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Electrochromic device modeling using an adaptive neuro-fuzzy inference system: A model-free approach

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ABSTRACT

This paper presents a new approach for the modeling of an Electrochromic (EC) device. The proposed system relies on an adaptive network-based fuzzy inference system or equivalently, Adaptive Neuro-Fuzzy Inference System (ANFIS). The ANFIS network has used 33 experimental data sets of which, 24 data sets were taken as training data and 9 data sets were taken as testing data. The ANFIS performance statistical indices mean absolute error (MAE), root mean square error (RMSE), and non-dimensional error index (NDEI) are found to be close to zero and coefficient of determination (R^2) and linear correlation coefficient (ρ) and variance account for (VAF) are found to be close to one. Some interpretability issues regarding the ANFIS models, such as rule consistency, rule separation, and rule completeness are discussed. Simulation examples are provided to illustrate the effectiveness of the proposed approach. This study also includes experiments that confirm the good performance and the potential of the ANFIS models for datasets with noise. The proposed models can be seen as virtual luminous transmittance sensors.

1. Introduction

Electrochromic devices are an emerging technology that has great potential for a plethora of applications. At present, electrochromics are principally used as smart windows for indoors daylight management and thermal gain control in energy-efficient buildings [1,2]. The advantages of electrochromic windows and their superior performance compared to other competing technologies have been demonstrated through modeling and experiment [3–7]. However, in order to fulfill their potential, advanced control strategies are necessary for their operation [2,8,9]. Such strategies can only be developed through comprehensive modeling of their properties.

1.1. Description of a typical EC device

In general, an EC device consists of two conductive glass pieces, one with an electrochromic thin film, the other with an ion storage and/or protective film, laminated by an electrolyte (solid, liquid or gel), which usually contains Li ions [2]. Tungsten oxide (WO_3) is the most promising electrochromic material, widely used in smart windows. The transmittance of WO_3 films can be altered by the intercalation/de-intercalation of small cations (H^+, Li^+, Na^+) into the film. The reversible electrochromic effect in the case of tungsten oxide can be expressed as a redox reaction [1]:

$$WO_3 + xe^- + xM^+ \rightarrow M_xWO_3 \quad \left(M = H^+, Li^+, Na^+\right) \tag{1}$$

1.2. A modeling challenge

A comprehensive modeling of an electrochromic device would require full knowledge of the processes that take place in the molecular level. Until now, several theories have been proposed for the coloration mechanism of electrochromic materials (and in particular WO_3), with that of polaron absorption being the most widely accepted, giving a good approximation of optical properties [1,2]. However, the electrochromic properties of tungsten oxide films depend on a number of factors, such as the method of deposition, the film structure, the content of incorporated gases and water, the oxygen deficiency and others [1,2,10]. To complicate things further, modeling of all the other parts of the device (e.g. transparent conductors, electrolyte and ion storage film) is also required for a complete treatment [11]. Furthermore, size and temperature effects that influence coloration kinetics would also need to be taken into account. Such analytical work is lacking at present. It would be tedious and would require large amounts

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of computational time. It would also be device-specific, requiring modifications for each different sample. Consequently, due to the complex nature of the relationship between the parameters of EC device, an exact mathematical model still remains unknown so far [12]. A much simpler approach is to treat the electrochromic device as a "black box", and use machine learning techniques which are data-driven, that is, experimental data are required for the modeling. Our approach is generic and is applicable to other electrochromic devices of this type.

1.3. Machine learning systems: A model-free approach

In the literature there is an increasing interest in developing models from experimental data using machine learning systems such as fuzzy logic systems (FLS), neural networks (NN) and hybridization of these.

A fuzzy logic system is a nonlinear mapping of a crisp input vector into a crisp scalar output. This employs subjective knowledge, that is, model-free approach in which rules are extracted from numerical data [13]. The architecture of a FLS is determined by type fuzzification, functional forms of membership function, parameters of membership functions, fuzzy rules, compositional rule of inference and defuzzifier [13]. In FLSs the parameters of membership functions and rules are determined by a trial and error procedure. It requires a significant time to obtain a reliable solution.

The neural networks are a basic scientific discipline of computational intelligence. Conventional NNs have many drawbacks for their learning process. The determination of suitable size of NN, multiple local minima, optimal structure of the neural net, overfitting problem and the need of a large number of data for their training constitute serious themes [14].

Combining the advantages of fuzzy logic systems and neural networks

1. The LLMs (local linear models) facilitate the "minimal disturbance principle": The adaption should reduce the output error for the current training pattern, with minimal disturbance to responses already learned [15].
2. The Takagi–Sugeno (*T–S*) fuzzy model is simpler to identify because it needs less rules and parameters can be trained from numerical data using optimization methods such as backpropagation and least-square algorithms.
3. *T–S* fuzzy model provides continuity of the output surface.
4. *T–S* fuzzy models with linear rule consequent are universal approximators of any smooth nonlinear system [16].
5. Fuzzy inference system can incorporate linguistic information as well as numerical data to achieve better performance.

1.4. Our approach

The neuro-fuzzy hybrid systems integrate the advantages of fuzzy systems and neural networks, that is, all parameters can be trained like a neural network within the structure of a fuzzy logic system. ANFIS is an adaptive neuro-fuzzy inference system which was first developed by Jang [17] and it is used to describe the overall behavior of the system under interest. ANFIS modeling is essentially a multimodal model technique where simple submodels are developed and aggregated to obtain an accurate overall model output. ANFIS approach has been applied to a wide range of areas, such as nonlinear function modeling, time series prediction [18], estimation of material properties [19–21], photovoltaic systems [22]. ANFIS can be used as an alternative way of model-free approach for the modeling of an EC device. Therefore, the objective of this study is to develop ANFIS models for modeling of the coloration/bleaching of the electrochromic device in relation to input variable charge density. These models can be used as a virtual sensor in achieving accurate monitoring of luminous transmittance of an EC device substituting costly and cumbersome equipments.

This paper proposes three ANFIS models (ANFIS-genfis1, ANFIS-genfis2 and ANFIS-genfis3) for the coloration/bleaching modeling of an EC device. ANFIS models performance is verified through simulations. It has been found that the models ANFIS-genfis1 and ANFIS-genfis2 attain better performance for coloration and bleaching modeling of the EC device, respectively.

2. Experimental methods

2.1. Fabrication and characterization of EC devices

Tungsten oxide thin films were prepared by electron beam gun deposition at room temperature in a vacuum chamber evacuated by a turbo-molecular and a mechanical pump. The starting material was 99.99% pure WO_3 powder in the form of compressed pellets. A quartz thickness controller has been used for the deposition of the desirable film thickness. As substrates, 10 cm by 10 cm pieces of a commercial SnO_2: F coated glass (trade name K-Glass) have been used. K-Glass is produced by spray pyrolysis with a thickness of 200–500 nm [23]. The thickness of the WO_3 films was also measured ex-situ by an Ambios XP-1 profilometer. It was found to be 550 nm.

The fabricated films were incorporated into electrochromic devices of the type Glass/SnO_2:F/WO_3/1 M $LiCLO_4$–PC-PMMA gel electrolyte/SnO_2: F/Glass.

The EC devices were prepared as follows: The electrochromic WO_3/SnO_2:F/Glass sheet and the SnO2:F/Glass piece were arranged facing each other, slightly displaced in order to preserve space for electrical contacts. The devices were sealed peripherally by a thermoplastic material (PV 5414, Dupont, with thickness 0.5 mm), that also served as a spacer. A mask with the desired dimensions was cut from the thermoplastic material and was placed between the two glass sheets. The assembly was heated at 120 °C for 20–30 min. Pressure was applied with use of metal clamps to ensure successful bonding. Thus, a cavity was formed between the two glass sheets, ensuring hermetic confinement of the electrolyte without leakage. The cavity was about 1 mm thick and that was achieved using 3 layers of the thermoplastic material placed on top of each other.

In order to facilitate pouring of the electrolyte, two small holes, 1 mm in diameter each, were drilled close to the edges of the SnO_2:F/Glass sheet prior to the device assembly. The electrolyte was inserted from one hole, with air leaking from the other. The holes were sealed with small pieces of glass placed on top of each hole, using the aforementioned thermoplastic sealant and a soldering iron for melting it. Copper adhesive tape has been used for the electrical contacts. Photographs of a typical device in the bleached and colored states together with fabrication details appear in Fig. 1.

For the preparation of the gel electrolyte Poly-methyl-methacrylate (PMMA, MW: 120.000) was first dehydrated at 80 °C under vacuum for 12 h. Then, it was dissolved in a solution containing 1 M $LiClO_4$ in propylene carbonate (PC) at 70–80 °C in a glove box, under continuous stirring. The resulting gel electrolyte had a 18% w/w concentration in PMMA. The gel electrolyte was heated at 80 °C before pouring into the device, in order to reduce its viscosity.

The EC devices were colored and bleached galvanostatically, with a potensiostat–galvanostat (AMEL, model 2053), a function generator (AMEL, model 586) and a noise reducer (AMEL NR 2000). In each coloration step, a prescribed charge density was intercalated into the WO_3 film, and measurement of the transmittance spectra followed. The same process was carried out for bleaching, with the polarity of the applied current reversed. The transmittance $T(\lambda)$ spectra of the EC devices were recorded in the visible at