LED junction temperature prediction using machine learning techniques

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***Abstract*— Light Emitting Diodes (LEDs) are the longest lasting source of artificial illumination whose duration can exceed 50.000 continuous working hours. Nevertheless, they show a gradual reduction of the luminous flux due to the increase of the device temperature. In this work, a Machine Learning algorithm will be introduced and discussed, able to predict the junction temperature value of a LED in real-time while connected in the end-user circuit, taking into account current and voltage flowing in the device and, further, the actual model and aging of the LED. The algorithm was implemented on a microcontroller, showing the feasibility of performing edge machine learning on tiny yet powerful devices.**

Keywords— machine learning, embedded systems, LED, junction temperature

I. Introduction

Light-emitting diodes (LEDs) are a good choice for general illumination due to low operating voltage, high luminous efficiency and long lifetime [1], [2]. The LED system is widely used in different field (signaling, automotive and consumer electronics) and they are composed by packages, optics, thermal and power management systems. The heat increasing in the LED may decrease its efficiency. Packaging materials have contributed toward improving the efficiency of LED packages [3], [4]. The thermal resistance greatly influences the junction temperature (T_j) of the LED and, in particular, a higher thermal resistance affects the luminous efficiency with variations in the light emitted. Consequently, the prediction of the junction temperature is fundamental to guarantee the performance of the LED; unfortunately, T_j cannot be measured directly. Generally, to estimate T_j, the principal method used is the transient thermal measurement using lab equipment [5], [6]. In this method, the correlation between forward voltage and temperature is predetermined in a temperature-controlled room with small sensing current (to avoid self-heating) [7]. However, this method is time consuming. Some studies numerically estimated the junction temperature and the temperature distribution around the LED device, such as Liu et al. [8]. Another method for T_j estimation is based on the InfraRed (IR) thermometry [9] but this technique manifests different problems [6], [10]. In this work an innovative method for the prediction of the LED junction temperature is proposed: we use machine learning techniques to monitor the junction temperature of a diode to eventually implement a management of the LED's heat and luminous flux, instead of using temperature sensors [11] that should be integrated with the LED fabrication technology. This work is moved by the spread of the cooling technology that is regarded as an important requirement for a reliable operation of electronics devices [12], [13]. The state of the art of LED thermal management lies in the use of techniques based on conduction and convention thermodynamics [14] (passive thermal management) or on subsystems that force the exit of heat outside the system (active thermal management) [15]. As LEDs use is increasing rapidly, power flow control can be carried out in an Internet of Things (IoT) scenario (e.g. Smart Cities) [16] through a machine learning system capable of predicting the junction temperature of the LED using tiny devices. This is made possible through the state of the art of machine learning, the Deep Neural Networks (DNNs)[17] which require less computational power in the application phase than in the training phase. This can be exploited to execute artificial intelligence algorithms on devices with small memory and computational power. In fact, in the learning phase, a large amount of data is used to calculate the weights and biases of the network and this involves the use of a powerful computational machine. Once the learning phase has been completed and the network has been trained, it can be used, with less computational demand, for real time applications on edge devices [18].

In our project, if the temperature expected by the model is above the limits or a threshold, it is possible to eventually reduce the current in the LED diode by modifying the value of the driving signal, a Pulse Width Modulated (PWM) digital signal generated by the microcontroller (PWM1 in Fig. 2).

The calculation of the junction temperature T_J is not in fact straightaway since it passes from the calculation of various resistance values, whose resulting value is the thermal resistance $R\Theta_{J-Ref}$, defined as the temperature variation per unit of heat:

$$R\Theta_{J-Ref} = \frac{T_J - T_{Ref}}{P_D}, \quad (1)$$

- $R\Theta_{J-Ref}$: thermal resistance between the junction and the reference point ($\frac{°C}{W}$);
- T_j : temperature junction ($°C$);
- P_D : power dissipated by the led (W);
- T_{Ref}: room temperature;

Since the room temperature T_{Ref} and the dissipated power P_D can be calculated directly, the only unknown parameter to

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solve the problem is hence the thermal resistance, which, however, depends on the various layers involved (junction resistance, PCB, filler and heat sink resistance). The various resistance values are difficult to be determined without the data provided by the manufacturer and therefore, to predict the junction temperature of the LED, we can automate the calculation by assigning the task to a machine learning algorithm.

In Section II, the hardware and software resources used in this study will be presented. Section III provides insights about the dataset extraction and the obtaining of the model. In Section IV and V, respectively, operation and validation of the edge machine learning algorithm are presented. Conclusions are depicted in Section VI.

II. Hardware and Tool

The microcontroller that was used in the realization of the control system is the STM32F401RE, mounted on the NUCLEO-F401RE development board. According to documentation [19], the CPU has a 32-bit ARM Cortex-M4 architecture, a maximum operating frequency of 84MHz, 512KB of Flash, 96KB of SRAM, 50 GPIO (on which an external interrupt can be set), a 12-bit ADC converter with 16 multiplexed input channels, 7 Timers and integrated serial communication protocol. The development board also supports connectivity with Arduino and allows for easy expansion of functionality with a wide selection of specialized shields. Finally, the board integrates a linker, the ST-LINK, which acts as both a debugger and a programmer. The STM32F401RE microcontroller has the task of processing the input data and predict the junction temperature of the LED according to the LED part number, aging of the device and, in particular, of voltage and current values measured from the LED. The current is measured through a 1 Ω shunt resistance in series with the LED by means of an INA285 Integrated Circuit (IC), used as a current amplifier. In addition, two transistors are used, whose gates are driven by two different PWM signals, in order to differentiate the measurement phase (PWM2 in Fig. 1) with that of normal LED operation (PWM1).

First, the DNN was realized in Python using as libraries Keras with Tensorflow in backend, then, in order to implement the model at an embedded level, we used the X-CUBE-AI tool [20] (vers. 4.0.0), an expansion of the STM32CubeMX environment that extends its potential by allowing an automatic conversion of pre-trained Neural Networks to more powerful hardware. X-CUBE-AI also optimizes libraries by modifying, for example, layers and reducing the number of weights - the reduction is only applicable to dense layers and is based on weight sharing algorithms such as K-means clustering - to make the network more "memory-friendly". Finally, the code generator produces a library that developers can use in their custom applications. X-CUBE-AI adds tools in the CubeMX application GUI that allow to analyze the model, compress the weights and validate the model both on the desktop and on the targets. X-CUBE-AI 4.0.0 only supports the conversion of DNN and no of SVR or Random Forest, although the accuracy of their models in Python is very high. Furthermore, a CNN has not been used as it is useful mainly when the number of inputs is very high.

III. Dataset and Model

In the creation of the dataset, 5 Led LUW CQUAR [21] by OSRAM were used. The LEDs, connected in series, are first stressed with a forward voltage value of 3.0 V and a current of 0.5 A for 900 hours. They are then treated in the thermostatic oven, within which they are brought to their maximum junction temperature (135 ° C), starting from the room temperature, with a step of 10 ° C.

During this process, the current-voltage characteristics (I-V) of each of the 5 LEDs are obtained using the Agilent 4155C instrument, setting a range of input currents. For each current value, the instrument returns a voltage value, until the entire curve typical of a LED is built, whose characteristic coincides with that of a diode (Figure 3). Note that, by increasing the temperature, the characteristic shift to the left [22], [23]. To derive the samples of our dataset, which consists of 165000 elements, the current was increased from 10 µA to 10 mA (region of the characteristic in which the diode behaves linearly) with a step of 10 µA, in order to realize a matrix table in which, at a given current value, corresponds a voltage value, but not necessarily the same temperature value, which is also a function of the aging to which the LED has been subjected.

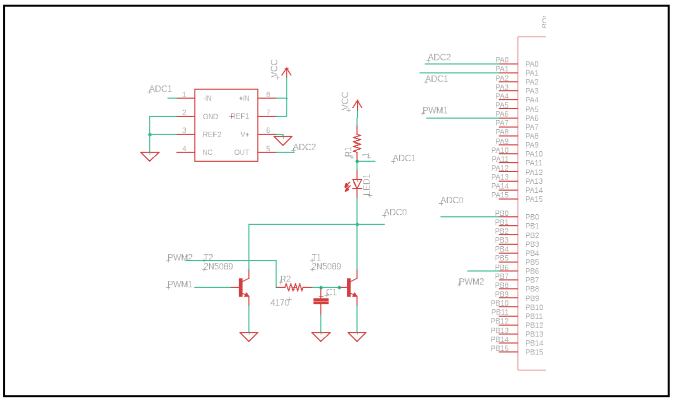

Fig. 1. Circuit schematic

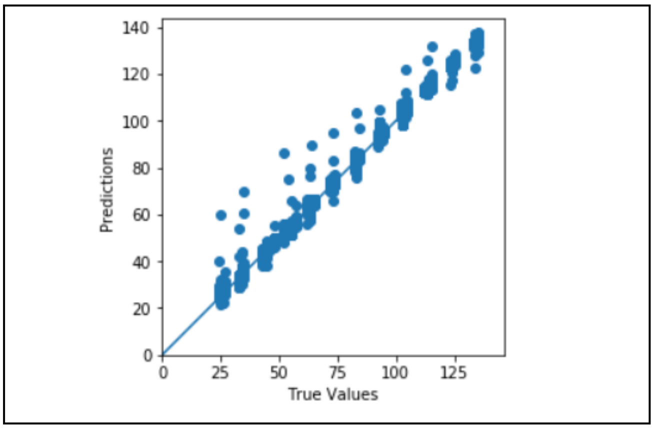

Fig. 2. Prediction on testing

Data pre-processing is fundamental in the training of the neural network. The dataset was balanced, performing both a mixing of the data - since these were taken incrementally - and a standardization of the input values, using the preprocessing method. Standardization is in fact a common practice, which allows the model to learn better and faster, taking advantage of a Gaussian distribution with zero mean and unit variance. Subsequently, we defined the model. The prediction of the LED junction temperature is in effect a regression problem. We provide the model with 4 input values: current (A), voltage (V), aging in hours and LED model; the target, instead, is the value that the model must predict, i.e. the temperature (expressed in degrees Celsius). In the model definition, we used 2 hidden layers, excluding the input and output level, and *relu* as activation function. Obviously, the output layer consists only of a *perceptron*, being the regression problem.

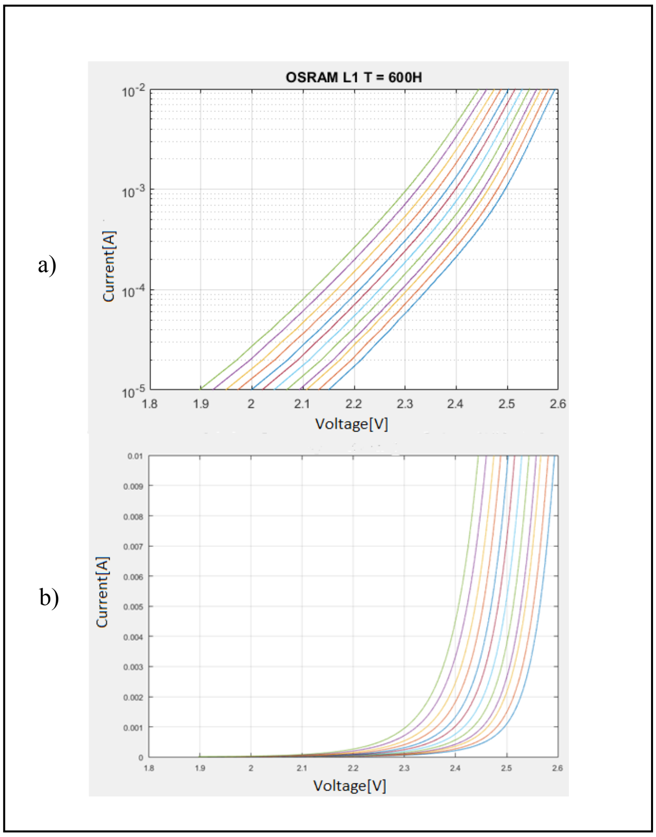

Fig. 3. LED's characteristic in a) logarithmic scale and b) in linear scale

Moreover, due the fact that the problem is not of classification type, as objective function we use the *mean squared error* instead of the cross entropy and, as an optimization function, the *Adam*.

To avoid overfitting and underfitting, we use techniques such as *L1-regularization* and *L2-regularization*; those techniques allow to apply penalties on the parameters of the layer or on the activity of the layer during the optimization. Moreover, to overcome a too strong adaptation to the dataset used for training, we also make use of batching, validation at the end of each epoch and early stopping.

The network was also reduced in the conversion phase by taking advantage of the compression provided by the X-CUBE-AI tool. The conversion allows the reduction of the memory space (from 104.8 KBytes to 14.7 KBytes using an 8-bit quantization), but not a variation of RAM and MACC.

IV. Workflow and Operation

As a demo of the functioning and also for testing purposes, a workflow that provides 5 seconds of LED ON and 3 seconds of LED OFF was conceived.

To manage the timings within the code, we use two timers (TIM3 and TIM4); overflow happens after 625 microseconds and, each time one of the two timers reach the overflow, a variable is incremented. Starting from the initial condition (condition of normal operation with the LED ON), the increase stops when the timer counts 5 seconds, after which the reading process will be started using the IA model. However, the reading process is not started immediately, but after 1.5 seconds, to allow time for the current to stabilize in the circuit following the enabling of the second PWM. 3 seconds after disabling the first PWM, the LED is enabled again. The model is initialized in the main function during the start-up phase and the neural network is defined according to the activation functions and weights stored in the Flash ROM.

V. Validation and Measurement

During the validation phase, through the validation on target with the STM32CubeMX tool, we analyzed the model's inference time on the microcontroller. In particular, using 10 inputs, the average inference time at the 84 MHz frequency was estimated to be 2 ms, meaning that the system is to predict the junction temperature of the LED in 2 ms.

Furthermore, we have also used the HAL_GetTick() method of the HAL library to be able to directly measure the run time of the model on the microcontroller at run time.

To verify the effective operation of the measurement system, we used the Fratelli Galli G-2100 thermostatic oven, which has inside a PT100 temperature sensor with an accuracy of 1 ° C. In the test phase, the PWM that regulates the normal operation of the LED has been disabled, not to influence the junction temperature of the diode with self-heating. The objective is, in fact, to force the temperature by means of the thermostatic oven, to be able to conclude that the junction temperature coincides with that of the system that we set. Therefore we only enabled the second PWM (at room temperature a current of 0.6mA flows), so that the power dissipated is minimal, and therefore the temperature does not differ from the one we set. The current flowing in the diode I_D is:

$$I_D = I_S(e^{\frac{qV_D}{\mu kT}} - 1), \tag{2}$$

and it strongly depends on the temperature. So, varying the temperature of the system - approximate to that of the junction for the hypotheses in which we have set - the current in the circuit varies and the model will succeed effectively in capturing the logic of the system. The test measurements were carried out starting from a temperature of 35 °C and, with a step of 5 °C, the temperature was brought to 130 °C. 5 values were taken every 5 degrees, to obtain the expected average temperature value. To be sure of the temperature reached in the climatic chamber, before taking the values, a temperature stabilization inside the chamber was expected. The data, during the testing phase, was sent by the microcontroller to a PC using the serial communication protocol USART.

VI. Conclusions

In this work, an innovative method for the prediction of the LED junction temperature is proposed using machine learning techniques. As reported in Fig. 4, the prediction error is more accurate for temperatures above 50 °C, typical values in standard LED operations. The model is therefore able to capture the logic of the problem with a good accuracy (±2 °C) in the temperature range of interest (50 °C – 110 °C). The system was implemented in an edge device. The inference time of the model is 2 ms, assuring at the same time low power consumption and quick response.

The results can be further improved. In fact, due to the connections and the breadboard used in the test phases, a parasitic resistance is introduced, variable with the temperature, which inevitably alters the input values to the ADC of the microcontroller. The engineering of a custom PCB (Fig. 5) will improve the accuracy of the measurement system. Related results with the improved testbed will be shown during the conference.

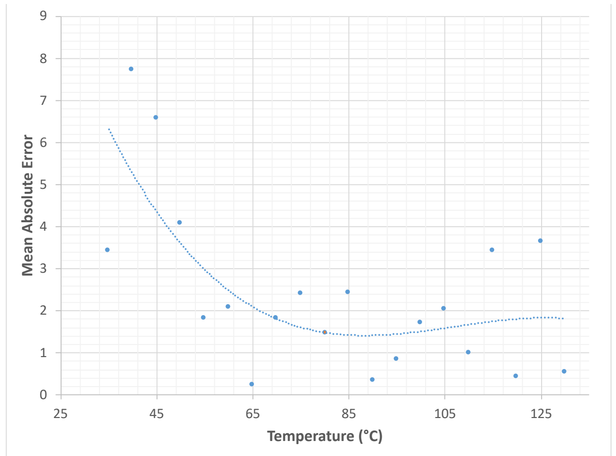

Fig. 4. Error on prediction

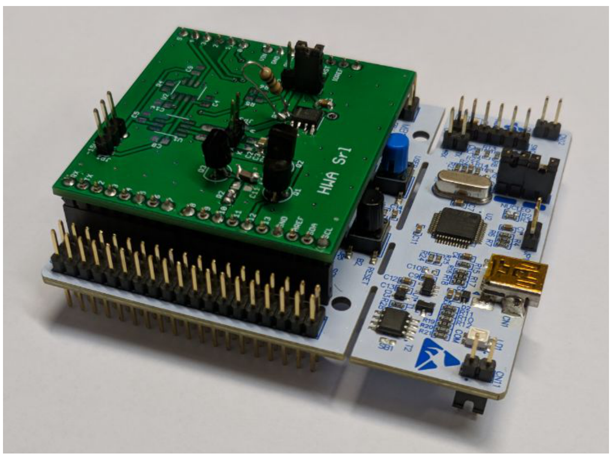

Fig. 5. Custom PCB shield mounted on a NUCLEO ST Board

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