An Application of Artificial Neural Networks in Brake Light Design for the Automobile Industry

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Abstract: - The advantages offered by the electronic component LED (Light Emitting Diode) have caused a quick and wide application of this device in replacement of incandescent lights. However, in its combined application, the relationship between the design variables and the desired effect or result is very complex and it becomes difficult to model by conventional techniques. This work consists of the development of a technique, through artificial neural networks, to make possible to obtain the luminous intensity values of brake lights using LEDs from design data.

Key-Words: - Brake light, LED, artificial neural networks, intelligent systems, automobile industry.

1 Introduction

The LED device is an electronic semiconductor component that emits light. At present time it has been used in replacement of incandescent lights because of its advantages, such as: longer useful life (around 100,000 hours), larger mechanic resistance to vibrations, lesser heating, lower electric current consumption and high fidelity of the emitted light color [1]. However, in designs where incandescent lights are replaced by LEDs, some of their main characteristics must be considered, such as: direct current, reverse current, vision angle and luminous intensity.

In automobile industry, incandescent lights have been replaced by LEDs in the brake lights, which are a third light of brakes [2]. In these brake lights are used sets of LEDs usually organized in a straight line. The approval of brake lights prototypes is made through measures of luminous intensity in different angles, and minimum value of luminous intensity for each angle is defined according to the application [3].

The main difficulty found in the development of brake lights is in finding the existent relationship between the following parameters: luminous intensity (I_V) of the LED, distance between LEDs (d) and number of LEDs (n), with the desired effect or result, that is, there is a complexity in making a model by conventional techniques of modeling, which are capable to identify properly the relationship between such variables. The prototype designs of brake lights have been made through trials and errors, causing increasing costs of implementation due to time spent in this stage. Moreover, the prototype approved from this system cannot represent the best relationship cost/benefit, since few variations are obtained from configurations of approved prototypes. The artificial neural networks are applied in cases like this one, where the traditional mathematic modeling becomes complex due to nonlinear characteristic of the system. These networks are able to learn from their environment and to generalize solutions, making them attractive to this type of application.

This paper shows an industrial application using artificial neural networks to estimate values of brake lights luminous intensity, from the design data. Although this work is aimed to the application of LEDs in brake lights, methods hereby developed and described can also be used in other applications, such as: traffic lights, electronic panels of messages or any other application where LEDs are used in groups.

This paper is organized as follows. In Section 2 is described the application of LEDs in brake lights. In Section 3 are presented some basic concepts related to artificial neural networks. Section 4 shows methodology and materials used. Results and discussion showing the validation of this work are described in Section 5. In Section 6 is presented the conclusions referent to proposed approach.

2 LEDs Applied in Brake Lights

LED is an electronic device composed by a chip of semiconductor junction that when traversed by an electric current provides a recombination of electrons and holes. Figure 1 shows the representation of a junction being polarized.

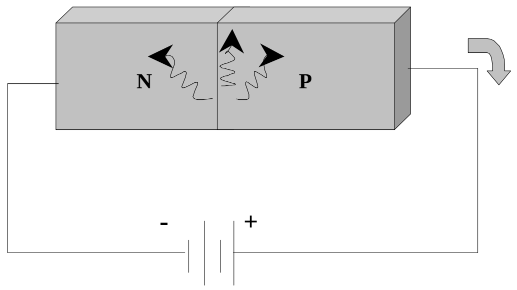

Fig. 1 - Junction PN being polarized.

However, this recombination demands that the energy produced by free electrons can be transferred to another state. In semiconductor junctions, this energy is released in form of heat and by emission of photons, that is, light emission [4]. In silicon and germanium the largest energy emission occurs in form of heat, with insignificant light emission. However, in other materials, such as GaAsP or GaP, the number of light photons emitted is sufficient to build a source of quite visible light [5]. This process of light emission, which is intrinsic characteristic of the LEDs, is called electroluminiscence.

Basically, the LED is manufactured in a frame of two terminals (Lead frame) with a semiconductor chip fixed in one terminal and connected to the other through a wire of gold (Wire bonding). This set is wrapped by an epoxy resin that constitutes a lens (Epoxy lens). In Figure 2 can be observed the representation of the basic structure of a LED.

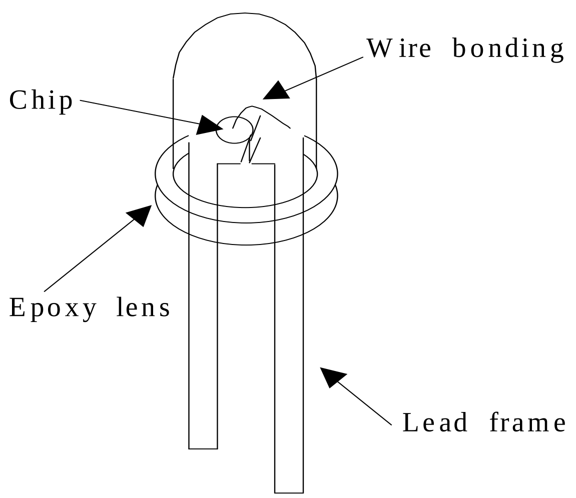

Fig. 2 - Representation of the basic structure of a LED.

In relation to the electronic diagram, the break lights are composed by LEDs and resistors connected in series and parallel (Figure 3).

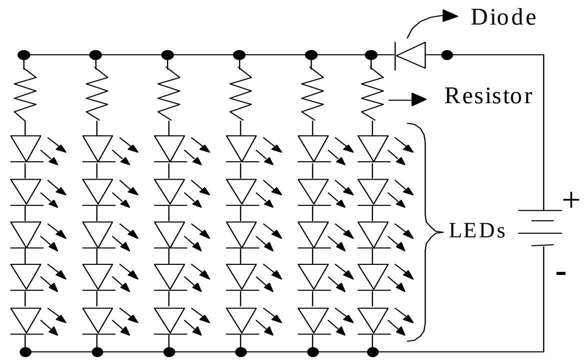

Fig. 3 - Electronic scheme of the brake light.

In brake lights the LEDs are applied in set and generally organized in a straight line on a printed circuit board (PCB). In this PCB, besides the LEDs, there are electronic components, basically resistors, which are responsible for the limitation of electric current that circulates through the LEDs. The main parameters used in brake lights designs are given by: LED luminous intensity (I_V), distance between LEDs (d) and number of LEDs (n). In Figure 4 is illustrated a basic representation of a brake light.

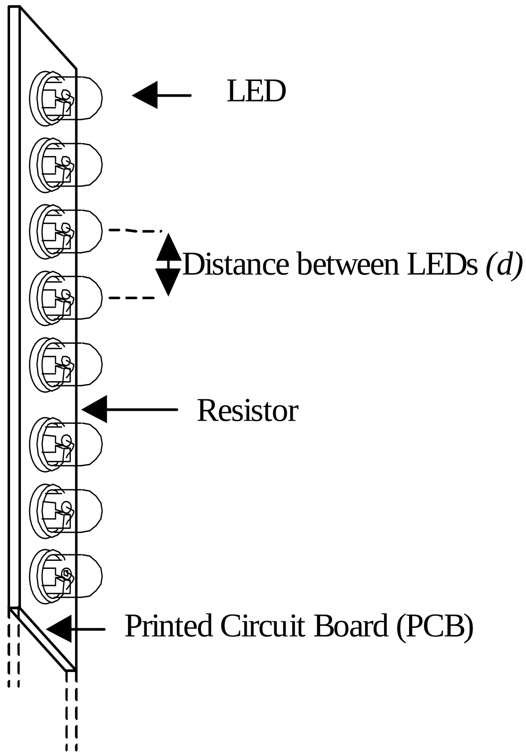

Fig. 4 - Representation of a brake light.

The main function of the brake light is to increase the safety of the vehicle (acting as a prevention system) and to reduce the risk of back collisions. Recent studies show the development of brake lights equipped with modulated signal transmitters containing information about the vehicle in which it is installed. Other vehicles that have the respective reception system of those modulated signals receive them, and their informations have been used to prevent back collisions [6]. In Figure 5 is illustrated a brake light installed.

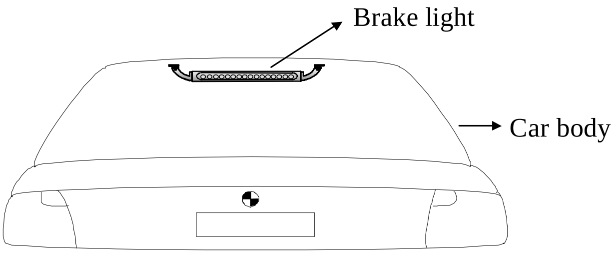

Fig. 5 - Representation of a brake light installed.

At the moment there is no model or technique for designs of brake lights and the prototypes are elaborated according to the common sense of designers, that is, through trial and error methods. This occurs because the relationship between the variables involved with the light emission process of brake lights is completely nonlinear.

After elaboration of the brake light prototype, it is necessary an approval of the sample. The process for the prototype validation is made by measuring the luminous intensity of the brake light in eighteen positions or different angles (Figure 6). After this process, the values obtained in each angle are compared with those values established by governmental rules. The minimum value of luminous intensity (I_{VBL}) in each angle varies according to the application. In Figure 6 is shown a representation of a generic distribution diagram of brake light luminous intensity (I_{VBL}) in relation to angle. The mean horizontal position is indicated by 0^oH and the mean vertical position is indicated by 0^oV. Thus, the position defined by the pair of angles (0^oV, 5^oL) is represented by the shaded position shown in Figure 6.

10^oU	I_{VBL}		I_{VBL}		I_{VBL}
5^oU	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}
0^oV	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}
5^oD	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}	I_{VBL}
	10^oL	5^oL	0^oH	5^oR	10^oR

Fig. 6 - Generic diagram of luminous intensity (I_{VBL}) in relation to angle.

3 Concepts of the Artificial Neural Networks

The artificial neural networks are computational models inspired in the human brain, structured by a set of interlinked processor units ("neurons"). The artificial neural network stands out for its capability to learn from its environment and to generalize solutions. Each neuron of the network can be modeled as shown in Figure 7.

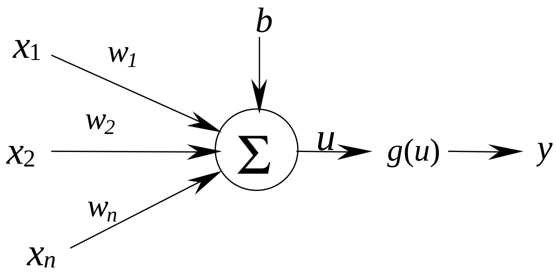

Fig. 7 - Scheme of the artificial neuron.

The mathematic model that describes the artificial neuron behavior is expressed by the following equation:

$$y = g(\sum_{i=1}^{n} w_i . x_i + b) \tag{1}$$

where:

n is the number of inputs of the neuron.
x_i is the i-th input of the neuron.
w_i is the weight associated with the i-th input.
b is the threshold associated with the neuron.
$g(.)$ is the activation function of the neuron.
y is the output of the neuron.

Basically, an artificial neuron works as follows:

a) Signals are presented to the inputs.
b) Each signal is multiplied by a weight that represents its influence in that unit.
c) It is made a weighted sum of the signals, resulting in a level of activity.
d) If this level of activity exceeds a certain threshold, the unit produces an output.

To approximate any nonlinear continuous function can be used a neural network with only a hidden layer. However, to approximate functions that are non-continuous in its domain there is the need of increasing the amount of hidden layers. Therefore, the neural networks present great importance to accomplish the mapping of nonlinear processes and to identify the relationship between the variables of these systems, which generally are difficult to obtain by conventional techniques.

In this work it was used a multilayer perceptron network [7] to estimate the existing relationship between the variables involved with brake lights design. As final result, it is aimed to obtain values that indicate the level of luminous intensity produced by the equipment.

The basic structure of a multilayer perceptron network, with *m*-inputs and *p*-outputs, is shown in Figure 8.

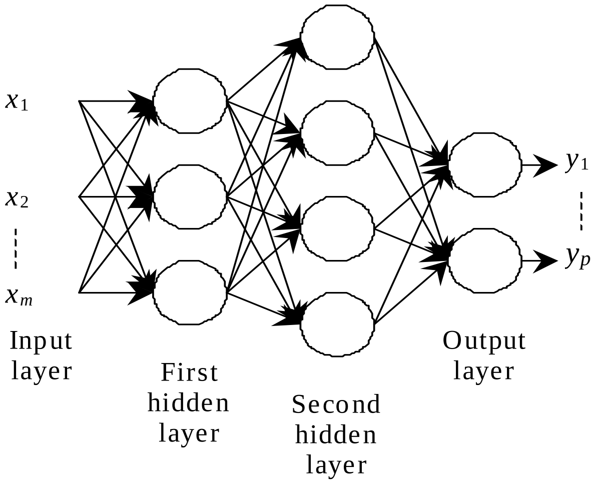

Fig. 8 - Scheme of a perceptron multilayer network.

According to Figure 8, information are introduced into the network through its input layer; in its hidden layers is occurred most of the processing, while the output layer is responsible by the network response.

4 Materials and Methods

For this work, it has been built 45 samples of break lights with the following parameter variations:

- Distance between LEDs (d): 7.0 mm , 8.5 mm and 10.0 mm.
- Number of LEDs (n): 20, 25 and 30.
- Luminous intensity of LED (I_v): 200 mcd, 400 mcd, 600 mcd, 1000 mcd and 1500 mcd.

This combination of parameters referent to each sample can be seen in Table 1.

Table 1 - Combination of parameters in each sample.

Sample	d (mm)	n (unit)	I_V (mcd)	Sample	d (mm)	n (unit)	I_V (mcd)
01	7.0	20	200	24	8.5	25	1000
02	7.0	20	400	25	8.5	25	1500
03	7.0	20	600	26	8.5	30	200
04	7.0	20	1000	27	8.5	30	400
05	7.0	20	1500	28	8.5	30	600
06	7.0	25	200	29	8.5	30	1000
07	7.0	25	400	30	8.5	30	1500
08	7.0	25	600	31	10.0	20	200
09	7.0	25	1000	32	10.0	20	400
10	7.0	25	1500	33	10.0	20	600
11	7.0	30	200	34	10.0	20	1000
12	7.0	30	400	35	10.0	20	1500
13	7.0	30	600	36	10.0	25	200
14	7.0	30	1000	37	10.0	25	400
15	7.0	30	1500	38	10.0	25	600
16	8.5	20	200	39	10.0	25	1000
17	8.5	20	400	40	10.0	25	1500
18	8.5	20	600	41	10.0	30	200
19	8.5	20	1000	42	10.0	30	400
20	8.5	20	1500	43	10.0	30	600
21	8.5	25	200	44	10.0	30	1000
22	8.5	25	400	45	10.0	30	1500
23	8.5	25	600				

It is important to remind that in design of samples, minimum and maximum values of each parameter must be chosen in such a way that they represent the domain for parameters variation of future designs, which will be made using the proposed neural network.

The equipment used to measure the luminous intensity of the samples was the LMT - System Photometer, model S 1000, where is coupled a device that allows angle variation in vertical and horizontal, this way it is possible to obtain the luminous intensity value in 18 different angles.

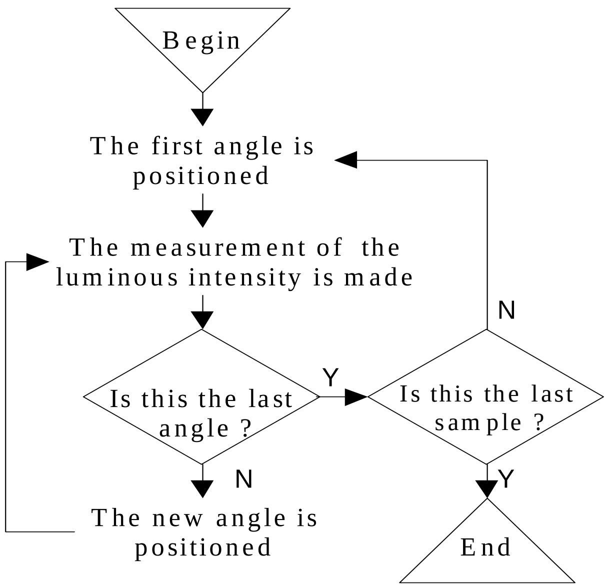

Fig. 9 - Flowchart referent to stage of measurements.

Initially, the first sample is placed on the measurement device. The first angle is positioned, the measurement of the luminous intensity is made and the value is registered. This procedure is repeated until registering the luminous intensity value referent to last angle of the sample.

The sample is removed the device and a new sample is placed on it to measure the luminous intensity, and is repeated all procedure until registering the last value referent to the last angle of the last sample. In Figure 9 is given a flowchart showing the sequence for the measurement stage of luminous intensity of the samples.

Through design data provided in Table 1 and measurements results of luminous intensity of brake lights samples in different angles, as previously described, it was carried out the training of a multilayer perceptron network. During this stage it was accomplished a variation of the main network parameters. The number of layers, the number of neurons by layer, the activation function of each layer and the type of training, were changed in order to obtain a topology of neural network that could generate an acceptable mean squared error, and it ensured also an efficient generalization.

The chosen topology was constituted of two hidden layers, with 5 neurons in the first one and 10 neurons in the second. The training algorithm was Levenberg-Marquardt [8]. Therefore, the network inputs are defined by the 3 main parameters involved with the brake lights design, that is:

- Distance between LEDs → d (mm).
- Number of LEDs → n .
- Luminous intensity of LED → I_V (mcd).

The network output is composed by a unique signal which provides what is the intensity level produced by the brake light in a given angle, that is:

- Luminous intensity of brake light → I_{VBL} (cd).

After training, using the 18 different angles, one training for each angle, it was possible to estimate the total luminous intensity produced by the brake light in different angles. To validate the proposed approach are used data coming from not used samples in the network training. A comparison between the estimated values by the network and those provided by experimental tests is accomplished to analyze the efficiency of the proposed approach.

5 Results and Discussion

After the training process, the neural modeling was used to obtain luminous intensity values of brake lights, as previously described. Figure 10 illustrates a comparison between luminous intensity values (I_{VBL}) obtained by experimental tests (ET) and those estimated by the artificial neural network (ANN). In this configuration (Situation I) the used sample presents the distance (d) between LEDs equal to 10.0 mm, the number of LEDs (n) is equal to 20 and the luminous intensity of each LED (I_v) has a value equal to 600 mcd.

	10°L	5°L	0°H	5°R	10°R
10°U	2.5 (ANN) 2.7 (ET)		3.3 (ANN) 3.0 (ET)		2.0 (ANN) 2.1 (ET)
5°U	5.1 (ANN) 4.8 (ET)	6.6 (ANN) 6.5 (ET)	7.1 (ANN) 6.8 (ET)	5.7 (ANN) 5.8 (ET)	2.8 (ANN) 3.0 (ET)
0°V	5.4 (ANN) 5.3 (ET)	6.2 (ANN) 5.8 (ET)	12.2 (ANN) 12.1 (ET)	5.6 (ANN) 5.6 (ET)	2.9 (ANN) 3.0 (ET)
5°D	4.1 (ANN) 4.0 (ET)	6.2 (ANN) 6.2 (ET)	8.6 (ANN) 8.3 (ET)	5.5 (ANN) 5.6 (ET)	2.8 (ANN) 2.7 (ET)

Fig. 10 - Comparative illustration (situation I).

From Figure 10 it is observed that the generalization produced by the network to estimate values of luminous intensity in several angles is satisfactory.

It is also possible to compare the validation of this work, observing the comparison between experimental values (ET) and values estimated by the network (ANN) for fixed angles in positions like (5°L, 0°V) and (0°H, 5°U) {Situation II}. This comparative analysis is shown in Table 2 for several samples. In this Table, the column "Error (%)" provides the relative error between values obtained by experimental tests and those computed by the neural approach.

Table 2 - Comparative analysis (situation II).

	Angles					
	(5°L, 0°V)			(0°H, 5°U)		
Sample	ANN	ET	Error (%)	ANN	ET	Error (%)
02	4.8	5.0	4.00	5.3	5.5	3.64
03	7.4	7.6	2.63	9.0	9.0	0.00
05	18.3	18.0	1.67	19.9	19.5	2.05
07	6.2	5.8	6.90	7.5	7.0	7.14
08	9.9	9.2	7.61	9.5	9.9	4.04
10	19.5	19.7	1.02	21.6	21.8	0.92
12	6.2	6.4	3.13	7.9	8.0	1.25
14	13.1	13.0	0.77	16.3	16.4	0.61
15	20.8	21.3	2.35	24.9	24.8	0.40
17	4.3	4.7	8.51	5.1	4.7	8.51
20	15.0	15.1	0.66	16.4	16.1	1.86

22	6.7	6.2	8.06	7.0	6.6	6.06
25	17.1	17.1	0.00	17.8	18.3	2.73
27	7.5	7.9	5.06	9.0	8.5	5.88
30	19.2	19.4	1.03	19.7	19.5	1.03
31	2.1	2.2	4.55	1.9	2.1	9.52
34	9.8	10.7	8.41	10.5	11.0	4.55
38	7.4	7.1	4.23	7.3	7.7	5.19
40	17.4	17.8	2.25	17.8	17.8	0.00
43	9.0	8.8	2.27	9.0	8.4	7.14
	Mean error		3.75	Mean error		3.63
	Variance		7.90	Variance		8.93

It is also possible to make another type of analysis by observing the direct comparison between luminous intensity values obtained by experimental tests (ET) and those estimated by the network (ANN), when using in each sample the same kind of LED. In Figure 11, it is shown a comparison between samples designed with distance between LEDs (d) equal to 8.5 mm and LEDs number (n) equal to 25, fixed in the position (5ºL, 5ºU) {Situation III}.

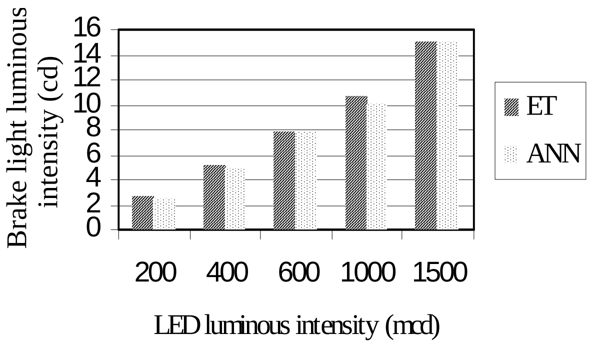

Fig. 11 - Comparative chart (situation III).

From Figure 11, it is observed that when LEDs of the sample have luminous intensity of 200 mcd, the results of I_{VBL} provided by the network are close to those provided by experimental tests, being the mean relative error in this case around 4.00%. For samples built with other kinds of LEDs {400 mcd, 600 mcd, 1000 mcd, 1500 mcd}, the mean relative errors have respectively been around the following values {4.26%, 4.29%, 6.00%, 0.00%}.

Through these results it is possible to infer that the network presented satisfactory results for estimation of luminous intensity values of brake lights. It should be taken into account that the proposed neural network has considered the main parameters involved with the design of brake lights.

In the selection process of the best neural architecture used in simulations was adopted the technique “cross-validation” [8].

6 Conclusion

This work presents a technique based on use of artificial neural networks for determination of luminous intensity values for brake lights (I_{VBL}), in which are considered the main designs characteristics. Therefore, the developed tool constitutes a new technique that can efficiently be applied in this type of problem.

The developed methodology can also be generalized and used in other applications that use groups of LEDs, such as in traffic lights and electronic panels of messages.

This developed tool has significantly contributed for reduction of costs in relation to implementation stage of brake lights, that is, it minimizes spent time in prototype designs. The tool has also allowed simulating many options for configurations of brake lights, providing the choice of a sample that offers an appropriate relationship between cost and benefit.

7 Acknowledges

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