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Machine Learning-based Estimation of Output Current Ripple in PFC-IBC Used in Battery Charger of Electrical Vehicles Control ANN with Fractional order PID Controller

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Abstract
In this study, an artificial neural network (ANN) with Factorial order pi (FOPI) model is developed for the purpose of estimating the output current ripple of a power factor correction (PFC) AC/DC interleaved boost converter (IBC) used in battery charger of electrical vehicles (EVs) based on the inductance current ripple, switching frequency and load changes. Besides, the improved ANN model is compared with some different machine learning (ML) techniques. The PFC-IBC is simulated with the PSIM simulation program to estimate the output current ripple. As a result, 336 output current ripple values are obtained based on inductance current ripple, different switching frequency and load changes. It is seen that the estimation value obtained with MLTs is quite compatible with the actual value obtained with the simulation. In addition, in the study carried out with the simulation, it takes a period of several days to obtain the estimation results; whereas, the operation of estimation with MLTs can be completed in a short period such as a few minutes. This clearly reveals the advantage of the MLTs. Therefore, this value is estimated through the MLTs with a high accuracy before the design of the charging device in order to maintain at a secure level the output current ripple posing considerable importance in electrical vehicle battery charge. The developed ANN FOPI model proposes better results than other techniques.

Keywords: Artificial Neural Network, FOPI, Electrical Vehicle, Battery Charging, Power Factor Correction.

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Introduction

Electrical vehicles (EVs) have an older history compared to the internal combustion engine vehicles, which are commonly used today. These vehicles are not able to show developments in those dates and are not intensively studied due to their long charging durations and low performance.

The PID controller is by far the most dominating form of feedback in use today. Due to its functional simplicity and performance robustness, the proportional-integral-derivative controller has been widely used in the process industries. The PID controllers have remained, by far; the most commonly used in practically all industrial feedback control applications. PID controllers have been used for several decades in industries for process control applications. The reason for their wide popularity lies in the simplicity of design and good performance including low percentage overshoot and small settling time for slow process plants. The most appreciated feature of the PID controllers is their relative easiness of use, because the three involved parameters have a clear physical meaning. This makes their tuning

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possible for the operators also by trial-and error and in any case a large number of tuning rules have been developed. Although all the existing techniques for the PID controller parameter tuning perform well, a continuous and an intensive research work is still underway towards system control quality enhancement and performance improvements. On the other hand, in recent years, it is remarkable to note the increasing number of studies related with the application of fractional controllers in many areas of science and engineering. This fact is due to a better understanding of the fractional calculus potentialities. In the field of automatic control, the fractional order controllers which are the generalization of classical integer order controllers would lead to more precise and robust control performances. Although it is reasonably true that the fractional order models require the fractional order controllers to achieve the best performance, in most cases the researchers consider the fractional order controllers applied to regular linear or non-linear dynamics to enhance the system control performances. For design and tuning of PID controller parameters we use optimization method. Specifications, stability, design, applications and performance of the PID controller have been widely treated, but generalization of the PID controller, namely the PIλD μ controller, involving an integrator of order λ and a differentiator of order μ has the better response in comparison with the classical PID controller.

However, interest in EVs has increased again since fossil fuels have been gradually becoming exhausted recently when alternative energy resources are popular and the legal regulations have been enacted for decreasing the harmful gases emitted. The associate editor coordinating the review of this manuscript and approving it for publication was Bilal Alatasby the internal combustion engines to the atmosphere and environmental pollution. The technology of electrical vehicle (EV) has been developing in three different ways as all-EVs, hybrid EVs, and fuel cell-EVs.

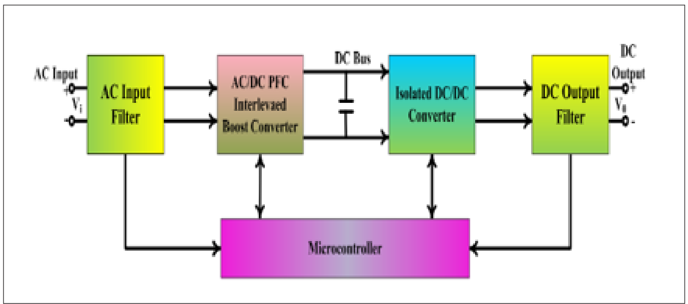

Figure 1: The Inner Structure of a Typical Switched Charger

The common point of these three technological advancements is the batteries used in the vehicle system and providing the chemical storage of the electrical energy. Aside from having high power and energy density for the batteries used, it is demanded for electrical vehicles to have fast charging ability and long-life span [1,2]. The battery system is an important factor among electrical vehicles. The distance of electrical vehicles is directly related to their battery capacities. Therefore, the need for batteries with higher energy capacity is gradually increasing.

These advancements bring together the development of the chargers suitable for the needed infrastructure. Today, the charging devices commonly used on electrical vehicles are the Ferro-resonant chargers, thyristor chargers, and switched chargers. The selection of the suitable charging device technology depends on the battery requirements and application needs. Ferro-resonant and thyristor chargers are durable and reliable and can endure for years. However, the switched chargers are better when compared to the ferro-resonant and thyristor chargers due to their characteristics such as being highly efficient, light-weight, low volume, quiet, and having the ability to respond fast to the changes [2]. Switched battery charger or in other words, the battery charge module, is an AC-DC/DC-DC converter implemented with a fully controlled semiconductor power switch. The response duration of these devices is very short since in these converters which are able to be operated at the considerably high frequencies since the turning on and off of the MOSFET and IGBTs are able to be controlled [3–5]. Figure 1 shows the structure of a typical switched charger. There is an AC filter in the input of switched charger. DC bus voltage is obtained through the interleaved boost converter (IBC) at the output of the rectifier by rectifying the AC filter output with the bridge diodes. The DC bus voltage is transferred to the output by regulating with an isolated-DC converter. The battery is charged by adjusting and filtering DC voltage obtained in the output.

The harmonic components are generated at every stage of this process. It is required to maintain the output current ripple of chargers at a certain level in order to guarantee the secure charging of electrical vehicle battery and their long-life span. Having high output current ripples of battery chargers leads to the overheating of batteries and them having a shortened lifespan. In fact, since the battery management system would cut off the charge in the event of overheating, the battery of EV would not be completely charged with full capacity. Thus, the way the vehicle will make would restrict the distance, as well. For these reasons, it is quite important to estimate accurately the value of output current ripple, obtained in the DC-DC converter output, before the design in the design and control of the battery chargers [6]. At this point, machine learning (ML) techniques can be used. This is because ML techniques can offer much more practical, fast and accurate solutions in difficult mathematical calculations or applications that are difficult to test and measure.

Input Line Filter

Input Line Filter: An internally or externally mounted low-pass or band-reject filter at the power supply input which reduces the noise fed into the power supply.

The input line filter consists of an electronic circuit connected between the ac mains and the rectifier input stage of the switching power supply. All the input a.c voltage must pass through the filter before reaching the rectifier. An effective filter should therefore attenuate all the higher frequencies and only let the mains 50Hz or 60 Hz pass through to the next stage.

The input line filters are incorporated in most switched mode power supplies to reduce the interference from the electromagnetic and other electrical noises present in the ac lines. The filters are also used to ensure that the power supplies comply with government regulations and agency standards.

The two primary functions of the input line filter are:

- Preventing the EMI signals generated within the power supply from reaching the input ac power line and affecting other equipment connected on the same line.
- Preventing high frequency voltage and EMI on the power line from passing through and reaching the supply's output.

The design and component selection of the input filter is important in ensuring that it does not unnecessarily increase the volume and cost of the supply or compromise the power supply performance.

Even though there are various filter designs with different characteristics and effects on power supply performance, the passive L-C filter achieves both the filter functions above while still offering the best balance between size, cost and performance. However, passive filters may introduce undesirable effects, it is therefore important to understand the load and use the appropriate filter design.

The L-C passive filters may father be classified according to the design and characteristics. The common types include the undamped LC filter, parallel damped filter and series damped filter.

Passive Filters

Passive implementations of linear filters are based on combinations of resistors (R), inductors (L) and capacitors (C). These types are collectively known as passive filters, because they do not depend upon an external power supply and they do not contain active components such as transistors.

Inductors block high-frequency signals and conduct low-frequency signals, while capacitors do the reverse. A filter in which the signal passes through an inductor, or in which a capacitor provides a path to ground, presents less attenuation to low-frequency signals than high-frequency signals and is therefore a low-pass filter. If the signal passes through a capacitor, or has a path to ground through an inductor, then the filter presents less attenuation to high-frequency signals than low-frequency signals and therefore is a high-pass filter. Resistors on their own have no frequency-selective properties, but are added to inductors and capacitors to determine the time-constants of the circuit, and therefore the frequencies to which it responds.

The inductors and capacitors are the reactive elements of the filter. The number of elements determines the order of the filter. In this context, an LC tuned circuit being used in a band-pass or band-stop filter is considered a single element even though it consists of two components.

Power Factor Correction Interleaved AC/DC Boost Converter

Power factor is defined as the ratio of energy a device is capable of transmitting to the output versus the total amount of energy it takes from the input power source. It is a key figure of merit for the design of electrical devices, especially due to the regulations put in place by countries and international organizations like the EU, which define the minimum power factor or maximum level of harmonics a device must have in order to be sold in the European market.

The reason why these organizations are so invested in improving power factor is because low-quality power is a real threat to the power grid, increasing heating losses and potentially causing a power failure.

There are two main causes of poor power factor:
Displacement: This occurs when a circuit's voltage and current waves are out of phase, usually due to the presence of reactive elements such as inductors or capacitors.

- **Distortion**: Defined as the alteration of the wave's original shape, this is usually caused by nonlinear circuits, such as rectifiers. These nonlinear waves have a lot of harmonic content, which distorts the voltage in the grid.

Power factor correction (PFC) is the series of methods used to try to improve a device's power factor.

In order to fix displacement issues, external reactive components are commonly used to compensate the circuit's total reactive power.

To solve distortion problems, there are two options:

- Passive power factor correction (PFC): Improves PF by filtering out harmonics using passive filters. This is typically used in low-power applications, but is not enough at high power.
- Active power factor correction (PFC): Uses a switching converter to modulate the distorted wave in order to shape it into a sine wave. The only harmonics present in the new signal are at the switching frequency, so they are easily filtered out. This is considered the best PFC method, but adds complexity to the design.

A good power factor correction circuit is a crucial element for any modern design, because a device with a bad power factor is going to be inefficient, will put an unnecessary strain on the grid, and possibly cause problems to the rest of connected devices.

The Need for Power Factor Correction (PFC) in AC/DC Power Supplies

As discussed in our previous article, an AC/DC power supply is made up of several circuits that transform an input AC voltage into a stable DC voltage at the output. The most essential of these circuits is the rectifier, which is responsible for transforming the AC voltage into a DC voltage; however, this circuit alone is not enough to ensure adequate operation.

In order for an AC/DC power supply to be efficient and safe, it needs to incorporate isolation, power factor correction (PFC), and voltage reduction. These elements protect the user, the grid, and any connected devices, and are each integrated to some extent in all switching power supplies.

The first step in any switching power supply is the rectification of the input voltage. Rectification is the process of converting a signal from AC to DC, and is done using a rectifier. The negative voltage in the AC wave can be either cut off using a half-wave rectifier, or inverted using a full-wave rectifier.

The spread of charges including non-linear units such as inverter and battery chargers lead to a significant increase in the voltage deformations and current harmonic distortion on electricity distribution systems. These harmonics may cause many problems including extreme neutral currents and the overheating of transformers on the power system. In order to decrease these harmonics negatively affecting the grid and increase the power factor, AC/DC power converters are used in battery charging. These converters are usually preferred as buck, boost and buck-boost converters. In the study proposed a buck converter is used has also been mitigated by applying the larger duty-cycle percentage variable width PWM signals. In the study proposed, the PFC controller regulates the battery voltage and controls the supply current of the converter to achieve unity power factor. In addition to these, boost converters are also widely used. Passive and active methods are used depending on the charge and application type for the power factor correction. Both methods have advantages and disadvantages.

In passive methods, coils and condensers are connected to the rectifier input or output in order to correct the input current. This system having a simple structure is quite awkward due to the use of the grid frequency inductances and capacitances. In addition, the power factor in this system is quite low and there are huge ripples in the non-controlled output voltage. In the active method intensively studied in recent years, it is tried to converge the current towards the sinus form and regulate the output voltage by connecting a type of boost DC-DC converter on the rectifier output in general. A separate circuit can also be used for the regulation of the output voltage.

In the recent years; IBC obtained through the parallelization of classic boost converters is preferred in high power applications. The voltage applied to the input in the classical boost converter circuit shown in Figure 2 is rectified through the diode bridge and the rectified voltage is transferred to the output by boosting. These converters used commonly especially in PFC applications are usually operated in continuous current mode. The converter shown in Figure 3 is an IBC circuit. Particularly in high power applications, the parallel operation (interleaved structure) of lower power boost converters is suggested for the same power instead of a single booster converter in order to decrease the high current stress on the circuit elements and use smaller circuit elements [7].

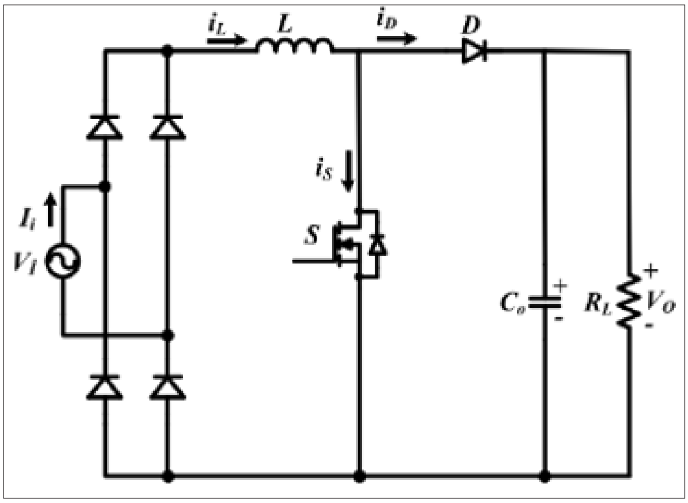

Figure 2: The Classical Boost Converter Circuit

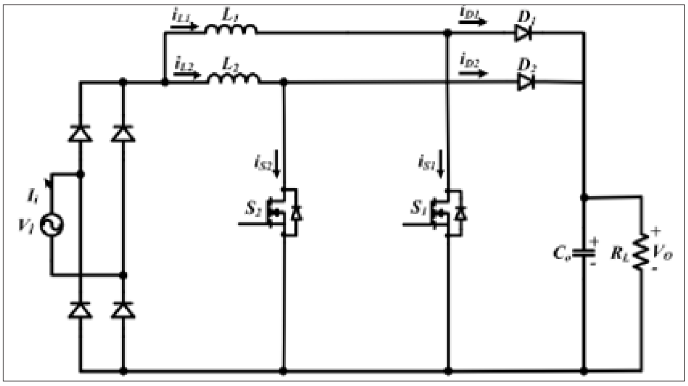

Figure 3: The Interleaved Boost Converter Circuit

In operated studies using IBC, better performance can be provided compared to the classical boost converters. This is because IBC has many advantages such as lower input current and output voltage ripple, fast transmission response, lower input filter dimensions and low current stress on semiconductor devices when compared to the classical boost converters for the same power conditions. Figure 4 shows wave forms of input inductance currents based on having higher or smaller than 50% of duty cycle (D). One of the most significant reasons for using IBC in this study is because the input current ripple is lower when compared to the classical boost converter. Thus, the current harmonics drawn from the grid and the total harmonic distortion (THD) in the battery charge are minimized. As seen from Figure 4, the average of L1 and L2 inductance currents provides the input current ripple. The equations between the input and

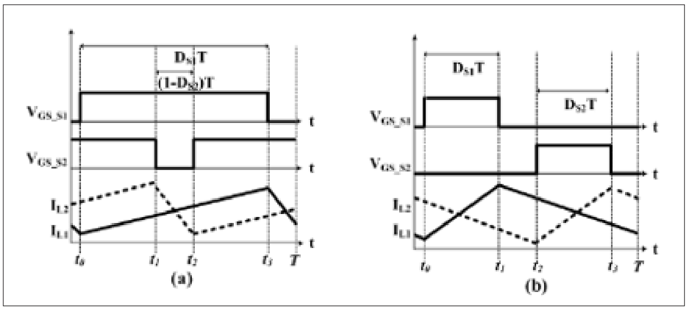

Figure 4: Control signals of the switches and the waveforms of boost inductor currents in (a) D > 50% mode, (b) D < 50% mode.

Output voltages for each of the switches in the converter can be provided as follows for the turning-on and off condition of a switch;

$$\sum_{S_1=on} \Delta i_{L1} = \frac{V_i \cdot (D_{S1}T)}{L_1} \qquad (1)$$

$$\sum_{S_1=off} \Delta i_{L1} = \frac{(V_o - V_i) \cdot [1-(D_{S1}T)]}{L_1} \qquad (2)$$

So, the input and output voltage ratio can be derived fromeq. (1) and (2) as:

$$\frac{V_o}{V_i} = \frac{1}{1-(D_{S1})} \qquad (3)$$

Imachine Learning (ML) Techniques-Based estimation

Machine learning is the ability of machines to extract data without being explicitly programmed. It is an artificial intelligence application or subset that enables learning. In artificial intelligence, making a goal-oriented prediction or decision-making is done by machine learning methods. There are extensive machine learning methods in the literature, some of which are; support vector machines are logistic regression, linear regression, and simple bayes, k nearest neighbour, random forest, ANN and decision tree. In this study, LR, RF and ANN techniques from machine learning techniques are used. The performance of the ANN model developed for estimation of output current ripple in PFC-IBC used in battery charger of electrical vehicles is compared with the LR and RF techniques.

Linear Regression (LR)

In statistics, linear regression is a linear approach for modelling the relationship between a scalar response and one or more explanatory variables (also known as dependent and independent variables). The case of one explanatory variable is called simple linear regression; for more than one, the process is called multiple linear regression. This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

In linear regression, the relationships are modelled using linear predictor functions whose unknown model parameters are estimated from the data. Such models are called linear models. Most commonly, the conditional mean of the response given the values of the explanatory variables (or predictors) is assumed to be an affine function of those values; less commonly, the conditional median or some other quantile is used. Like all forms of regression analysis, linear regression focuses on the conditional probability distribution of the response given the values of the predictors, rather than on the joint probability distribution of all of these variables, which is the domain of multivariate analysis.

Linear regression was the first type of regression analysis to be studied rigorously, and to be used extensively in practical applications. This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine.

Linear regression has many practical uses. Most applications fall into one of the following two broad categories:

- If the goal is error reduction in prediction or forecasting, linear regression can be used to fit a predictive model to an observed data set of values of the response and explanatory variables. After developing such a model, if additional values of the explanatory variables are collected without an accompanying response value, the fitted model can be used to make a prediction of the response.
- If the goal is to explain variation in the response variable that can be attributed to variation in the explanatory variables, linear regression analysis can be applied to quantify the strength of the relationship between the response and the explanatory variables, and in particular to determine whether some explanatory variables may have no linear relationship with the response at all, or to identify which subsets of explanatory variables may contain redundant information about the response.

Linear regression models are often fitted using the least squares approach, but they may also be fitted in other ways, such as by minimizing the "lack of fit" in some other norm (as with least absolute deviations regression), or by minimizing a penalized version of the least squares cost function as in ridge regression (L2-norm penalty) and lasso (L1-norm penalty). Use of the Mean Squared Error (MSE) as the cost on a dataset that has many large outliers, can result in a model that fits the outliers more than the true data due to the higher importance assigned by MSE to large errors. So, a cost functions that are robust to outliers should be used if the dataset has many large outliers. Conversely, the least squares approach can be used to fit models that are not linear models. Thus, although the terms "least squares" and "linear model" are closely linked, they are not synonymous.

Linear regression is a well-known and frequently used algorithm in statistics and machine learning. Linear regression models a target predictive value based on independent variables. It is mostly used to find the relationship between variables and prediction [8]. Different regression models differ in the relationship between dependent and independent variables and the number of independent variables used [9]. Linear regression's general equation is

$$y = c + mx \tag{4}$$

c is the y-intercepts and m are the slope.

The best fit line is

$$y = mx \tag{5}$$

In statistics, this equation is being represented generally as

$$y = \beta_0 + \beta_1 x_1 \tag{6}$$

If (x1, x2, . . ., xn) are the n number of predictors then the equation is

$$y = \beta_0 + \beta_1 x_1 + \ldots\ldots.. + \beta_n x_n \tag{7}$$

Artificial Neural Network (ANN)

Artificial neural network (ANN) is an information processing system inspired by biological neural networks and containing some performance features similar to biological neural networks. ANNs, which simply imitate the way the human brain works, can learn from data, generalize, work with an unlimited number of variables, etc. It has many important features is one of the powerful and general-purpose data mining methods and can be applied in estimation, classification, and grouping problems [10].

The smallest unit of ANN is called artificial neuron or processing element. The simplest artificial neuron consists of 5 main components: inputs, weights, coupling function, activation function and output. Inputs (x1, x2. . .. xn) are information entering the cell from other cells or external environments. These are determined by the examples the network is asked to learn. Weights (w1, w2. . . . .wn) are values that express the effect of another processing element in the input set or a previous layer on this processing element. Each input is aggregated through the sum function, multiplied by the weight that connects that input to the processing element. The sum function is as follows [11].

$$net = \sum_{i=1}^{n} w_i x_i + b \tag{8}$$

The output of the processing element is calculated bypassing the value obtained as a result of the sum function through a linear or nonlinear differentiable transfer function.

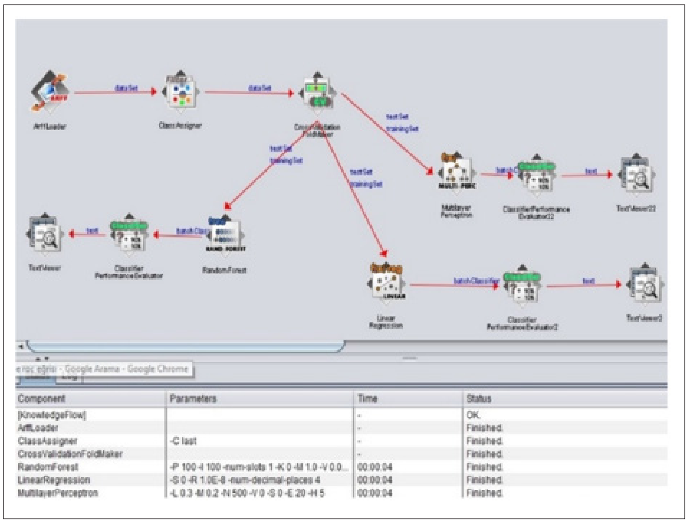

Figure 5: The Knowledge Flow of the Used Techniques in WEKA

$$y = f\,(net) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{9}$$

A multi-layer perceptron (MLP) artificial neural network is used in this study. MLP is a forward-looking neural network with one or more layers between the input and output layers. Feed forward means that data flows in a (forward) direction from the input to the output layer. This type of network is trained with back propagation learning algorithm. MLPs are widely used for pattern classification, recognition, prediction and approximation. MLP can solve non-linearly separated problems. A MLP is a forward-looking neural network that contains one or more layers between the input and output layers. Feed forward means that data flows in a (forward) direction from the input to the output layer. This type of network is trained with back propagation learning algorithm. MLPs are widely used for pattern classification, recognition, prediction and approximation. MLP can solve non-linearly separated problems. Multilayer neural networks are used in solving complex problems, especially in predictions. Because in these networks, a series of operations in the structure of the hidden layer have the ability to automatically turn into a non-linear structure [12-15].

In this study these three supervised machine learning techniques, namely LR, RF and ANN are built using the WEKA Explorer module. These techniques are classification models.

In the Classify tab of the WEKA Explorer 10-fold cross validation testing and a batch size of 100 is used for all the optimization trials. The knowledge flow of the used techniques is displayed in Figure 5.

The results of LR, RF and developed ANN model in this study are given based on mean square error (MSE), root mean square error (RMSE), correlation coefficient (R2), mean absolute error (MAE) metrics, mean absolute percentage error (MAPE) and mean absolute scaled error (MASE).MSE is the value obtained by adding the difference of the data values observed and estimated in the series, and dividing it into the total data number. It is the parameter quadratically indicating the error between the desired value and the output generated by the prediction model. This value being close torero indicated that the estimated value converged strongly to the line. RMSE is a quadratic metric that measures the magnitude of error of a machine learning model, which is often used to find the distance between the predictor's predicted values and the true values. The RMSE is the standard deviation of the estimation errors. A zero RMSE value means that the model made no errors. R2indicates how much of the change in the dependent variable can be explained by the independent variable [16].

The determination coefficient range equal to the square of the correlation coefficient is indicated with the equation0 ≤ R2 ≤ 1. This value being close to 1 indicates that a great part of the variance in the dependent variable explains the independent variable in the model. MAE represents the absolute mean error and is used to measure errors in the forecasting model. It shows how close the estimated value is to the actual value. MAPE is the demonstration of the average absolute values of errors as the percentage of actual values. The estimation models having a MAPE value under 10% are classified as having "high accuracy" level; whereas the models having a value between10% and 20% are classified as accurate estimations. MASE is the mean absolute error of the forecast values, divided by the mean absolute error of the in-sample one-step naïve forecast. It is a measure of the accuracy of predictions. The mean absolute scale error has favourable properties compared to other methods used to calculate forecast errors, such as root mean square deviation, and is therefore recommended for determining the comparative accuracy of forecasts. The metrics used in the assessment of estimation results in this study are provided in the following equations, respectively. In the equations, O refers to the observed parameter and P refers to the predicted parameter [17-20].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \tag{11}$$

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - O_{ave})(P_i - P_{ave})}{\sqrt{\sum_{i=1}^{n}(O_i - O_{ave})\sum_{i=1}^{n}(P_i - P_{ave})}} \tag{12}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|O_i - P_i| \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \times 100 \tag{14}$$

$$MASE = \frac{\frac{1}{n}\sum_{i=1}^{n}|O_i - P_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|P_i - P_{i-1}|} \tag{15}$$

Fractional Order PID Controllers

One of the primary controllers is PID controller, which is widely used. Fractional controller is denoted by PIλD μ was proposed by Igor Podlubny in 1997, here λ and μ have non-integer values. Figure 6 shows the block diagram of fractional order PID Controller

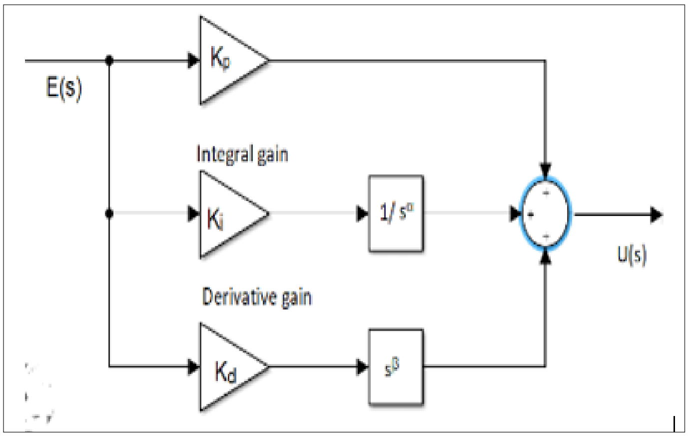

Figure 6: Fractional Order PID controller

The transfer function for conventional PID controller is

$$G_{PID}(S) = \frac{u(s)}{e(s)} = K_c\left(1 + \frac{1}{T_i S} + T_d S\right)$$

The transfer function for fractional order PID controller is where λ and μ are an arbitrary real number, Kc is amplification (gain), Ti is integration constant and Td is differentiation constant. Taking λ=1 and μ=1, a classical PID controller is obtained. For further practical digital realization, the derivative part has to be complemented by first order filter. The filter is used to remove high frequency noise [21,22].

$$G_{FOPID}(S) = \frac{u(s)}{e(s)} = K_c\left(1 + \frac{1}{T_i S^{\lambda}} + \frac{T_d S^{\mu}}{\frac{T_d}{N}S+1}\right)$$

The PIλ D μ controller is more flexible and gives an opportunity to better adjust the dynamics of control system. Its compact and simple but the analogy realization of fractional order system is very difficult. Intuitively, the FOPID has more degree of freedom than the conventional PID. It can be expected that the FOPID can provide better performance with proper choice of controller parameters. However, with more parameters to be tuned, the associated optimization problem will be more difficult to deal with. It is motivated to develop a systematic procedure for the FOPID optimization to achieve a certain performance [23].

Results and Discussion

The metal-oxide-semiconductor field-impact semiconductor (MOSFET, MOS-FET, or MOS FET) is a sort of field-impact semiconductor (FET), most commonly made by the controlled oxidation of silicon. It has a protected entrance, whose voltage picks the conductivity of the gadget. This capacity to change conductivity with how much applied voltage can be utilized for improving or exchanging electronic signs. A metal-separator semiconductor field-impact semiconductor or MISFET is a term basically unbreakable from MOSFET. Another similar is IGFET for shielded entrance field-impact semiconductor [24-28].

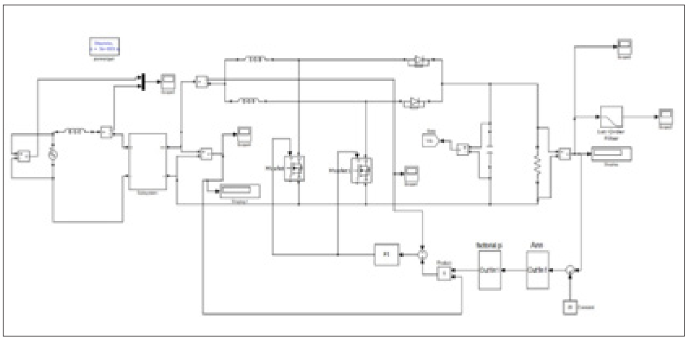
Figure 7: Simulation Circuit Schema and Control Block of the PFC-IBC Converter

Figure 7 shows the simulation circuit schema of the PFC-IBC converter which is used in the study and its data of which are obtained from PSIM 9.1.1 program. The reference measurements taken from the input and output by using PI controllers are included in control block so that the control signals of the semiconductor power switches in the IBC are obtained foreface purpose. The data obtained from the simulation study are separated as training and testing data and used in the developed ANN model. The PFC operation of the converter is also experimentally verified by setup an experimental circuit prototype of the converter [29].

Figure 7 shows the simulation results of PFC-IBC. As shown in Figure, the results obtained from the simulation and the results obtained from the experimental study are compatible with each other. The input current and voltage waveforms are approximately in phase and the power factor is measured as 0.998. Therefore, the PFC process is successful. By several machine learning techniques in this study, the value of output current ripple (1Io) is estimated as output parameter when the input parameters are switching frequency (fp), load resistance (RL) and boost inductance current ripple (1IL). Table 1 shows all the input and output parameter values in the converter used in the simulation study consisting of the used techniques [30]. In here, the switching frequency (fp) is

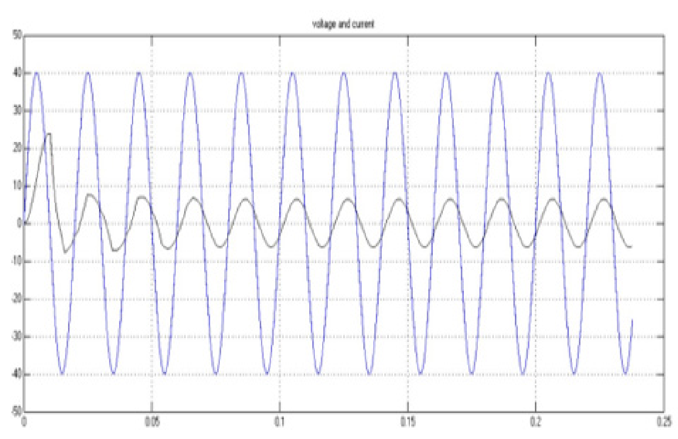

Figure 8: The Input Voltage and Current Waveforms Obtained from Simulation Results

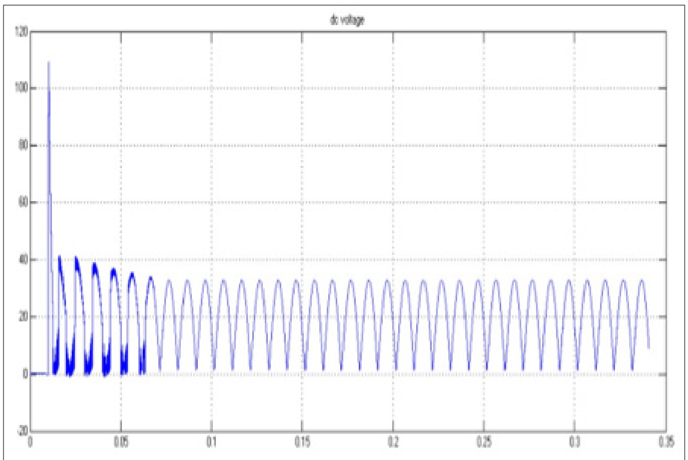

Figure 9: PFC Output

Table 1: The Parameters of Circuit

Parameter	Symbol	Value
Input Voltage	V_i	220 V_{AC}
Output Voltage	V_O	800 V_{DC}
Output Capacitor	C_o	470 µF
Boost Inductors	L_1, L_2	750 µH
Switching Frequency	f_p	10-40 kHz (Variable in 2 kHz intervals)
Load Resistance	R_L	160-200 Ω (Variable in 2 Ω intervals)

Increased in twos between 10-40 kHz and the load resistance (RL) is increased in twos between 160-200 in the dataset in this study. Thus, 336 data is obtained from simulation operation in total.

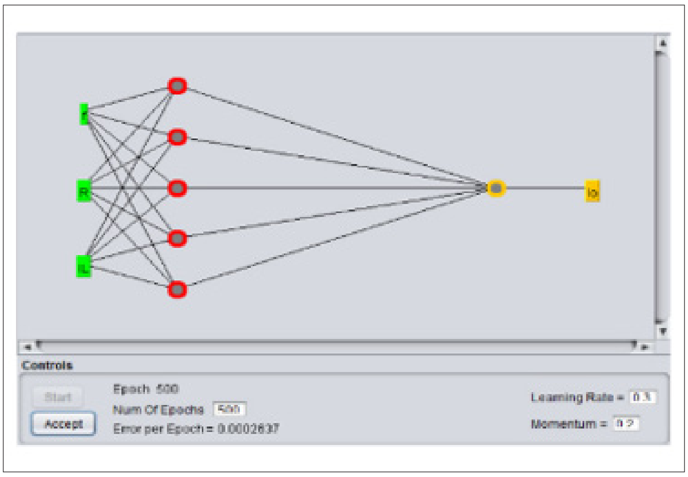

Figure 10: ANN Model Structure for Output Current Ripple

Figure 10 shows the structure of the ANN with FOPI model generated for the estimation of output current ripple. In the optimum model generated for the study after the made many tests, there are a three-neural input layer, a five-neural secret layer and a single neural output layer as seen from figure [31-36].

Conclusion

In this study, an ANN model is developed for the purpose of estimating the output current ripple of a PFC AC/DC interleaved boost converter used in battery charger of electrical vehicles based on the inductance current ripple, switching frequency and load changes. Besides, the improved ANN model is compared with some different machine learning techniques like linear regression, random forest. The dataset used for estimation is obtained by simulating the converter in the PSIM 9.1.1 program. In this study, not only the power factor is corrected, but also the estimation of output current ripple is separately made through LR, RF MLTs and the ANN model developed for the secure charging of the battery. The MLTs estimation results are compared based on the R2, MSE, RMSE, MAE, MASE and MAPE performance criteria. It is observed that the developed ANN model is more successful than the LR and RF techniques. In ANN model, R2, MSE, RMSE, MAE, MASE and MAPE values are calculated as0.9995, 0.0006, 0.0245, 0.0002, 0.0714 and 0.2216, respectively. Consequently, a highly accurate estimation is made with the developed ANN model. Due to this estimation is produced in a much shorter time than the simulation, the output current fluctuation can be predicted in order to ensure reliable charging and longer life of electric vehicle batteries, providing both time saving and convenience for charger designers.

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