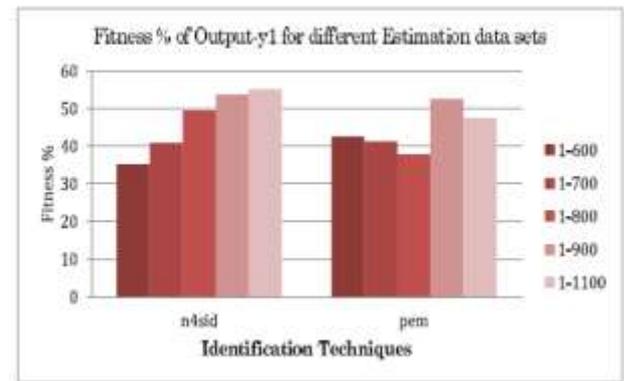


Fig 6. Fitness comparison of different n4sid models and pem models

III. Control Design Stage

The problem now is to determine the controller to be applied to the identified Philips glass furnace model to achieve a desired steady-state temperature profile. The methods of control design considered in the present work is divided into two distinct categories: non-adaptive category including linear-quadratic regulator (LQR), linear-quadratic Gaussian regulator (LQGR), optimal H_2 and optimal H_{∞} and adaptive category including MRAC, L1 methods. The theory of these methods omitted due to space limitations

A. Non-Adaptive Control Design

In this category of control design methods, we considered

- Linear quadratic regulator (LQR)
- Linear quadratic Gaussian regulator (LQGR)
- H_2 and H_{∞} Control

In simulation, we used Matlab and Simulink. Optimal and robust controllers are designed for the identified glass furnace model. The output trajectories are shown in Figs 7–10. The following observations are deduced from the simulation results:

- With H_2 controller, the overshoot in the output and the settling time are relatively less.
- The output experiences a large overshoot with H_{∞} controller.
- The response of LQR and LQGR is exactly similar and is better than the H_{∞} controller response.

Among the four non-adaptive controllers, it appears that

H_2 controller provides best closed-loop performance for the identified glass furnace model.

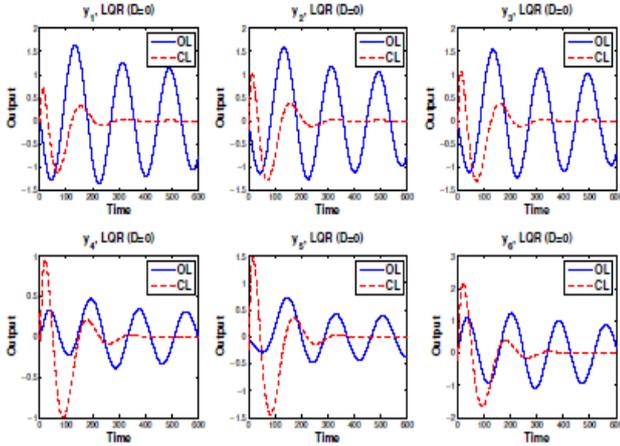


Fig 7. LQR: Output trajectories for open loop and closed-loop systems

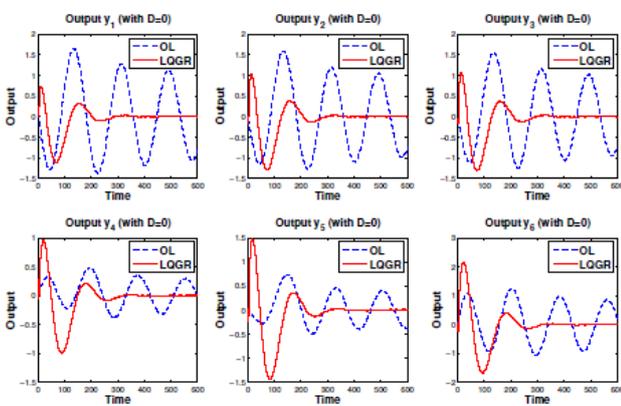


Fig 8. LQGR: Output trajectories for open loop and closed-loop systems

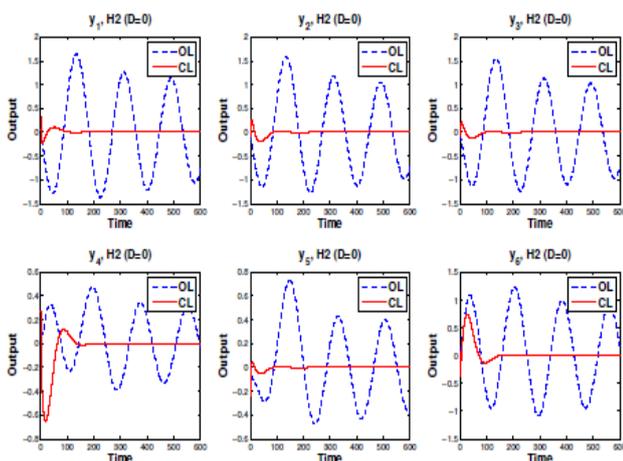


Fig 9. H_2 : Output trajectories for open loop and closed-loop systems

B. Adaptive Control Design

Adaptive controller is a combination of control law (based on the known parameters) and online parameter estimation (through which unknown parameters are estimated at each instant) [5]. This online parameter estimator is known as

adaptive law or update law, or adjustment mechanism. Based on this way of combining the control law and the adaptation law, the adaptive control is categorized into two types as *direct* adaptive control and *indirect* adaptive control.

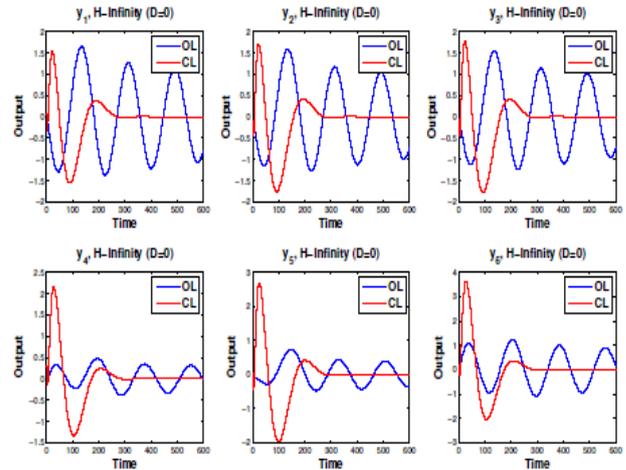


Fig 10. H_{∞} : Output trajectories for open loop and closed-loop systems

In the sequel, we consider the direct model-reference adaptive control (MRAC), and the L_1 adaptive control, shown in Figs. 11-12 and their implementation on the identified glass furnace model. We recall in MRAC that, the use of high adaptation gain results in high gain feedback control which further results in high-frequency oscillations in the control signal and reduced tolerance to time delays. Proper tuning (selection of appropriate adaptive gain) of MRAC is a difficult task. The L_1 adaptive control method considers uniform performance bounds on the L_1 -norms of the errors in model states and control signals. As these error norms are (uniformly) inversely proportional to the square root of the adaptation gain, this method enables the use of high adaptation gains. The simulation is based on the theory in [5], [6]. The advantages of using the L_1 adaptive controller is illustrated by comparing the simulation results of L_1 adaptive control and MRAC.

The L_1 adaptive control architecture consists of direct MRAC and a bandwidth-limited filter as shown in figure 12. The filter is used for the filtering of control signal in order to avoid high frequencies in the control signal and for shaping the nominal response. In adaptive control, though the increase in adaptation rate improves the tracking performance, it degrades the robustness of the controller. Hence, the adaptation rate is the key to tradeoff between performance and robustness. L_1 adaptive control theory deals with this problem by setting up an architecture that separates the adaptation and robustness and thereby guarantees the transient performance and robustness in the presence of fast adaptation, without introducing or enforcing persistence of excitation, without any gain scheduling in the controller parameters, and without resorting to high-gain feedback [6].

The simulation results of L_1 adaptive control are shown in Fig. 13 for the controlled output y_2 for various bandwidths of the low-pass filter $C(s) = \omega_c/s + \omega_c$ of the L_1 adaptive controller. The best response is obtained with a bandwidth

$\omega_c = 0.02$ rad/sec. From the plots shown in this figure, it is observed that for bandwidths higher than $\omega_c = 0.02$ rad/sec, as the bandwidth increases, the overshoot in the response of the system also increases and for bandwidths below this value the response is sluggish.

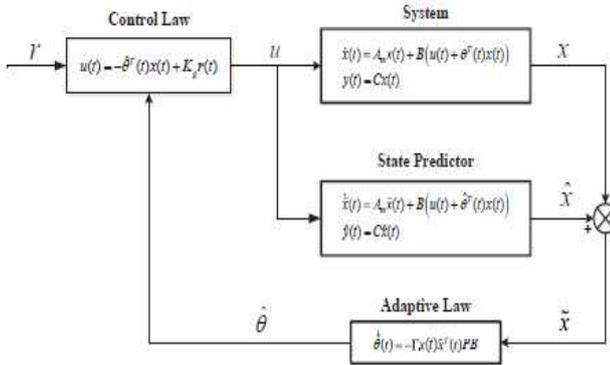


Fig 11. Direct MRAC with state predictor

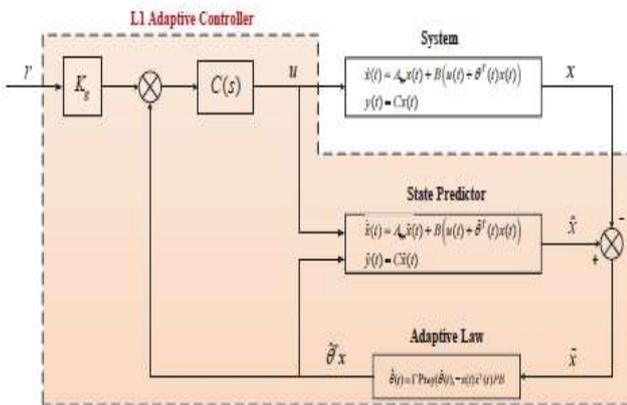


Fig 12. Closed-loop L_1 adaptive system

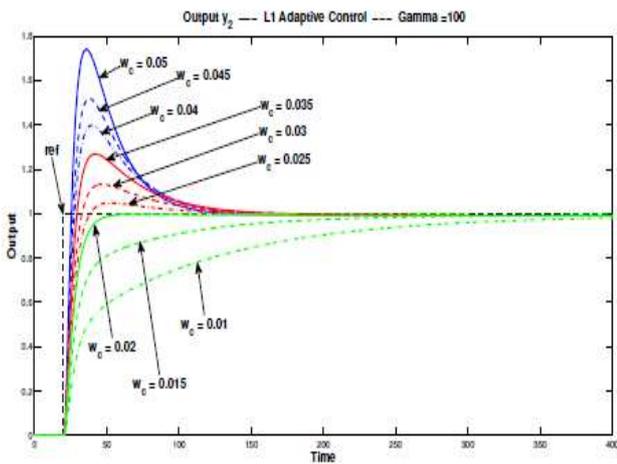


Fig 13. Output y_2 with L_1 adaptive control at various filter bandwidths

Fig. 14 shows the plots of control inputs (unfiltered and filtered) of the L_1 adaptive controller with the parameters $\omega_c = 0.02$ rad/sec, and $\Gamma = 100$. A step input of magnitude of 1 unit is given as a reference signal. The output trajectories of this closed-loop system are presented in Fig. 15.

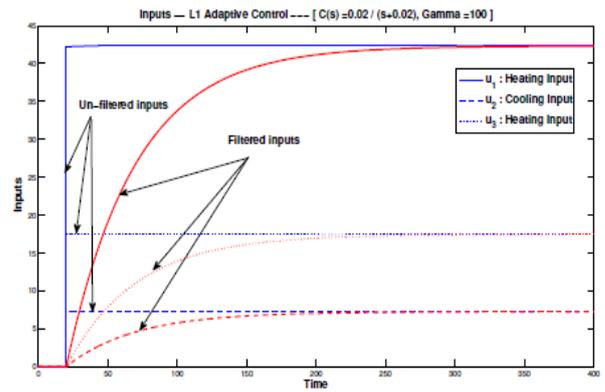


Fig 14. L_1 adaptive system: control input trajectories

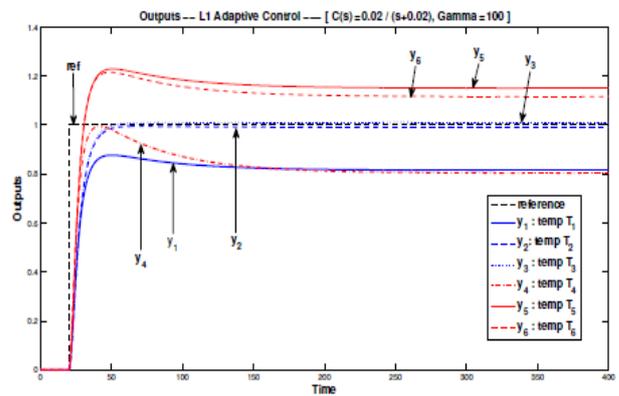


Fig 15. L_1 adaptive system: output trajectories

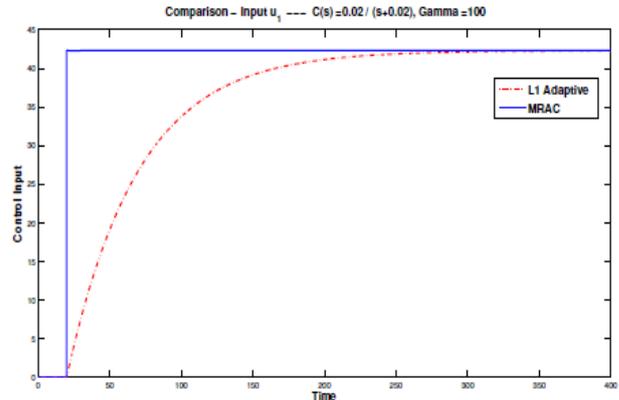


Fig 16. L_1 adaptive vs MRAC: control input u_1

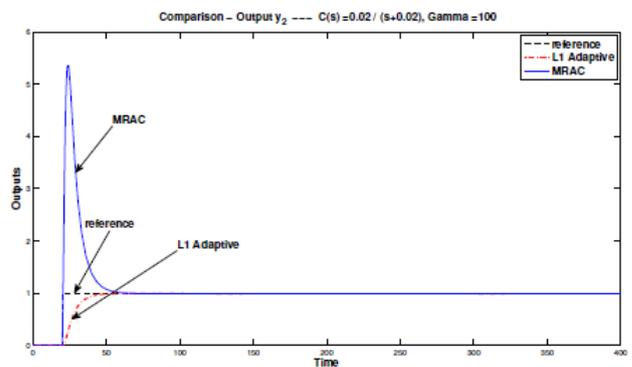


Fig 17. L_1 adaptive vs MRAC: control input u_2

Direct (MRAC) with state predictor has also been applied to this glass furnace model. The closed-loop responses of MRAC system and L_1 adaptive system illustrated by control input u_1 and output y_2 in Figs. 16 and 17 respectively. It is seen that the system with L_1 adaptive controller has a better transient response than the system with MRAC.

IV. Conclusions

This paper has addressed a two-stage identification-control approach for a Philips glass furnace. Identification of the glass furnace system was performed using prediction error and N4SID methods. The estimated models were validated and their model fitness was compared. On comparison, it is found that the PEM model has the best fitness. The optimal and robust non-adaptive controllers (LQR, LQGR, H_2 and H_{∞}) have been designed and applied to the identified glass furnace model. Implementing these controllers in closed-loop with the glass furnace model resulted in satisfying results. In this regard, H_2 controller has provided the best closed-loop performance. Model-reference adaptive control (MRAC) and L_1 adaptive control methods were considered and it was found that the latter method has provided results with good transient response and good robustness characteristics.

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About Author:



He has been a professor of engineering since 1984. He is now a Distinguished Professor at KFUPM, Saudi Arabia. He was on the faculty at different universities worldwide including Egypt (CU, AUC), Kuwait (KU), UAE (UAEU), UK (UMIST), USA (Pitt, Case Western), Singapore (Nanyang) and Australia (Adelaide). He lectured in Venezuela (Caracas), Germany (Hanover), UK ((Kent), USA (UoSA), Canada (Montreal) and China (BIT, Yanshan). He is the principal author of thirty-six (36) books, inclusive book-chapters and the author/co-author of more than 525 peer-reviewed papers. He is the recipient of two national, one regional and several university prizes for outstanding research in engineering and applied mathematics. He is a fellow of the IEE, a senior member of the IEEE, the CEI (UK), and a registered consultant engineer of information engineering and systems (Egypt). He is a fellow of the IEE, a senior member of the IEEE, the CEI (UK), and a registered consultant engineer of information engineering and systems Egypt.