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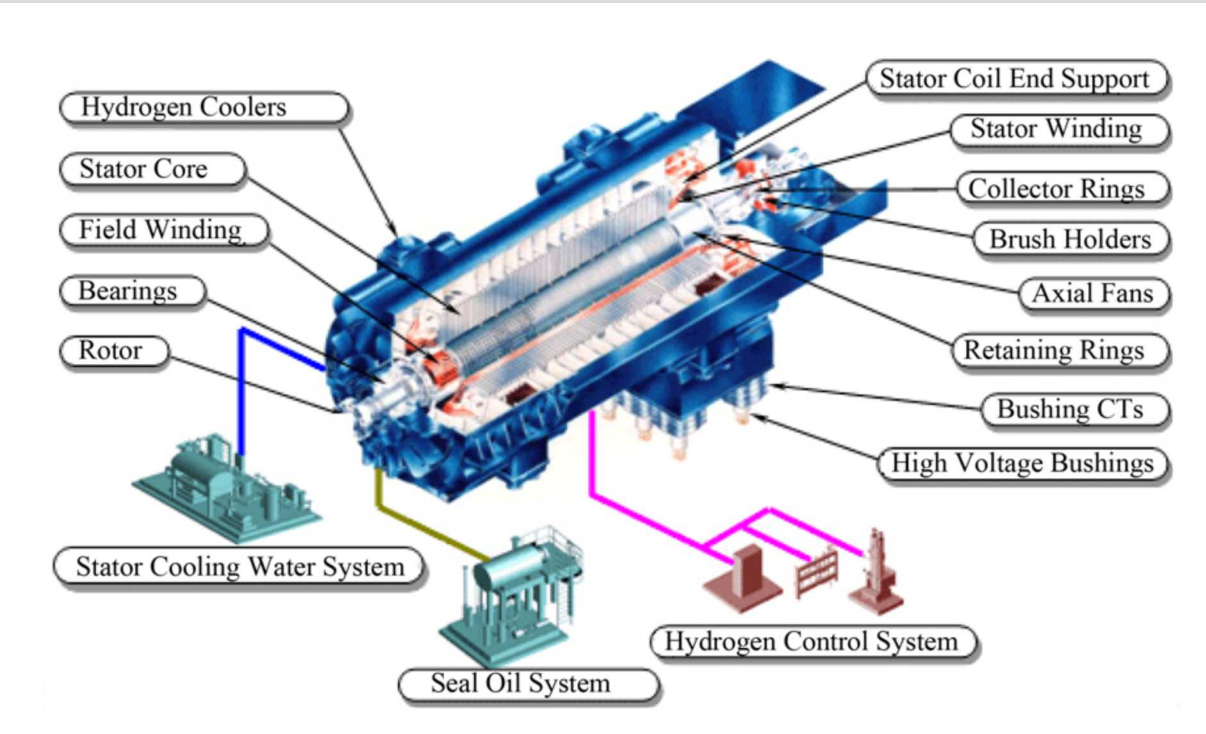

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Using Neural Networks for Simulating and Predicting Core-End Temperatures in Electrical Generators: Power Uprate Application

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Abstract

Power uprates pose a threat to electrical generators due to possible parasite effects that can develop potential failure sources with catastrophic consequences in most cases. In that sense, it is important to pay close attention to overheating, which results from excessive system losses and cooling system inefficiency. The end region of a stator is the most sensitive part to overheating. The calculation of magnetic fields, the evaluation of eddy-current losses and the determination of loss-derived temperature increases, are challenging problems requiring the use of simulation methods. The most usual methodology is the finite element method, or linear regression. In order to address this methodology, a calculation method was developed to determine temperature increases in the last stator package. The mathematical model developed was based on an artificial intelligence technique, more specifically neural networks. The model was successfully applied to estimate temperatures associated to 108% power and used to extrapolate temperature values for a power uprate to 113.48%. This last scenario was also useful to test extrapolation accuracy. The method is applied to determine core-end temperature when power is uprated to 117.78%. At that point, the temperature value will be compared to with the values obtained using finite elements method and multivariate regression.

Keywords

Neural Network, Error, Temperature, Core-End, Generator, Power Uprate

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1. Introduction

In the power generation industry, there is a question with no consistent answer over time: should we invest in new generation assets and increase installed power? Or on the contrary, should we improve existing installations to increase their performance and therefore their power output as well?

In economic scenarios such as the current one, in which power demand is stagnated and the expansion policies of most Western Europe utilities are a thing of the past, the question answered is the second one, relating to increased performance and power output of existing generation assets. By choosing the second option, investment is minimized and production unit costs optimized because, although actual production expenditure remains stable, energy generation increases.

For all these reasons, many authors develop solutions based on power uprates or comprehensive performance enhancements [1]. The solution presented in this paper involves a power uprate applied to a synchronous generator, which considering that voltage is constant and increased intensity through stator coils. Without getting into the peculiarities of steam generation process limitations or combustion improvements, this type of solutions has a common bottleneck: the thermal capacity and margin of generator winding insulation. In terms of power uprate, these essential parameters are constraining because an increase of associated intensity results in higher generator conductor temperature, especially in the critical area known as end-core. That is the reason why it is vital to determine expected temperatures in these generator areas beforehand, as actual temperature values will condition the feasibility of power uprate and additional power. In other words, this determination will ultimately impact power uprate viability.

After determining end-core temperature as a limiting parameter [2], it is time to perform calculations and extrapolations aimed at verifying if final extrapolated or calculated temperature is in fact below the acceptance criterion, which in this case will be the type B insulation limit (130˚C) [3]-[7].

Currently, there are two types of techniques to estimate end-core temperature: the finite element method (FEM) [8] and the regression estimation method [9]. The first method (FEM) is numerical, complex, more precise, resource intensive and requires an accurate internal generator geometry knowledge, which means that it is usually limited to OEMs or costly reverse engineering processes. Mathematically speaking, the second method is simpler and more accessible, but it renders more inaccurate results since the simulated process is significantly non-linear. The method proposed here is based on artificial neural networks because of their predictability, universal prediction, reality-adapted results, accessibility and easy implementation. The main challenge of this method is the need to have operational data from the machine under analysis so as to learn and create a reliable database from which to extrapolate power uprate results. Out of all neural networks, Feedforward architecture is chosen as it adapts to the purpose of adjusting and extrapolating.

Using the abovementioned neural network requires a training process based on actual machine conditions and data, which means that it is necessary to have information on known operating states. Once the network simulates end-core temperatures with a minimum error under known conditions, it is time to extrapolate temperature values under power uprate conditions. In this case, there are available data for generator and end-core temperatures for an initial rated generator power of up to 108.57%. These data will be used to train the network and extrapolate end-core temperature values for power levels of up to 113.48%. Once this power is reached, the accuracy of the first extrapolation value will be checked. If extrapolation is accurate, the network will be rendered adequate and data will be gathered for a 113.48% power level which, together with available 108.57% power values, will be used to train the network and extrapolate data for a power level of 117.78%, which is what the licensee actually wants. The extrapolated value will be compared to the results obtained using the abovementioned two methods so as to analyze numerical values, calculation capabilities and method advantages.

2. Case Description and Methodology

The problem described will be analyzed in an energy production plant with the aim of determining the expected electrical generator core-end temperature for a power uprate.

The model is developed to estimate, simulate or extrapolate the core-end temperature in a liquid and gas cooled 4-pole [10] [11], electrical generator once the power uprate is finalized. That is the simulation should provide the expected temperature under conditions in which the generator has never operated or being tested. The ultimate reason for this simulation and its results is to verify that type B insulation limits are not exceeded. An example of this type of generators is seen in **Figure 1**.

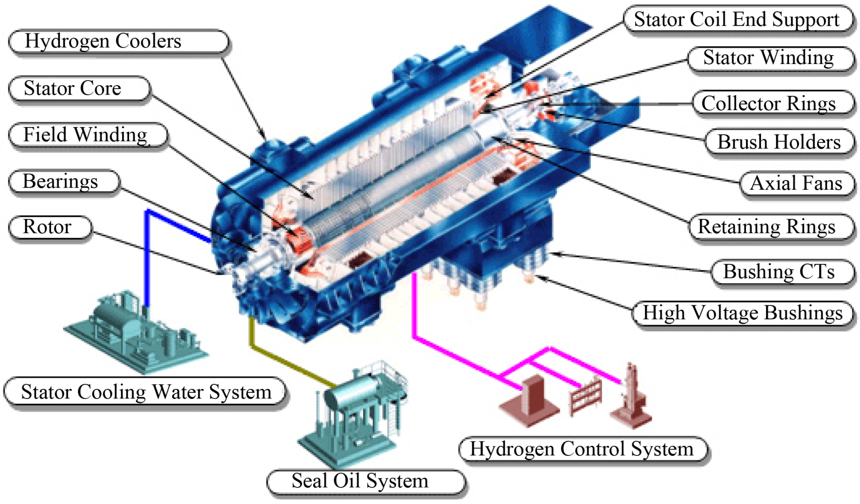

Figure 1. Modeled generator layout.

After defining the problem and determining the equipment (generator) on which power uprate simulations and forecasts will be carried out, it is time to establish the physical model so that target parameters can be known, calculated and extrapolated.

Inside the generator there are several physical phenomena: electrical, magnetic, thermal and fluid-mechanical. The phenomenon favoring energy creation inside the generator is the rotation of the magnetic field, which is in turn caused by the electrical phenomenon of rotor turning and subjected to intensity. In this case study, turning speed is considered to be constant. A secondary phenomenon is stator electricity, characterized mostly by phase (3) intensity and terminal voltage. These two phenomena are responsible, together with grid conditions (reactive power), for heat and thermal generation due to parasite processes and losses.

Inside the water-and hydrogen-cooled generator there are two heat sinks: one for water and the other for hydrogen. The variables regulating the hydrogen heat sink are hydrogen purity and pressure as they impact the thermal coefficient of the gas, the thermal difference of hydrogen inside the coolers and also hydrogen temperature at the cooler outlet. In the case of coil water, the key variables are coil water flow rate and water temperature in generator inlet and outlet.

These variables, which can be seen in **Table 1**, will be used to develop the model. These parameters will be neural network inputs.

The critical part in this type of generators is the core-end, which is exposed to magnetic flux and significant eddy current-induced losses in the tooth tips of the first magnetic plate packs. In this location the cooling effect of the hydrogen and water is not fully developed so the temperature is always higher than any other location. Output variables will be the core-end tooth tip. **Table 2** shows the name and location of thermocouples installed in these unfavorable locations.

For the purposes of this study, an artificial neural network has been selected as the best method because it is a general tool [12] and therefore works well for both lineal and non-lineal phenomena, hence covering a wide range of possibilities. It is important to take into consideration that the neural network is a universal approximator [13] [14] allowing for generalization and extrapolation [15].

Once the conceptual model, tool and calculation process input and output variables have been determined, it is time to present the model scheme in which calculation stages, acceptance criteria values and admissible error rates will be developed. **Figure 2** shows a graphic representation of this process.

The process starts by measuring the value of variables in **Table 1** and **Table 2** under operating conditions in which generator power is below 108.57%. These data are used to test the network based on the following criterion: variable values in **Table 1** should allow the network to generate **Table 2** values which should be compared to real values to ensure a maximum difference of 0.1˚C. This neural network is used to extrapolate end-core temperature values (**Table 2**) for a power level of 113.48% of initial rated generator power. Extrapolated values are compared to those obtained when the plant reaches the specific power level. If extrapolation values have a difference of less than 5% compared to plant-measured values, the network is rendered adequate and can be used

Table 1. Independent variables.

Description	Units
Gross generator power	MW
Reactive generator power	MVAR
Generator phase A current	A
Generator phase B current	A
Generator phase C current	A
Generator field voltage	V
Generator field current	A
H_2 generator purity	%
H_2 generator pressure	KG/CM^2
Hydrogen temperature, cooler 1 inlet	˚C
Hydrogen temperature, cooler 1 oulet	˚C
Hydrogen temperature, cooler 2 inlet	˚C
Hydrogen temperature, cooler 2 oulet	˚C
Water temperature, stator inlet coils	˚C
Water temperature, stator outlet coils	˚C

Table 2. Model output variables.

Description	Units
Temperature between slots 70 & 71 (tooth tip) TC80	˚C
Temperature between slots 69 & 70 (tooth tip) TC82	˚C
Temperature between slots 68 & 69 (tooth tip) TC84	˚C
Temperature between slots 67 & 68 (tooth tip) TC86	˚C
Temperature between slots 64 & 65 (tooth tip) TC89	˚C
Temperature between slots 63 & 62 (tooth tip) TC93	˚C

for final extrapolation.

As previously mentioned, the power uprate value targeted by the licensee is 117.78%, for an apparent power of 1277 MVA and a power factor of 0.95. For end-core temperature value extrapolation, a network entry data sheet needs to be put together, similar to **Table 1**. Values should include measurements of up to 108.57% plus those measured at the 113.48% stage of initial rated power. The same variables (**Table 2**) measured under the same conditions, are used to establish network training parameters.

In parallel, the values of **Table 1** variables are established, as determined by design, for an extended power level of 117.78% (represented in **Table 3**).

Given extrapolation criticality and the stochastic nature of neural networks, this final step will be described in further detail. The neural network will be tested using known data (108.57% and 113.48%). When the point in which the calculated error of end-core temperature values is lower than 0.1˚C, temperature values are calculated in the same point for a power level of 117.78%. In this case, the input variables included in **Table 3** will be used as input neural network data. This process will be repeated 30 times, which means that for every point of interest (**Table 2**), 30 temperature values will be obtained. The expected value will be the average of all of them in each point of interest; temperature values will be determined for a confidence interval of 95%.

3. Model Definition

The method based on artificial neural networks provides a solution of acceptable quality with very little effort.

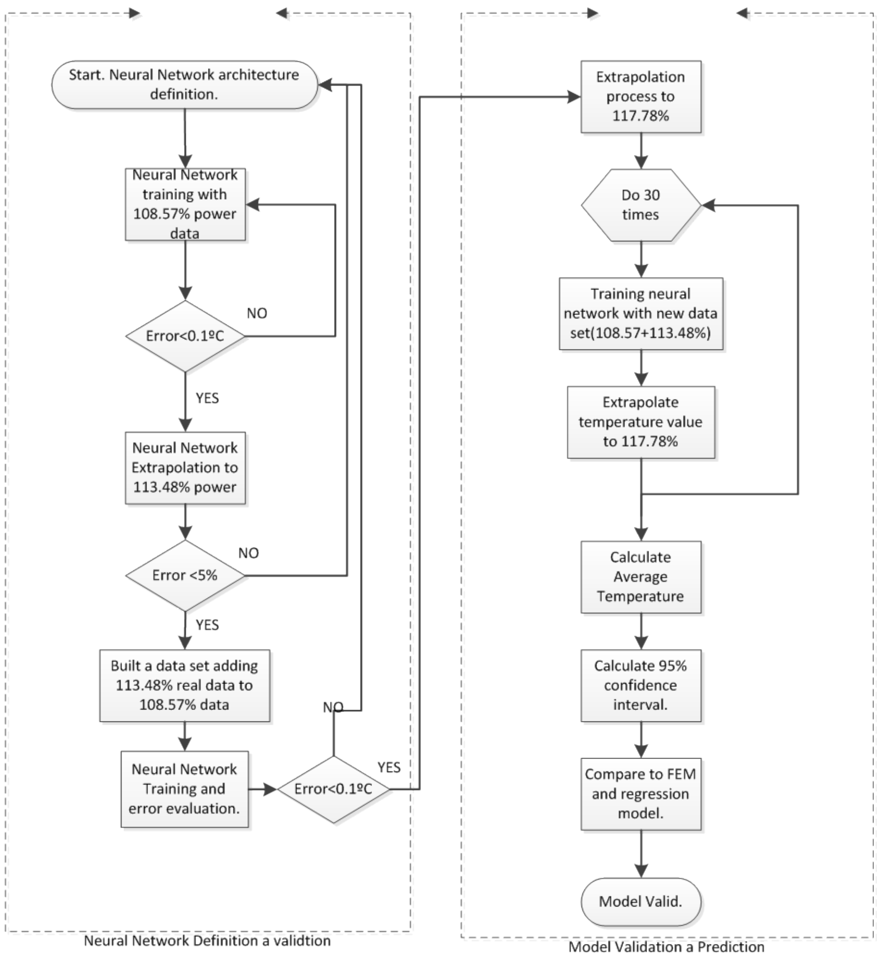

Figure 2. Flow schematic of the temperature determination process at 117.78% power.

Table 3. Variables and values used in the extrapolation to 117.78%.

Description	Value	Units
Gross generator power	1150	MW
Reactive generator power	−378	MVAR
Generator phase A current	34940	A
Generator phase B current	34940	A
Generator phase C current	34940	A
Generator field voltage	424	V
Generator field current	5831	A
H_2 generator purity	98	%
H_2 generator pressure	5.27	KG/CM^2
Hydrogen temperature, cooler 1 inlet	52	˚C
Hydrogen temperature, cooler 1 oulet	38	˚C
Hydrogen temperature, cooler 2 inlet	43	˚C
Hydrogen temperature, cooler 2 oulet	38	˚C
Water temperature, stator inlet coils	27.5	˚C
Water temperature, stator outlet coils	45	˚C

A multilayer neural network (Feedforward) has a feature that was mentioned before: it is a universal approximator. The neural network is conditioned by the input layer, the output layer, as well as the transfer functions that together with the synaptic weights and biases, make up network parameters. **Figure 3** shows a proposed network layout.

Focusing on the problem under analysis, a multilayer Feedforward network will be adopted. The neural network will have three layers: input, output and hidden. The first layer (input) will have as many neurons as variables in **Table 1** [15]. The output layer will have six neurons, one for each output variable included in **Table 2**. The design of the hidden layer is critical to convergence, error evolution and training performance [16] [17]. The number of neurons in the hidden layer will be selected as follows:

- The number of hidden neurons should be in the range between the size of the input layer and the size of the output layer. So the range will be between 15 and 6.
- The number of hidden neurons should be 2/3 of the input layer size, plus the size of the output layer. In this particular case they are 16.
- The number of hidden neurons should be less than twice the input layer size, so the number should be less than 12.

Obviously only the second condition is not coherent with the first and third, therefore, it will be neglected. So finally 12 neurons will be implemented in the hidden layer (see **Figure 4**).

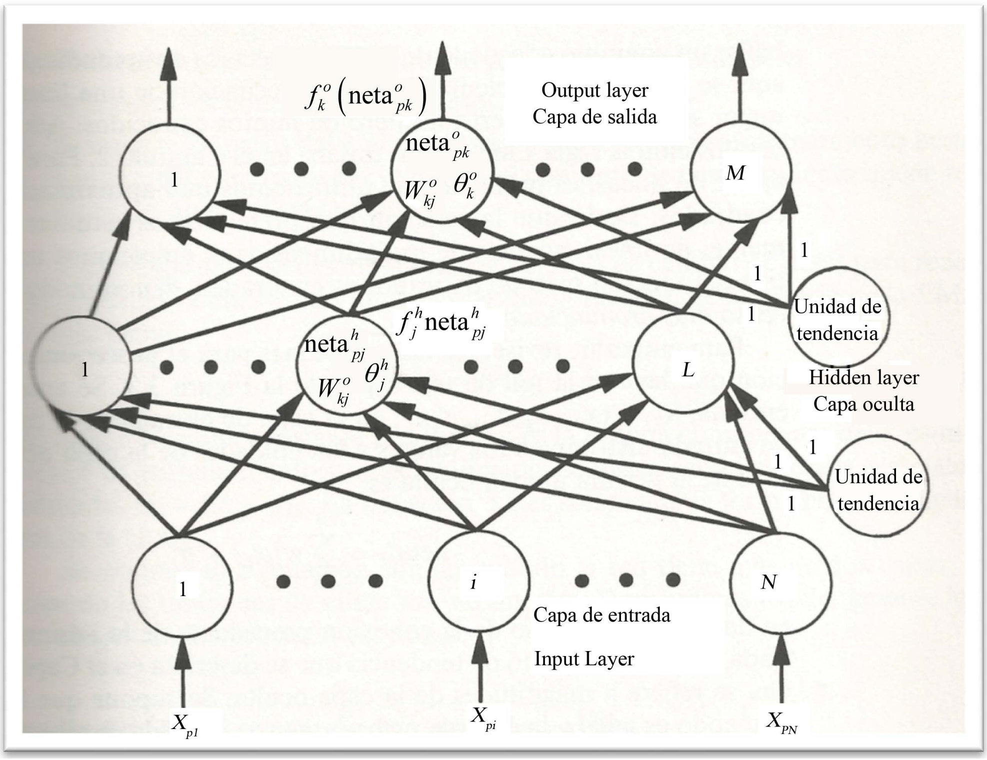

Figure 3. Typical layout of a Feedforward-type neural network.

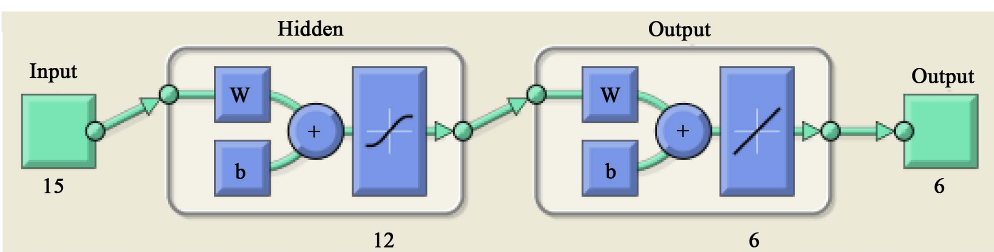

Figure 4. Neural network architecture for this model.

3.1. Training

Once the architecture to be used in a particular problem has been defined, it is necessary to adjust the neural network weight through the training process. The training process is composed of three sub-processes: learning, validation and test. The learning algorithm includes a problem of inference associated to free network parameters and related neuron connections.

The learning process of a Feedforward neural network is ought to be supervised because network parameters, known as weights and biases, are estimates based on a set of training patterns (including input and output patterns). In order to estimate network parameters, a backpropagation algorithm is used as generalization of the delta rule proposed by Widrow-Hoff [13] [14]. Learning implies weight adjustment by comparing the neural network output to measured value, to minimize error. The error will be calculated as the mean squared error between the simulated temperature and the real (measured) temperature.

Figure 5 shows a detailed training process including three clearly differentiated phases. The first phase is learning as such. In this phase, weights and biases characterizing neurons and their connections are determined by means of the learning process described above. In this phase, 90% of available data is used. After training, it is necessary to determine the error made when comparing network output to actual data and if error is lower than a specific value (0.1˚C in this case), the next phase can be initiated. The second phase is validation. In this phase, output values are calculated using 5% of available data not used during the training phase. If error is less than 0.1, a test is performed and the network rendered "trained"; if the error is not less than 0.1˚C, the learning phase must be repeated until the validation error value meets the target.

Figure 6 shows the evolution of the learning error, validation and test.

This error estimates how the neural network can be adapted to the problem under analysis. Process results include not only error evolution during the learning phase, but also error distribution throughout the different phases as well as fitting between network-simulated values and real values. These results are specifically addressed in the following section.

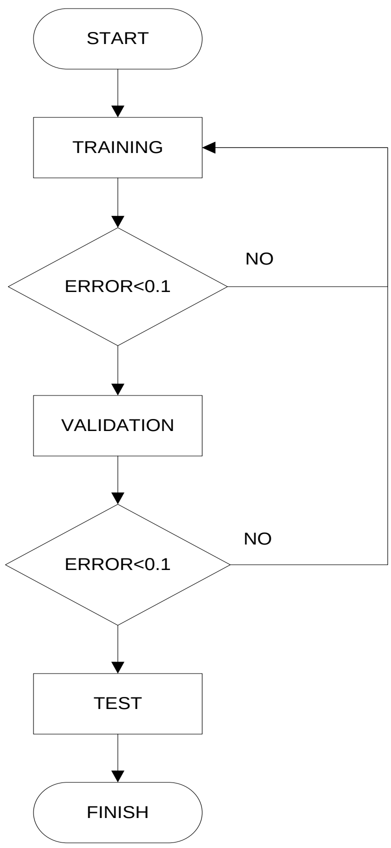

Figure 5. Training flow diagram.

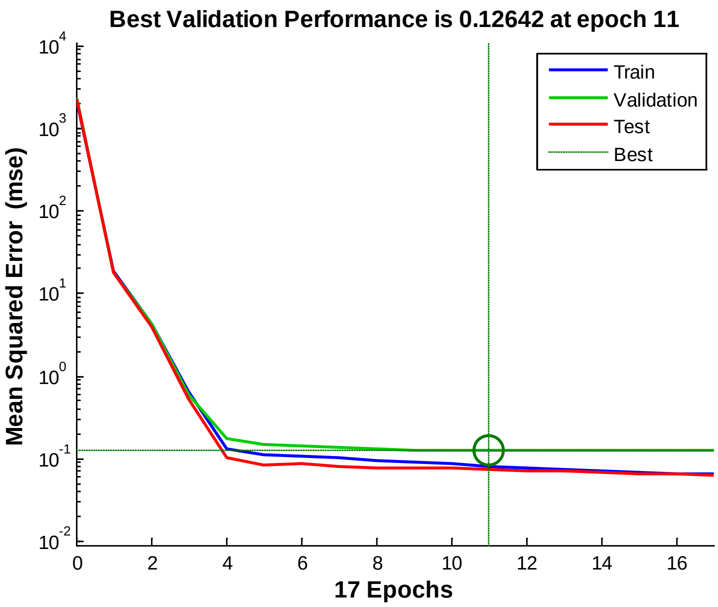

Figure 6. Error evolution during the training, validation and test phases.

3.2. Error Evaluation

This section will address network errors, both in the training and validation phases. The analysis will be more thorough than a mere evaluation of **Figure 7**, focusing on aspects such as error biases, error morphology, error evaluation and inter-phase error adjustment. **Figure 7** and **Figure 8** illustrate the analysis.

The first analyzed figure (**Figure 7**) is a histogram of error values that are associated to the learning, validation and test phases. The figure shows the error probability function as normal distribution, with an average near zero and a very small variance (<0.1˚C). As a result, it is considered white noise, being very consistent, structureless and not causing any bias.

In order to support the previous analysis, a linear regression between the data obtained by the trained neural network and the data actually measured (**Figure 8**), was conducted. This comparison was made in four different scenarios: the last learning, the last validation, the test and finally, a joint analysis. This analysis results in three important parameters related to one another and to the previously presented concept of normal probability function error. The three parameters are: R or correlation coefficient, slope of the regression line and the value of output data when the target data is zero.

- R values or correlation coefficient are near 1; this means that neural network temperature output values match real values. It is also worth mentioning that data dispersion near the line is very small or null.
- Line slope values are 1 in all cases, meaning that simulated values and measured values have a 1:1 equivalence. The result obtained is very close to reality, with an average error value of zero.
- The simulation is slightly biased (value lower than 0.1), but it is considered residual and therefore negligible. The former analysis concludes that simulated values are realistic, with a high degree of accuracy.

4. Simulation Results

In the previous section, the neural network was dimensioned and trained, and errors and results were analyzed in scenarios in which the temperature value provided by the trained neural network was taken as real.

According to the scheme in **Figure 2**, the next step is the simulation or extrapolation of end-core temperature values for operating conditions of up to 113.85% of the original rated power. The full set for this extrapolation (simulation) is comprised of 145 sets of variables (**Table 1**), which means the network will provide 145 sets of 6 different temperatures, as described in **Table 2**.

In parallel and considering that this operational condition is feasible for the plant, real temperature measurements are taken at the selected points (**Table 2**).

Measured points are compared to extrapolated (simulated) data by means of four graphs or techniques:

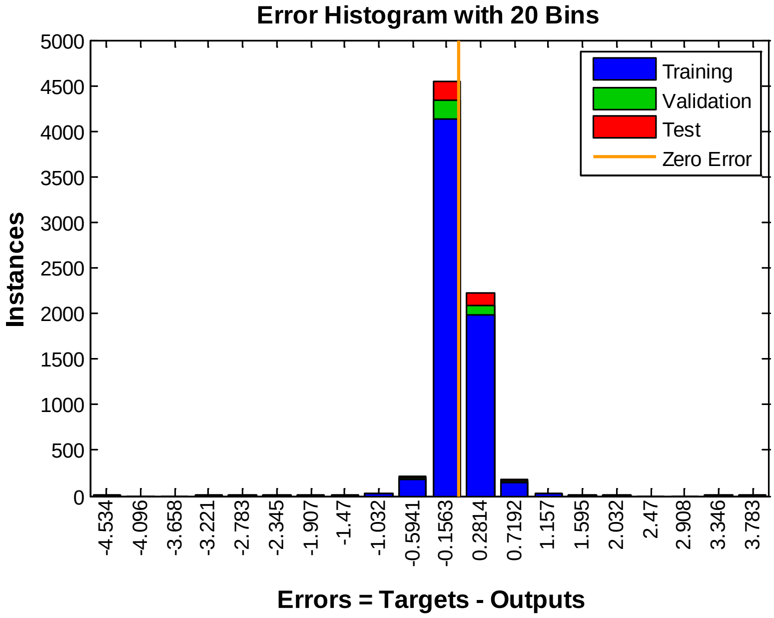

Figure 7. Error histogram.

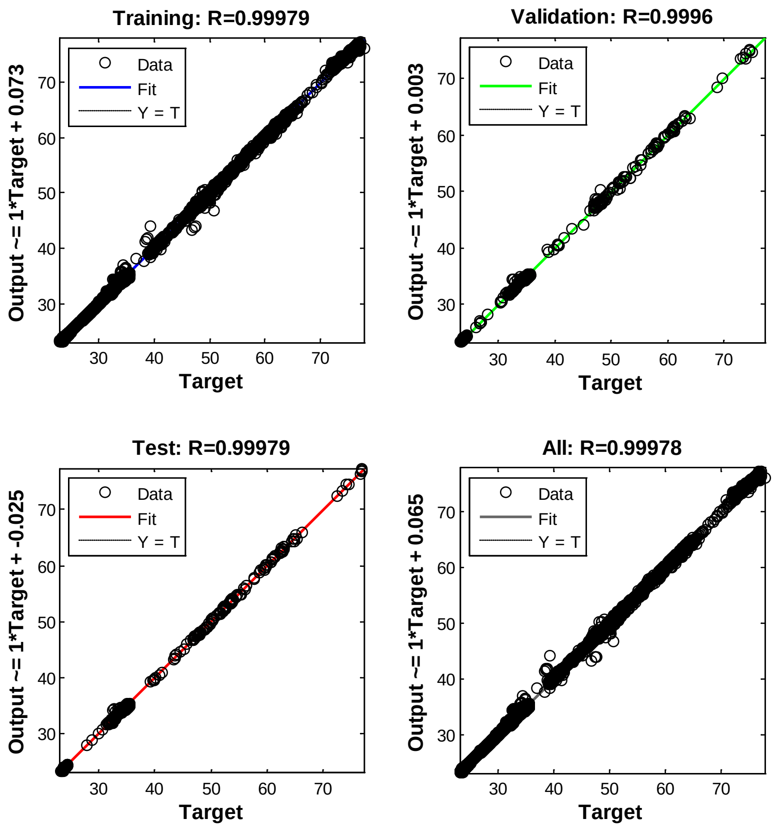

Figure 8. Training phase distribution and goodness of fit.

correlation, histogram, error-active power correlation and temperature versus time plot for extrapolated (simulated) and measured cases.

An analysis of linear correlation between extrapolated (simulated) and measured temperature data leads to the conclusion that the simulation is good when the adjustment value obtained is 0.94092 (**Figure 9**).

A histogram analysis (**Figure 10**) reveals that in absolute terms, error has an average value of 0.4082˚C. Furthermore, the negative sign indicates that extrapolation (simulation) provides results exceeding average machine values, indication that gets confirmed after observing in **Figure 9** that, for the most part, points are above the y = x equation line. This fact supports the purpose of this work as it provides extrapolated (simulated) values with a slight safety margin.

According to **Figure 10**, the extrapolation error is a normal probability function, with an average of −0.4082˚C (negative) and a standard deviation of 0.2984. The absolute error value represents an error of 0.68% above the real value. The 95% error confidence interval is between −1.005˚C and 0.1886˚C. The error is lower than 5%, so the extrapolation is considered to be valid.

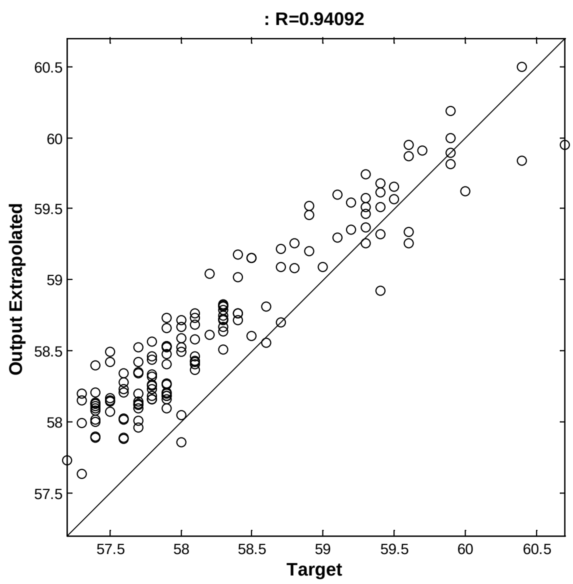

Figure 9. Correlation between real values and simulated values.

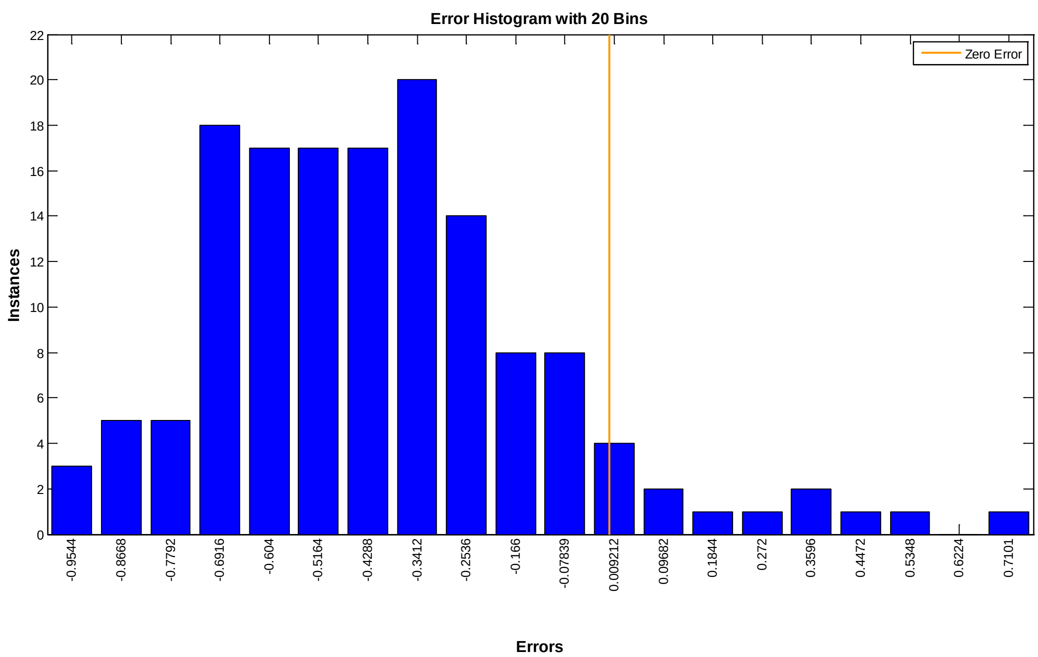

Figure 10. Histogram of errors made during the extrapolation.

An analysis of active power and error correlation (**Figure 11**) leads to the conclusion that there are no clusters. It is also noted that as power increases, error reduces. This behavior is coherent with the information in **Figure 9**, which shows that a temperature increase (real and simulated) shortens the gap between both temperature values (eventually tending to zero). As a result to temperature increases, the points in **Figure 9** tend to be above the y = x line.

Finally and for information purposes, **Figure 12** shows the time evolution of extrapolated (simulated) and measured machine temperatures, noting that they are well adjusted and look similar. It is also confirmed that simulated or extrapolated values are slightly higher than measured values.

In summary, it was verified that during the training phase, error is lower than 0.1˚C whereas in the extrapolation

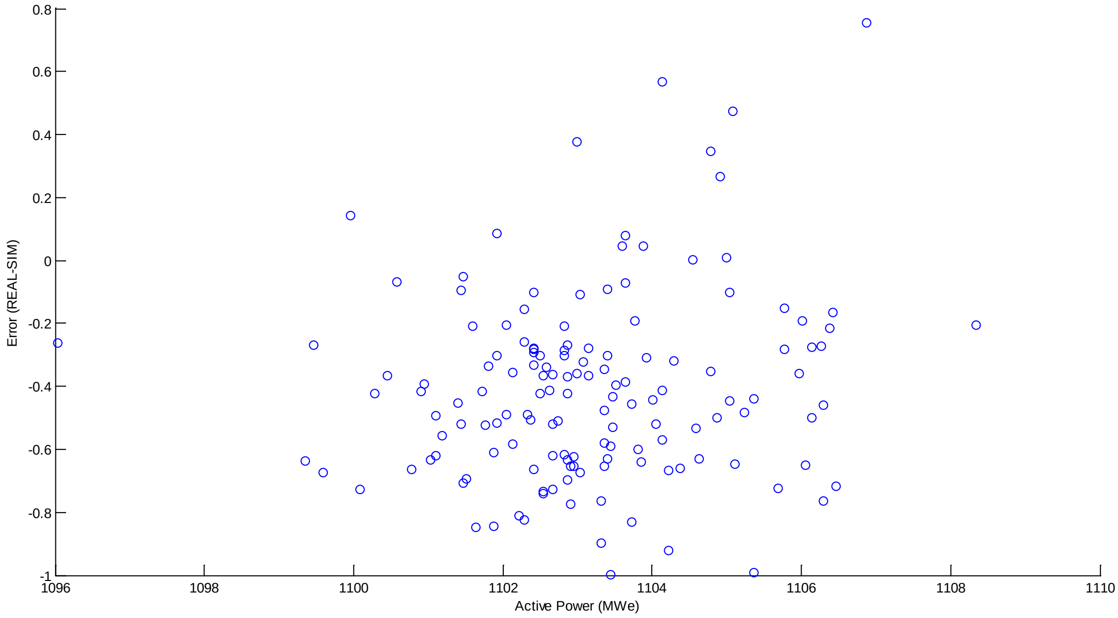

Figure 11. Error vs. active power (MWe).

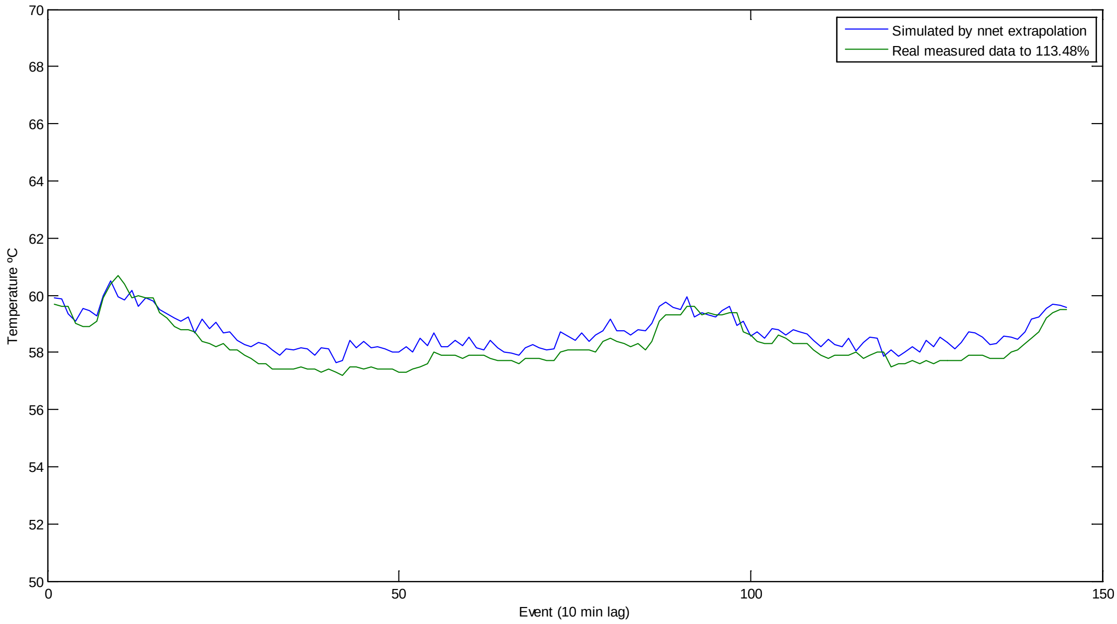

Figure 12. Extrapolation in the time domain.

phase for values at a power level 113.85%, error is under 5%. Thus, it is concluded that the neural network simulates well the thermal status of the generator and its core-end. The data and analyses provided in previous paragraphs support the credibility and robustness of the method, which is ultimately aimed at determining core-end temperature in advance, for a 117.78% power level in relation to initial generator rated power.

This is a clear, extreme case of extrapolation, which as opposed to a 113.85% power level (in relation to initial rated power), will render values that cannot be checked. That is precisely the motive for this work: obtaining an estimate to make decisions on the viability of a power uprate. In this case other simulated values are available. For this additional simulation, the finite element method (FEM) and regression method have been used.

As established in the introduction and the sequence of **Figure 2**, the network will be retrained using initial data for a power level of 108.57%, before increasing those values based on measured data for a power level of 113.85%. This will render a trained network with an error nearing zero in the training phase, as seen in **Figure 13**, which also shows that the error confidence interval at 95% is ±1.00˚C.

In order to be coherent with previous analyses, correlations between real measures and neural network results during the training, validation and testing phases are shown in **Figure 14**. The correlations included in **Figure 14** have correlation index values of 0.999, (*i.e.*, very near to 1), which indicates highly accurate linear adjustment between simulated and real values, indication confirmed by the fact that all points in the correlation graphs are on the y = x equation line. With regards to the bias, the regression line intercept is considered to be 0.066˚C, a negligible value leading to the conclusion that network-simulated values are equal to real values.

Once the network is trained and due to the stochastic nature of neural networks, the training-simulation process should be repeated at least 30 times. In other words, it is important to train the network before applying the entry values of variables included in **Table 3**. One measurement point, thermocouple Tc82, has an average temperature of 87˚C with a standard deviation of 3.15˚C. In light of this, expected thermocouple temperature for a power uprate condition (117.78%) will range between 93.30˚C and 80.70˚C, with a probability of 95%.

Comparison with the values of other evaluation methods is shown in **Table 4**.

The values of **Table 4** allow us to conclude that finite element method values and neural network results are consistent, with similar magnitudes and values. Going a step further, it is possible to state that the temperature value obtained with the FEM is covered by the statistical result of the neural network. As for the extrapolation method, values are high and near the limit, although below the acceptability criterion for type-B insulation.

Considering all these information and findings, it is possible to assert that the required power increase is viable without the need to modify any auxiliary generator parameter.

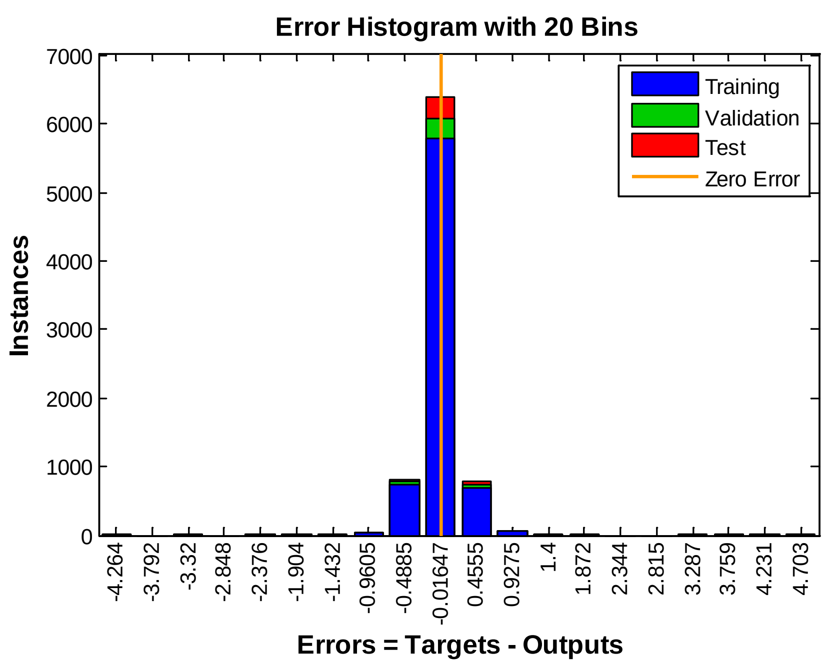

Figure 13. Error histogram during the second training sequence.

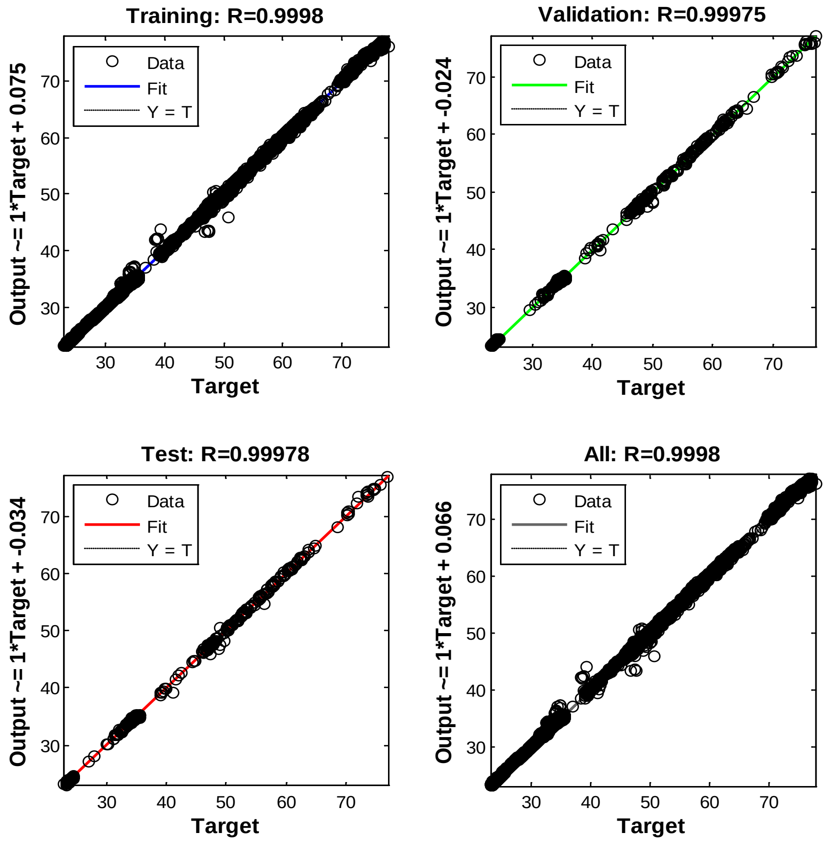

Figure 14. Value adjustment and correlation with measured values.

Table 4. Values simulated by the neural network and other systems for the worst case.

End core temperature	Method
87.48˚C	Neural network (average)
81.3˚C	Finite elements
127˚C	Multivariate regression

5. Conclusions

This study leads to many conclusions. Firstly, the neural network used is found to be not only a good simulator of the core-end temperature value in an electrical generator, but also a valid option to predict and determine the expected power uprate core end temperatures. This concept can be broadened by using the network to determine core-end temperatures for non-tested conditions, hence considering this a forecasting model.

After looking at the three models used (Table 4), a study and analysis strategy can be established. When the dataset is scarce, the expected temperature can be determined using a multivariate regression model. If it is determined that the expected temperature is lower than the specification for a type B insulation, the process can move forward. In the next step, it is necessary to gather generator data using a monitoring system and to develop the neural network so that thermal generator behavior can be modeled for a wide spectrum of operational conditions. In this case, it is also possible to extrapolate core-end temperatures for power uprate conditions. If it is verified that the expected temperature is still below the type B insulation criterion, then a finite element model can be developed when the value is very near to the limit or very far from the upper limit. This strategy ensures reliability while minimizing costs and risk levels.

This tool allows a sensitivity study to determine the effect of each of the 15 input variables on the final result, hence favoring the establishment of cooling strategies if needed and anticipating unexpected scenarios and the best way to respond to them. This model is a very useful generator simulator, improving decision-making processes and training strategies for power plant operators.

Finally some remarks about the performance of the simulated electrical generator should be highlighted. The simulated electrical generator has an apparent power of 1120 MVA, and is working at a point of 0.98 power factor. In situations in which the grid has a capacitive behavior, the operator must reduce active power to avoid unwanted situations or cross the URAL curve (limit). This power reduction constitutes an economic impact. The proposed power uprate, in addition to setting the thermal behavior of the magnetic core, and new URAL curve based on that, leads to optimize the operation of the generator and the benefits of its exploitation. The other important point is that no plant modifications are required for the power uprate because none auxiliary system is limiting.

References

[1] Katayama, H., Takahasi, S., Nakamura, H., Shimada, H., Ito, H., Coetezee, G.J. and Claassens, F.A. (2006) A Successful Retrofit of Old Turbo-Generators Having Various Technical Problems. CIGRE. Ref. A1-206.

[2] Gunar, K. (2008) Stator Core-End Region Heating of Air Cooled Turbine Generators. Ed. VDM.

[3] IEC 60085-1 (2007) Thermal Evaluation and Classification of Electrical Insulation.

[4] IEEE Std 56 (1977) IEEE Guide for Insulation Maintenance of Large Alternating-Current Rotating Machinery (10,000 kVA and Larger).

[5] IEEE Std 95 (1977) IEEE Recommended Practice for Insulation Testing of Large AC Rotating Machinery with High Direct Voltage.

[6] IEEE Std 433 (1974) IEEE Recommended Practice for Insulation Testing of Large AC Rotating Machinery with High Voltage at Very Low Frequency.

[7] IEEE Std 434 (1973) IEEE Guide for Functional Evaluation of Insulation Systems for Large High-Voltage Machines.

[8] Lu, D.Q., Huang, X.L. and Hu, M.Q. (2001) Using Finite Element Method to Calculate 3D Thermal Distribution in the End Region of Turbo Generator. *Proceedings of the CSEE*, **21**, 82-85.

[9] Li, J.Q., Li, H.M. and Lu, Z.P. (2003) Research on Temperature Rise of Stator Iron-Core End Region of Turbine Generator. *The* 5*th International Conference on Power Electronics and Drive Systems*, **1**, 766-770.

[10] Klempner, G. and Kerszenbaum, I. (2008) Handbook of Large Turbo-Generator Operation and Maintenance. Wiley, Hoboken.

[11] Boldea, I. (2006) Syncronous Generator. Taylor and Francis, UK.

[12] Kortesis, S. and Panagiotopoulos, P.D. (1993) Neural Network for Computing in Structural Analysis: Methods and Prospects of Applications. *International Journal for Numerical Methods in Engineering*, **36**, 2305-2318. http://dx.doi.org/10.1002/nme.1620361310

[13] Dsissanayake, M.W.M. and Phan-Thien, N. (1994) Neural Network-Based Approximations for Solving Partial Differential Equations. *Communications in Numerical Methods in Engineering*, **10**, 195-201. http://dx.doi.org/10.1002/cnm.1640100303

[14] Hornik, K., Stinchcombe, M. and White, H. (1989) Multilayer Feedforward Networks Are Universal Approximators. *Neural Networks*, **2**, 359-366. http://dx.doi.org/10.1016/0893-6080(89)90020-8

[15] Garrido, L., Gaitan, V., Serra-Ricahrt, M. and Calbet, X. (1995) Use of Multilayer Feedfordward Neural Network as a Display Method for Multidimensional Distributions. *International Journal of Neural Network*, **6**, 273-282.

[16] Romaunke, V. (2013) Setting the Hidden Layer Neuron Number in Feed Forward Neural Network for an Image Recognition Problem under Gaussian Noise of Distortion. *Computer and Information Science*, **6**, 38-54.

[17] Heaton, J. (2007) Introduction to Neural Networks with Java. Heaton Research.

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Efficiency of Portable Electronic Vulcanizer

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Abstract

This research was aimed at finding out the efficiency of the portable electronic vulcanizer. The old vulcanizing equipment was upgraded to save time, investment, manpower and to eliminate the problem of gas emission in vulcanization. The study also determined the accurate temperature setting and duration of vulcanizing process using electronic vulcanizer which eliminated the problem of gas emission produced by the conventional (gas fired) vulcanizer of about 2.772 kg of carbon dioxide for 1 liter of diesel fuel and/or 2.331 kg of carbon dioxide for 1 liter of petrol into the atmosphere. In constructing this vulcanizer, a letter G body configuration made of GI pipe with 31.5 cm long lag bolt with some electronic parts were installed, like the analog temperature gauge, digital timer, relay, LED, buzzer, switch, and heating element. Specifically, the product is divided into three components: base or body, control panel board and the heating unit. The effectiveness level of the equipment was tested utilizing five different temperatures at a constant and variable time. For Class A gum, the best temperature which bonded the gum exactly to the rubber tire was 60˚C in 1 minute while Class B gum was bonded at 60˚C in 2 minutes. The rate of energy consumed by the electronic vulcanizer for Class A gum was Php 0.0757 with an efficiency of 85.22% and for Class B gum was Php 0.15 with an efficiency of 85.22% and for conventional vulcanizer for Class A gum was Php 1.08 with an efficiency of 43.38% and for Class B gum was Php 1.52, with an efficiency of 78.08%. The study revealed that more tires could be vulcanized in a short period of time, therefore providing greater income over time. It is also environment-friendly since it does not emit carbon dioxide as compared to the conventional vulcanizing.

Keywords

Electric Vulcanizer, Portable Electronic Vulcanizer, Environment-Friendly Machine

1. Introduction

This research is about the upgrading of the vulcanizing equipment for automobile, motorcycle, bicycle and any

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tire tubes. The gadget is electronically operated and environment-friendly.

The upgraded vulcanizing equipment has additional features such as buzzer, timer and temperature gauge which can greatly increase its efficiency and accuracy.

This experimental research was conceived to help reduce global warming, and to encourage investors in this small scale business industry.

This study aimed at finding out the accurate temperature and duration of vulcanizing process using the electronic vulcanizer which eliminated the problem of gas emission (carbon dioxide) produced by the conventional (gas fired) vulcanizer of about 2.772 kg of carbon dioxide for 1 liter of diesel fuel and/or 2.331 kg of carbon dioxide for 1 liter of petrol into the atmosphere [1].

2. Technical Description

2.1. Objectives

The portable electronic vulcanizer was tested to find out its efficiency and convenience, which is beneficial to the community, the environment and industry.

Specifically, this study was conducted to:

1) identify the design of a portable electronic vulcanizer;

2) determine its material components;

3) determine the appropriateness of the heating element used in this electronic vulcanizer;

4) determine the desirable temperature to exactly bond the Class A and B vulcanizing gum to the rubber tire in one and two minutes, respectively; and

5) find out the efficiency and cost of the portable electronic vulcanizer.

2.2. Rationale

The underlying principle of this study is to determine the efficiency of the portable electronic vulcanizer and to eliminate the problem of gas emission in vulcanizing shops.

2.3. State of the Art

The upgrading of the conventional vulcanizer (gas emitting apparatus) requires the researcher to introduce a new idea in this field of technology. The experimental set-up was made of different temperatures at a constant time in vulcanization. Five trials were conducted to find the perfect temperature on which the gum will bond to the rubber perfectly at 1 minute for Class A vulcanizing gum and 2 minutes for Class B vulcanizing gum.

2.4. Analysis of the Problem

The electric vulcanizer and the conventional vulcanizer (gas emitting apparatus) have a common problem. The electric vulcanizer, if not undertaken properly during the vulcanization process, can damage the rubber tire. In the conventional vulcanizer, if the gas is not properly measured or controlled, burning of the rubber tire will occur. To solve the aforementioned problem as well as on gas emission, this innovative technology (electronic operated vulcanizer) was studied to cut down cost on investment and manpower in the vulcanizing industry.

2.5. Flowchart of the Study

Figure 1 shows the flow chart of the study. The input includes the heating elements, temperature and timer meter, LED monitors, buzzer, steel plate and power switch in making the product. The process includes the steps in making the product and data gathering. The output is the portable electronic vulcanizing (PEV) equipment.

3. Review of Literature

The work environment refers to the aggregate of surrounding things and conditions that affect the quality of work life and the individual itself being an employee or an entrepreneur.

Former President Fidel V. Ramos [2] stressed that the living condition of the people in every sector of society must be improved by initiating family investment or group. He wanted then to make the Philippines a New

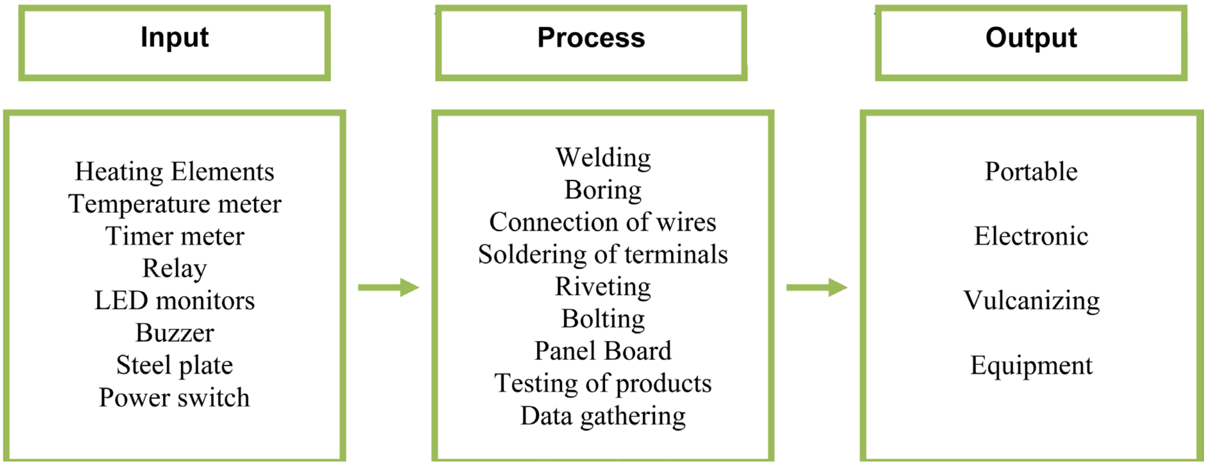

Figure 1. Flow chart of the study.

Industrialize Country (NIC) in Asia and the Pacific, by 2000 and beyond. Thus, Executive Order No. 318, s. 1991, was passed to reinforce functional program in the implementation toward industrial reform and development.

Technical Education Skills Development Authority (TESDA), reported that the government's quest to realign technical education program be of paramount importance. On the other hand, the Presidential Commission on Educational Development (EDCOM), on their survey resulted in recommending to conduct feasibility studies and projected modern educational design to revitalize the nation's changing demand of the youth for effective manpower development. Mismatch problem of the education sector and industry is of vital issue as regards the graduation rates of colleges and universities which most of them cannot find job, because of lack of skills needed by the industry. Hence, technical graduates have wider range of employment compared to those graduates of white collar profession [3].

Vulcanization is the chemical process by which the physical properties of natural or synthetic rubber are improved; finished rubber has higher strength and resistance to swelling and abrasion, and elastic over a greater range of temperature. In its simplest form, heating rubber with sulfur brings about vulcanization.

In modern practice, temperature of about 140˚C - 180˚C is deployed, and in addition to sulfur and accelerations, carbon black oxide is usually added, not merely as an extender, but improves further the qualities of the rubber. Vulcanizing gum, which is a classified as "ready to heat" rubber, is now utilized to repair worn out interior/exterior rubber tires with the help of vulcanizing equipment. Certain problems such as inaccuracy of the product are evident in third-world countries, as the first-worlds never used some [4].

3.1. The Discovery of Vulcanization

Goodyear thought that rubber might be improved by processing it with other substances. As Goodyear was displaying a mixture of rubber and sulfur, the piece slipped from his hand into the fire. When he looked it out he found to his amazement that the mass has charred without melting. Goodyear named this process of combining rubber with sulfur by heat "vulcanization". Later he discovered that the addition of lime, magnesia, and lead compounds speeded up vulcanization process. Elastic substance obtained from the exudations of certain tropical plants (natural rubber) or derived from petroleum and alcohol (synthetic rubber) [5].

In the process of vulcanization, sulfur atoms form cross-links between the chain molecules of rubber, tying them firmly together. The vulcanization process causes some striking changes in the property of rubber. The rubber remains elastic at both low and high temperatures. Its strength is increased and it can be stretched to greater lengths than before. It will no longer dissolve in gasoline or benzene, though it will swell up if it is soaked in them.

Newly discovered rubber class such as vulcanizing gum is now utilized in repairing worn-out rubbers such as an automobile tire. Vulcanizing gum is classified according to its texture, bonding temperature and the content of accelerators. The three classes of the gum were as follows [5]:

- Class A—usually bonds on the rubber 30˚C - 70˚C and is smooth;

- Class B—usually bonds on the rubber 35˚C - 80˚C and is moderately rough;
- Class C—usually bonds on the rubber 45˚C - 90˚C and is very rough.

3.2. Related Studies

A tire vulcanizer which can make a bladder supply pressurized fluid at a tire vulcanization position and a shaping position, disconnects the channel during movement of a lower container, and can move the bladder while keeping the internal pressure of the bladder. Under a state where the lower container (2) moved to the shaping position N, a downstream side moving tube (5) is connected to a second fixed tube (62) through a second joint (72), and pressurized fluid is supplied from a fluid supply unit (42) to the bladder (3) so that a green tire can be shaped. Under a state where the lower container moved to the tire vulcanization position M, the downstream side moving tube (5) is connected to a first fixed tube (61) [6].

A tire vulcanizer is equipped with an inner circumferential wall which surrounds a center post, an outer circumferential wall which surrounds the aforementioned inner circumferential wall, a partitioning wall which radially divides the space between the aforementioned inner circumferential wall and the aforementioned outer circumferential wall into an inner space toward the aforementioned inner circumferential wall and connected to a bladder, and an outer space toward the aforementioned outer circumferential wall and connected to the aforementioned bladder, and a circulation means which cyclically supplies and discharges a heated liquid into and out of the aforementioned bladder via the aforementioned inner space and the aforementioned outer [7].

Ramis [8] cited in his dissertation that technological development begins with basic research, when a scientist discovers some new phenomenon or advances new theory. Other researchers examined the breakthrough for its potential utility. If further developed, it leads to a prototype and engineering refinement makes commercial exploitation practical. Then, the technology is finally put to, use may be widely adopted.

Technological change takes place in many directions at once, that is, it is multi-final. Bar codes, for example, are used to track items not only in grocery stores but also in warehouses, assembly lines, shipping docks, libraries, even in the Department of Defense. Technological changes are also nonlinear; Developments take irregularly. There are many dead ends, and each highly visible advance may depend on a host of small developments (including failures) [8].

Actually, there are now vulcanizing equipment in the market plus the Internet ads, there are roughly 1000 vulcanizers that are electric/electronic operated but they don't have timer nor temperature control and none of them beat my design. Commercial vulcanizer (electric & manual) if not properly used, the vulcanizing gum may be burned same with the tire; this holds true with manually operated machine. Compared to the manually operated vulcanizing equipment, this electronic operated vulcanizer saves time, labor, money and manpower in the vulcanizing shop operation.

4. Methodology

This section discusses the processes that were done during the experimentation.

4.1. Research Design

The study utilized experimental research method which included the new design, selection and identification of materials, assemblage fabrication, and testing process:

1) *New design.* The design of the vulcanizing equipment was based on its portability and light weight of 6.30 kilograms, and environment-friendly machine. Its body configuration is a letter G in appearance that is made of GI pipe of schedule 40 and 3 cm in diameter; the base was made of 0.3 cm flat bar that serves as foundation of the equipment; a flat type 300 watts heating element and a box type panel board.

2) *Selection and identification of materials.* Selection and identification of materials were seriously considered in this study. The timer that controls the duration of the vulcanizing process; temperature gauge that controls the temperature in the process; power switch that is used for cutting the power supply to the machine; LED as light monitoring device and the buzzer that sounds when the vulcanizing process is completed; a stainless circular handle with 315 mm by 12 mm lag bolt, used for pressing the heating element and the rubber tire, and a flat type 300 watts heating element was connected to the circuit which is enclosed by a panel board made of galvalum sheet to complete the portable electronic vulcanizer.

3) *Fabrication*. Based on the plans and design, the body was molded in a pipe bender to form a letter G configuration, the flat bar was cut to its desired length then welded to form the base and welded it again to the body of the vulcanizer. Fabrication of the panel board was undertaken to house the circuit board of this machine.

4) *Testing process.* Testing of the machine was undertaken to determine the workability of the machine.

Figure 2 shows the schematic diagram of the electronic vulcanizing equipment.

Figure 3 shows the full view of the portable electronic vulcanizer (PEV).

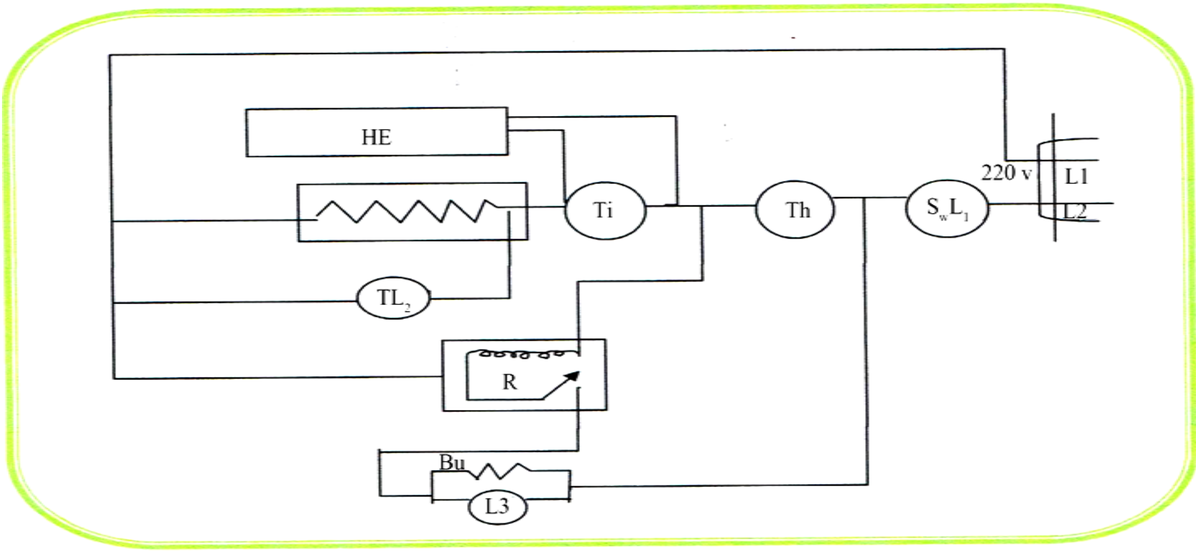

Figure 2. Schematic diagram of the vulcanizing equipment. Legend: L_1/L_2 = power supply 220 volts. Ti = digital timer. TL_2 = LED monitor for heating element. R = relay. Bu = buzzer. S_wL_1 = power switch/LED monitor. Th = analog temperature gauge (thermostat). L_3 = LED monitor for relay. HE = heating element. [resistor symbol] = resistor.

Figure 3. The portable electronic vulcanizer (PEV).

4.2. Materials

The materials and methods used in the construction and experimentation of this study were:

- a heating element, a 300 watts heating device that heats the vulcanizing gum and rubber or interior tire for vulcanizing process;
- an analogue temperature gauge used to set specific degrees in centigrade for the duration of the vulcanization process;
- a digital timer device used to set a specified time in seconds/minutes/hours for the burning operation of the vulcanizing equipment;
- a printed circuit board (PCB) on which all of the electronic parts were installed;
- a light emitting diode (LED) that serves as light monitoring device;
- boring tools used for drilling holes in the PCB for placement of the electronic parts;
- a relay to conduct power to the timer, temperature gauges once the vulcanization process takes place;
- a buzzer that sounds when the heating activity is finished;
- bolts and nut used to tighten some electronic parts to the PCB and as holder of the PCB circuit;
- a circuit is made in a PCB so that current will flow;
- a hacksaw that is used for cutting metals as parts of the machine;
- a welding machine is used to join metals for assembling the vulcanizer;
- aluminum sheeting is used as shield or protector of the rubber tire during vulcanizing process;
- a control panel houses the component parts of the electronic vulcanizer;
- power switches for power connection to the circuit or vulcanization process;
- the main source provides a prescribed current to any circuit connected to it; and
- the body of vulcanizer that is the holder of all the component parts used in this vulcanizer.

The connection of wirings was assessed by the researcher with the assistance of an electronic expert to ensure workability of the equipment. For mass production, this machine costs Php 5700.00 (US $101.79) only.

To determine the efficiency of the product in vulcanization, the researcher used some worn-out automobile tires to be vulcanized. Several tires were vulcanized at different temperatures and time with the temperature interval of 10˚C ranging from 30˚C to 60˚C and a constant time of 1 minute. The results were then recorded and determined what temperature and time the vulcanizing gum exactly bonded to the tire.

5. Results and Discussion

The following are the data collected based on the actual testing, observation and experimentation of the researcher.

The design of the portable electronic vulcanizer machine is made of steel materials. Its body is like big letter G configuration and on the bottom part of the machine is the heating element were the processes of vulcanization takes place.

The design and fabrication of the portable electronic vulcanizer are illustrated below:

- The galvanized iron (GI) Pipe with the dimension of 600 cm and gauge 20 and 3 cm in diameter was formed into big letter G;
- The finished product, the portable electronic vulcanizer stands perpendicular to the ground with the height of 43 cm;
- In the back side of the vulcanizer is the housing of the panel board where the control gadget is located;
- The PCB is located under the housing of the panel board where the switch, timer, digital temperature gauge, LED monitors, buzzer and relay are interconnected to form a circuit;
- The circuit is connected to the heating element of the electronic vulcanizer;
- Then a power cord is connected to the circuit for power supply connection.

Data on **Table 1** shows that the electronic vulcanizer had the best temperature in which the gum was bonded exactly to the rubber tire. It was 60˚C in 1 minute for Class A gum with a power consumption of 0.005 kW·h valued at Php 0.0757 and an efficiency of 85.22%, while the Class B gum bonded at 2 minutes at 60˚C, with power consumption of 0.10 kW·h valued at Php 0.15 and an efficiency of 85.22%.

For the conventional vulcanizer, the best temperature in which the gum was bonded exactly to the rubber tire was 60˚C in 5 minutes for Class A gum, with fuel consumption of 20 ml valued at Php 1.08 and an efficiency of 43.38%, while the Class B gum was bonded at 10 minutes at 60˚C, fuel consumption of 30 ml valued at Php

Table 1. Efficiency and rate of energy consumption of electronic/conventional vulcanizing using Class A and Class B vulcanizing gum.

<table>
<tr><th rowspan="3">Type of vulcanizer</th><th colspan="2">Time Minutes</th><th colspan="2">Temperature ˚C</th><th colspan="2">Power/fuel consumed</th><th colspan="2">Cost in kWh/ Gas-ml</th><th colspan="2">Rate of energy consumption</th><th colspan="2">Results</th><th colspan="2">Efficiency (%)</th></tr>
<tr><th colspan="2">Class</th><th colspan="2">Class</th><th colspan="2">Class</th><th colspan="2">Class</th><th colspan="2">Class</th><th colspan="2">Class</th><th colspan="2">Class</th></tr>
<tr><th>A</th><th>B</th><th>A</th><th>B</th><th>A</th><th>B</th><th>A</th><th>B</th><th>A</th><th>B</th><th>A</th><th>B</th><th>A</th><th>B</th></tr>
<tr><td>Electronic</td><td>1</td><td>2</td><td colspan="2" rowspan="2">60</td><td>0.005 kw·h</td><td>0.10 kw·h</td><td colspan="2">Php 15.1441</td><td>Php 0.0757</td><td>Php 0.15</td><td colspan="2" rowspan="2">Good bonding</td><td colspan="2">85.22%</td></tr>
<tr><td>Conventional</td><td>5</td><td>10</td><td>20 ml</td><td>30 ml</td><td colspan="2">Php 0.054</td><td>Php 1.08</td><td>Php 1.52</td><td>43.38%</td><td>78.08%</td></tr>
</table>

1.52 and with an efficiency of 78.08%.

Figure 3 and **Figure 4** compare the result of the vulcanizing process using the electronic and the conventional vulcanizer at 60˚C temperature.

Figure 5, shows the graphical data of the conventional (gas fired) vulcanizer that the gum was bonded to the rubber tire at 60˚C in 5 minutes for a Class A gum, with a fuel consumption of 20 ml valued at Php 1.08 and an efficiency of 43.38%, while Class B gum was bonded at 10 minutes at 60˚C, with a fuel consumption of 30 ml valued at Php 1.52 and with an efficiency of 78.08%.

Therefore, the portable electronic vulcanizer is most efficient than the convention vulcanizer and it is an environment-friendly machine.

Thus, this portable electronic vulcanizing machine saves time and cuts cost in investment and manpower, with 85.22% efficiency in the performance of vulcanizing.

6. Summary, Conclusions, Implication and Recommendations

This section summarizes the facts, the results of experiments and data computed on the study; answers the questions stated on the research work and recommends what can be improved in the research study.

6.1. Summary

This study was conducted to make a design and fabrication of a portable electronic vulcanizer. The testing was undertaken at the Bachelor of Technology Department, College of Engineering, University of Eastern Philippines this second semester school year 2005-2006.

The experimental method of research was used. The researcher was responsible for the purchase of the materials needed for the study.

It was found out in this study that portable electronic vulcanizer was effective in vulcanizing interior tires of the automobiles, motorcycles and bicycles. It further showed that the best temperature in which the gum was bonded exactly to the rubber tire was 60˚C in 1 minute for Class A gum and 2 minutes for Class B gum.

The rate of energy consumed for the portable electronic vulcanizer was Php 0.0757 for Class A gum and Php 0.15 for Class B gum with an efficiency of 85.22%, while the conventional vulcanizer for Class A gum consumed a fuel equivalent to Php 1.08 with an efficiency of 43.38% while the Class B gum fuel consumption was equivalent to Php 1.52 with an efficiency of 78.08%.

For mass production, this machine cost Php 5700.00 (US $101.79) only.

6.2. Conclusions

Based on the findings of the study, the following conclusions were derived:

1) The design of the portable electronic vulcanizer that weighs 6.30 kg is made of letter G body which is made of gauge 20 GI pipe, 3 cm in diameter with 0.05 cm thickness flat bar as base. The height of the body is 43 cm; the base is 23.5 cm length and 10 cm width; and the panel board with dimension of 27.5 for the height, 22.5 cm for the width, 8 cm for the thickness.

2) The material components of the electronic vulcanizer are composed of the timer, temperature gauge/ thermostat, LED, buzzer, relay and 300 watts heating element.

3) The appropriateness of the heating element was demonstrated in the experimentation of this portable

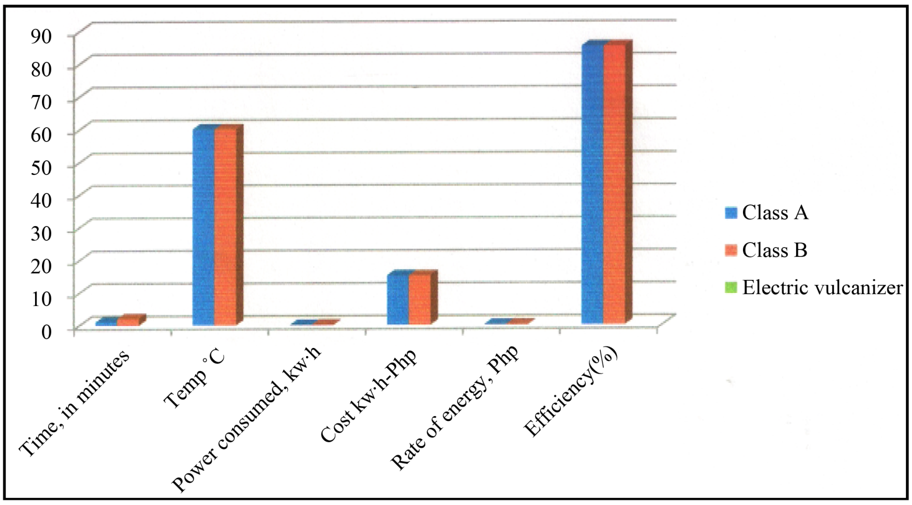

Figure 4. Electronic vulcanizer.

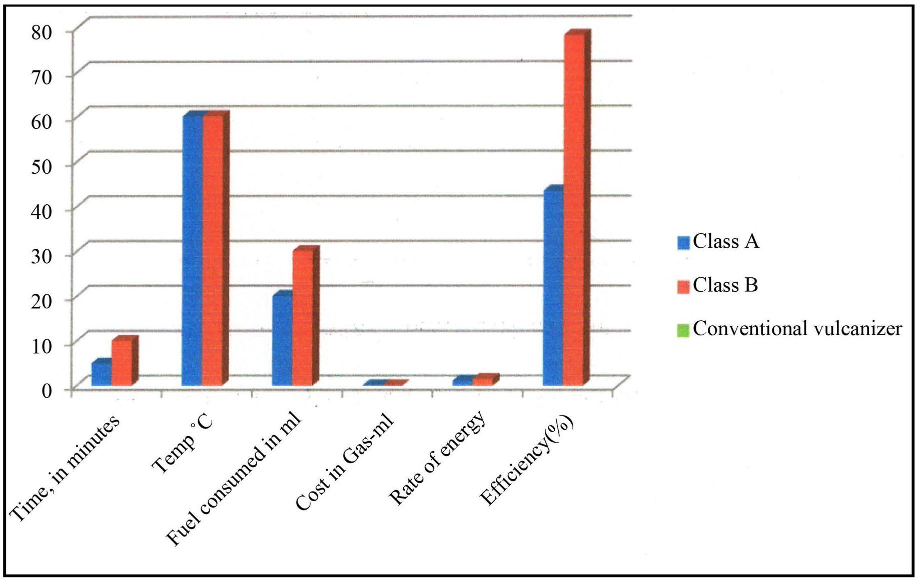

Figure 5. Conventional (gas fired) vulcanizer.

electronic vulcanizer which was a unique flat type heating element material with a 300 wattage output for a low cost power generation consumption.

4) The portable electronic vulcanizer requires 60˚C temperature in one minute to exactly bond the gum to the rubber tire for Class A vulcanizing gum and 2 minutes at 60˚C temperature to exactly bond to the rubber tire for Class B vulcanizing gum. The electronic vulcanizer is therefore efficient as it requires only one and two minute (Class A and B vulcanizing gum) to vulcanize as compared to the conventional vulcanizer that needs five minutes to finish the task.

5) In terms of energy consumption rate, the portable electronic vulcanizer is more economical as it consumes an energy equivalent to Php 0.0757 (Class A vulcanizing gum) and Php 0.15 (Class B vulcanizing gum) with an efficiency of 85.22%, as compared to the Php 1.08 (Class A vulcanizing gum) with an efficiency of 43.38% and Php 1.52 (Class B vulcanizing gum) with an efficiency 78.08% of the conventional vulcanizer. The efficiency of portable electronic vulcanizer is limited only for the vulcanization of gum to the rubber tires or inner tubes of the automobiles, motorcycle and bicycle or any inflatable rubber materials.

The payback period (PP) of the vulcanizing shop with capitalization of Php 185100.00 (US $3305.36) including this new electronic vulcanizer is only 3.3356 years operation.

This study determined the accurate temperature and duration of the vulcanizing process using the electronic vulcanizer which eliminated the problem of gas emission (carbon dioxide) produced by the conventional (gas fired) vulcanizer of about 2.772 kg of carbon dioxide for 1 liter of diesel fuel and/or 2.331 kg of carbon dioxide for 1 liter of petrol into the atmosphere.

6.3. Implication

The findings of this study have an important implication for future it provides enhancement and improvement of the study. More tires can be vulcanized in a short period of time; there for greater income over time. It is environment-friendly since it does not emit gas as compared to the conventional vulcanizing; and much more is lesser health hazard to the operator.

6.4. Recommendations

1) It is recommended that this portable electronic vulcanizer be used in every welding, automotive and machine shop to save time and investment in their operations;

2) S mall time businesses like vulcanizing shops in the Philippines are encouraged to provide this portable electronic vulcanizing machine so that they can save money and labor in their operation;

3) It is recommended also that this study be innovated thru additional features like automatic shutdown of power supply or may be a remote controlled operation on the power switch.

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References

[1] US EPA (2014) Green Gas Emission from Typical Passenger Vehicle. http://www.epa.gov/otaq/climate/documents/420f14040.pdf

[2] Ramos, F.V. (1991) Executive Order 318, s. 1991. Making Philippines Industrializing Country (NIC-Hood Philippines), Manila.

[3] Annual Report (1993) Secretary of the Department of Education, Manila.

[4] Encyclopedia Britannica. 15th Edition.

[5] Compton's Encyclopedia. 1995 Edition.

[6] (2008) Tire Vulcanizer. Hirotek Inc., Japan.

[7] (2010) Tire Vulcanizer. Hirata Corporation, Japan.

[8] Ramis, E.Z. (2002) Determinants of Professionalism of Graduate School Students, Faculty and Administrator in State Universities and Colleges in Region VIII. Technological University of the Philippines, Manila.

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Data Engineering
Ecological Science and Technology
Electrical and Computer Engineering
Engineering Education
Engineering Geology
Engineering Physics
Environmental Sciences
Food Science and Engineering
Genetic Engineering and Biotechnology
Green Energy Engineering and Technology
Hydraulic Engineering
Industrial Technology
Information Technology
Manufacturing Engineering and Technology
Materials Science and Engineering
Medical and Biomedical Engineering
Micro-System Technology
Military Technology and Equipment
Nano-System Technology
Naval Engineering
Nuclear Science and Technology
Opto-Mechatronics
Particle Physics
Petroleum Engineering
Pharmaceutical Engineering
Polymer Engineering
Reservoir Engineering
Security Engineering
Structural Engineering
Textile Engineering
Traffic Engineering
Visualization Technology

We are also interested in: 1) Short reports—2-5 page papers where an author can either present an idea with theoretical background but has not yet completed the research needed for a complete paper or preliminary data; 2) Book reviews—Comments and critiques.

Website and E-Mail

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