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Enhancement of electronic protection to reduce e-waste

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ABSTRACT

The electronic devices turn to e-waste due to their insufficient electrical protection which is provided by a ceramic core varistor. The ceramic consists of the surrounded ZnO grains of melted an additives layer. The layer is origin of the quality of the protection. To enhance the quality and consequently prevent e-waste, the fabrication of the varistor was modeled by artificial neural network. The model predicted the optimized condition that was experimentally fabricated and electrically characterized. The results confirmed the model predictability. In conclusion, the optimization which has industrial scales up potential warranties the electronic protection that controls the global e-waste.

Introduction

Due to the short useful lifetime of electronic products they turn to e-waste which originates pollution problem for hydrosphere, biosphere even atmosphere [1–3]. Generally the harmful materials of estimated global e-waste which is about 35 to 50 million tons per year includes nano-materials that contains lead, chromium, mercury, cadmium and arsenic into environment [4–12]. To control the e-waste, the existed current methods are including reusing, refurbished and recycling process of second-hand electronics. Recycling process covers only 23% of the e-waste which may not be fully recovered even the amount of the hazardous materials [13]. In addition, the reusing and refurbished processes are unable to even postpone the old technology any more while the generation rate of very short lifetime electronic devices is quite high around the world [14].

On the other hand, the lifetime could be improved by high quality electrical protection from common generated overvoltage including lightning strikes, power outages tripped circuits, power transitions, power malfunctions, electromagnetic pulses and inductive spikes in the associated circuit [15]. The overvoltage damages the electrical devices which designed to operate at normal voltages. Currently, the protection as a preventive action is carried out by a voltage-limiting device such as varistor which is associated in parallel of electronics into the electrical circuit. It means the varistor has presented high resistance ohmic behavior within the operating normal voltage that the normal electrical current never flows through the associated varistors [16]. On the other hand, the varistor changes into non-ohmic behavior at the overvoltage and allows the current to flow through itself. In this way, the varistor diverts the overvoltage safely from the device at certain threshold voltage [17,18]. However, most discarded electronic appliances were damaged due to the overvoltage that must be deflected by the associated varistors. It is obvious that the varistors unable to protect the devices during surge due to their insufficient non-ohmic behavior which is originated from the used ceramic core.

The used ceramic in the varistors has been made of n-type semiconductor such as zinc oxide (ZnO) and other metal oxides as

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additive [19,20]. Since, the microstructure of the ceramic is made of ZnO grains that is surrounded by narrow boundaries of melted additives as segregation layer [21,22]. The additives are included Bi_2O_3, TiO_2, Co_3O_4, Mn_2O_3, Sb_2O_3, V_2O_5, and Al_2O_3 which initially mixed with a large amount of ZnO by physical or chemical methods [23–25]. Thereafter the mixed final powder is compacted and heated to occupy the grains boundaries [26–31]. In fact, the melting points of the additives are less than the melting point of ZnO by reason of they are melted to fill up the boundaries [32,33]. In the layer, Bi_2O_3 is used as former and other additives are subordinate which often included improving the ceramic electrical properties [17,33–35]. For instance, TiO_2 prevents the vaporization of Bi_2O_3 and also facilitates ZnO grain growth; Sb_2O_3 stabilizes the electrical properties and diminishes the leakage current of the varistor during performance [17,29,30,36]. The other additive such as Co_3O_4, Mn_2O_3, and Al_2O_3 are involved in the formation of interfacial states which contribute to the highly non-ohmic property (non-linear property) [18,37]. Obviously, some of the additives make the property while others improve it. As a result, to enhance the non-ohmic property, the additives should be optimized in the starting powder of the ceramic.

In the case of the optimization, the method of 'one variable at a time' has been widely used by varying one of the additives while other parameters are kept constant while the additives are not completely independent; it affects the electrical property of the ceramic [36–39]. Moreover, the number of experiments is quite high due to the variety of the additives which entail time consumption and possible misinterpretation of the related results. More than that, the different reactions including formation and decomposition of spinels phase, kinetic of ZnO grain growth, densification and evaporation of additives during the varistor fabrication add to the complexity. Likewise, the importance of the variable which uses to determine the level of initial additives is impossible for the methods.

On the other side, the multivariate methods such as response surface methodology (RSM) and artificial neural networks (ANNs) contemplate the simultaneous effect of the input variables on the output free of the mentioned complexity [40–44]. However, RSM involves the complicated statistical calculation of fitting process as well as the regression analysis while ANNs are free of the mathematic functionalization [16,42,45,46]. ANNs have been successfully used for modeling of productive processes such as photodegradation of many environmental organic pollutants including ethylene-diamine-tetra-acetic acid [47], nitrogen oxides [48], nitrilotriacetic acid [49], C.I. Basic Red 46 [50], 2,4-dihydroxybenzoic acid [51] and 4-nitrophenol [52]. To the best of our knowledge, no study has shown the modeling of the additives as input variables of the ceramic fabrication.

In this work, ANN was used to model the fabrication of 26 ceramic cores which used to prepare the same numbers of ZnO based low voltage varistor. The amounts of the mentioned additives were selected as input effective variables while the calculated non-linear coefficients (alpha = α, from $I = KV^{\alpha}$) of the experimental varistor's electrical characterization were used as outputs (responses). The modeling was carried out by four particular training algorithm programs which included Quick propagation (QP), Incremental back-propagation (IBP), Batch back-propagation (BBP) and Levenberg–Marquardt (LM) back-propagation algorithm [53,54]. Thereafter, the produced models of the algorithms are compared to find the optimized final model by the root means squared error (RMSE), the coefficient of determination (R^2) and the percentage of absolute average deviation (AAD) of the obtained models for each algorithm. The final model was used for navigation of the fabrication to determine the narrow levels and importance of the additives as well as predicting the points of the additives that maximize the non-linearity of the varistors. The predicted condition was experimentally prepared and electrically validated to determine the protectiveness and sustainability of the optimized varistor. The result of the validation was quite close to the predicted condition.

Experiment

Materials and methods

The used chemicals were included ZnO (99.99%), Bi_2O_3 (99.975%), TiO_2 (99.9%), Co_3O_4 (99.7%), Sb_2O_3 (99.6%), Mn_3O_4 (98%) and $Al(NO_3)_3$ (100%)which provided from Alfa Aesar for preparation the ceramic starting powder. For fabricate a varistor, the appropriate amount of each above chemicals was mixed and grounded by dry form and then wet ball milled for 24 h to prepare initial homogenous mixed powder. The mixed powder was overnight dried by a hot oven at 100 °C then it was pressed into pellet forms (10 mm in diameter and 0.70 mm thickness) at 200 Mpa by a uniaxial presser machine. The pellet was sintered for holding time of 1 h at 1260 °C while the heating and cooling rate were 5 °C/min by a box furnace (CMTS model HTS 1400) [40]. Thereafter, the both sides of the sintered pellet as ceramic core of the varistor were painted by silver electrodes to scan DC current–voltage. The scan was carried out from 0 to 100 volts in step size of 2.5 V by a Keithley source-meter 2400. The current–voltage (I–V) was used to calculate the current density, J (mA/cm^2) and electrical field, E (V/mm) where 'mm' is the thickness of pellets and 'cm^2' is the surface of the painted silver electrodes. The "E" was plotted vs."J" to calculate the alpha of the varistor at different values according to the following equation [55]:

$$\text{Alpha} = \frac{(\log J_2 - \log J_1)}{(\log E_2 - \log E_1)} \quad (1)$$

where J_1 was 0.1, J_2 was 1 mA/cm^2, E_1 and E_2 were measured at J_1 and J_2, respectively. The process was carried out for 26 varistors with different mol% of starting powders in their ceramic core (Table 1). The data of the varistors were randomly split up into two sets as training and testing data sets (Table 1) using the option available in NeuralPower software version 2.5 [56,57]. The training and testing data were used to compute and ensure robustness of the network parameters, respectively.

Theory of the modeling

ANNs are semi-empirical modeling methods which use the actual processing condition and corresponding responses to govern a network to avoid of the process complexity. The network consists of input, hidden and output layers which are made of appropriate connected units (nodes). The nodes are simple artificial neurons which mimic a biological neural network. The nodes of input layer are the effective variables and in output layer is the responses. In the hidden layer, the number of nodes is determined by learning process [58,59]. In the network, the nodes are connected by multilayer normal feed-forward or feed-back connection formula [53]. To qualify the network, the input layer acts as distributor and sends data via the weights to the nodes of second layer (hidden layer) [60]. The weighted data is saved as processing nodes in the hidden layer and then transferred to the output layer by particular transferred function [61,62]. Therefore, the qualified data are passed into the input layer, propagated to hidden layer and then transfers into the output layer of the network by iterative procedure [63]. The iteration is an act of repeating a process to approach a desire result. After appeared the first input–output iteration result, the second period is processed and so on. The network changes the weights in order to reduce the