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Virtual and Self-Validating Sensor for Speed Estimation of a DC Motor in a Prototype Plant

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Abstract: In applications where the speed control of a motor may not be interrupted, even for maintenance of the speed sensor or speed sensor unavailability, the virtual sensing is a powerful tool. The proposed virtual speed sensor uses artificial neural networks to provide motor speed estimation when an encoder is not operating for this purpose. The artificial neural network uses motor load information, armature current measured with a shunt resistor and armature applied voltage as input parameters to provide the estimated speed. In parallel, self-validating sensor status is analyzed, coordinating the speed control actions for plant maintenance. For self-validating purposes, a known current flow is applied in the shunt resistor to generate the sensor status. A microcontroller is responsible for control of the applied voltage in the DC motor and also for data acquisition. This microcontroller is slave of an application running in a personal computer, where all the information is processed to make control decisions and to alert the user accordingly with the previously artificial neural network train. The application presents the sensor status and the measured and estimated speed graphs, allowing the user to monitor and to analyze the plant behavior. Some fail situations were tested in a closed loop system, demonstrating the virtual sensor operation in these cases, including the sensor status detection and its correspondent control actions. *Copyright © 2015 IFSA Publishing, S. L.*

Keywords: Virtual sensor, Self-validating sensor, Speed control.

1. Introduction

The classical instrumentation methods are mainly focused on translate the process variables, which are representatives of physical phenomena, into coherent readout values for an observer who adjusts the system to achieve a desired value, like in tire pressure gauges [1]. Some systems need intermediate blocks to adapt the measured magnitude to an observer comprehensive value. In classical systems these blocks remain each other physically apart and consist, usually, of a transducer, a signal conditioning and a measure indication circuit. This physical separation can insert noise in the measured signal due to its interface connectors, wires and others.

In some cases the signal conditioning enhances the performance of the sensor [2], allowing operation in more specific situations, as microvolts electroencephalography signals. Also, these blocks are all discrete circuits in the classical instrumentation, with simple or without digital signal processing. The evolution of the instrumentation tends to integrate the major quantity of the discrete blocks into a single digital system more reliable, robust and accessible.

A classical process that still must be used is the calibration. The sensor measurement credibility is related to its calibration. In general the manufacturers realize the sensors calibration. However, in some cases the sensor measurement is degraded with operation time and the users not necessarily know the criticality of the sensor condition. Therefore, if the sensor operation is not monitored automatically, the system can be working with a wrong sensor measurement or can be stopped for calibration without need [3].

The measuring process complexity has grown, requiring more complicated and specific measurement systems. Nowadays, the industrial evolution needs more features than only sensor measurements. These improvements are developed over the sensor scheme, through the addition of specific characteristics like failures compensation, self-validating tests, self-calibration process, self-adaptive capacity and others. All of them linked with digital-processing technologies, attracting a high volume of consumers through intelligence incorporation in instrumentation systems [2]. This market is projected to reach US$ 7.8 billion by 2015 [4].

Intelligent Instrumentation is closely related to sensor evolution. According with [5], these evolutions respond to issues of power consumption, data communication and system integration at the sensor level. Also, the improvements work beyond a sensor raw signal or data. They add an important level of information or knowledge to the sensor response through some features as diagnosis or advanced functionalities in collected data manipulation. In control applications, all these features contribute to improve the overall control system [6].

In this evolutionary way, redundancy or secondary measurements can be used in main sensor failures compensation [7] and in data validation (for applications with complex sensors located at remote sites) [8]. They aggregate more reliability to the process and maintain it running under critical situations of fail or incoherent measured data.

However, even the main or the secondary sensor can be out of the normal operation and this would cause wrong system actions. Thus, self-validating specific tests can be done to evaluate the sensor condition and performance through the use of all system available knowledge [9]. The sensor evolution to the known virtual sensor and the self-validating concept will be seen in more details below, after a brief description of the artificial neural networks.

The use of Artificial Neural Networks (ANN) has gained interest in the development of soft-sensors, who allows estimation of several process variables that might would need expensive sensors for its measure. Also, ANNs are applied broadly because the signals are transmitted in one direction (from the network inputs to its outputs) as in automatically control systems, they can learn from samples of different measurements and they have adaptability [10].

An artificial neural network is a simplified mathematical approach of the human brain structure. It is a powerful mechanism to simulate an adaptive intelligent behavior because its learn capability. But the network learn quality is totally related to the knowledge passed to it through the training samples. The network structure basically has interconnected nodes (process units) constituting specific tracks that are adapted through weighted links. This adaptation culminates in the minimum output measuring error related to the target. One class of adaptive neural network is the feed forward. In this class, the nodes perform specific functions on its incoming signals and the generated node output flows to the next node in a kind of mapping.

The network input-output mapping occurs based on training. A set of known inputs are applied to the network and its outputs are compared to the desired target values. The number of these inputs and outputs is fixed and related to the specific application. Also, there are several learning rules and adaptation algorithms for network training with different approaches and objectives. All of them work to adapt the network weights links to obtain a desired output behavior. The virtual sensors features can be developed by using ANN models, as will be checked in the methodology description.

Virtual sensors are designed to substitute the momentary or permanent unavailability of a sensor in a plant. This unavailability may occur when the actual sensor has failed, or when it is has been removed for maintenance, or then because there is no sensor available [7]. A virtual sensor can also be designed to estimate a main process variable that is hard to measure, from a set of secondary variables. These selected secondary measurements should satisfy the system requirements as sensitivity, accuracy and robustness [11].

Fig. 1 shows a representation of a virtual sensor connected to a process plant for fail compensation. When the sensor is working, the switch is positioned to the measured value direction and the controller device uses the sensor information for the control of the system.

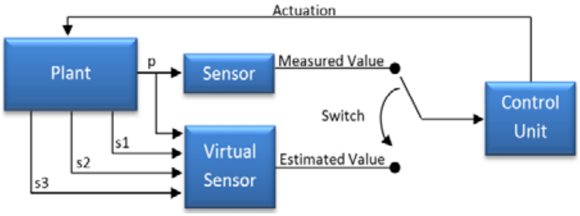


Fig. 1. Virtual sensor scheme.

When the sensor information is no longer available the switch is positioned at the estimated value and the control loop uses the information provided by the virtual sensor. In this case the virtual sensor uses, besides the main variable *p*, the secondary variables *s1*, *s2* and *s3* to estimate the value of the sensor. The fuzzy models or models based on artificial neural networks may be appropriate in certain virtual sensors applications [7].

Other important concept in intelligent instrumentation is the sensor self-validating scheme. In the classical instrumentation the calibration in short time scheduling could result in unnecessary consume of manpower and material resources. The self-validating procedures can continually monitor the sensor, giving the reliability of the measurement value [3].

In this way, Henry and Clarke [12] presented the concept of SEVA sensor. A SEVA sensor has more components than a traditional sensor, including hardware and software, which are used for fault diagnosis, data recovery and to provide specific parameters about the measurement value, its uncertainty and status [12-13]. Some of the information provided by a SEVA sensor includes:

- Validated Measurement Value (VMV), which corresponds to the conventional measurement, but if a fault occurs, the VMV is a best estimate of the true measuring value;
- Validated Uncertainty (VU), which is the metrological uncertainty, or probably error of the VMV. Uncertainty is based on existing metrological standards, and its value is calculated based upon all error sources affecting the online measurement. Thus, the VU provides useful information about measurement quality;
- Measurement Value Status (MVS) is a discrete parameter that indicates how the VMV has been calculated. As VMV must be provided at all circumstances (even in a fault) it is important to inform the user in what circumstances the VMV has been generated.

The SEVA MVS metric takes the following status: CLEAR (normal measurement), DAZZLED (abnormal measurement), BLURRED (fault that impair the measurement) and BLIND (a critical fault that destroy the measuring capability of the sensor) [9, 13-14]. In addition, the use of self-validating methods has primarily importance in safety. The system protection aspects can be guaranteed through the measurement quality assurance. This can be done because the sensor has the self-diagnosis capability through the internal signals accessibility or knowledge generated by specific device tests [12].

This work aims to develop a virtual sensor for DC motor speed estimation in a prototype plant through the use of ANNs. The virtual sensor uses information about current, voltage and the load applied to the motor, in order to estimate the speed of the DC motor. Experiments were conducted to verify the proposed approach performance. Besides, we present a self-validating module that is incorporated in the virtual sensor. In this module, a fail test circuit provides information about the virtual sensor condition with the purpose of evaluating the estimated speed quality. Depending on the combination of the speed value measured with an encoder, estimated speed and conditions of the current sensor, the information about the measurement value (based on the SEVA status) is provided by the system through a graphical interface in a computer. These features are included in a closed-loop system that uses the encoder or the estimated speed dynamically to control the DC motor speed. Also, it uses the sensor status to maintain the plant security in critical fail moments. It was conducted tests in this system and some fails were simulated to verify the self-validating status identification.

Some previous works focus only on virtual sensing [7] [10] [15], or self-validating schemes [13] [9], or smart sensors [5]. In this work we aggregate all these concepts in one speed sensor, more robust than a simple encoder or than just a speed estimator. It is capable of keeping a plant with a DC motor running, in a secure manner, during situations that normally need the motor to be stopped due to operation impairments.

2. Experimental Section

2.1. The Sensor System

The proposed system is illustrated in Fig. 2. It is basically constituted by a DC motor, its pulse-width modulation (PWM) power driver, an incremental encoder, a load variation block, a microcontroller and a personal computer.

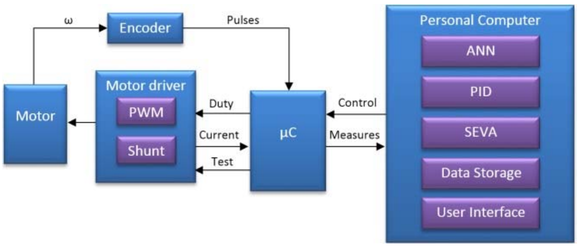


Fig. 2. Block diagram of the proposed system.

The motor is controlled by its armature voltage, which is directly related to the duty cycle of the pulse-width modulated signal applied to the motor. The motor driver is the PWM signal provider. The PWM duty cycle is the control signal from the PID controller, present in the personal computer application, and it is applied to the motor driver through the microcontroller. The motor driver has also a shunt module, this block has, besides the shunt current resistor, a fixed shunt test circuit that is coordinated by the microcontroller to help in getting the SEVA status.

Beyond that, the encoder block is always measuring the motor speed and providing this information to the microcontroller through pulses related to the motor rotation. The motor load variation is done through a generator coupled to the motor axis. This load variation is monitored by the microcontroller and manually controlled during the experiments.

The microcontroller connects the software application to the system, receiving the control signal and transmitting the shunt current, the measured motor speed and the load status. It also switches the shunt module to the test circuit when the application in the personal computer is evaluating the SEVA status.

The application running in the personal computer receives the information of the system and controls it through the microcontroller. The measures are stored and used to estimate the speed by the ANN and to evaluate the SEVA status. The SEVA status defines, between the measured and estimated speed, which one will be used as a PID input. Then, the PID is calculated and, if the system is working normally, the control signal is applied to the system. Furthermore, a user interface allows the speeds graphical monitoring, the sensor status analysis and experiments controlling.

The use of ANNs with DC motors can have the objectives of speed estimation, control purposes [10] or motor parameters identification [16]. In this work, the neural network was utilized for speed estimation and SEVA status diagnosis.

It was needed to train the artificial neural network before the experiments to compensate possible plant parameters variations due to ambient changes and/or components uncertainties. It was used the backpropagation learning rule for training because it meets the requirements of our application. The central part of this learning rule concerns in how to recursively obtain a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter. From this, it is possible to dynamically change the network weights as a manner to reach better results. In general, a typical architecture for a network is the use of three layers, an input layer, a hidden layer and an output layer. The used network has 30 neurons in the hidden layer and has as inputs the motor applied load, armature current and voltage, to estimate the motor speed.

2.2. The Self-Validating Methodology

The sensor diagnosis for self-validating methods is based on the motor current sensor (shunt resistor) tests and on the measured and estimated speed difference. The first one is necessary because the motor current is used as a neural network input and affects directly the estimated speed. Thus, when the shunt is in good conditions, an encoder failure is detected by comparing the measured speed with the neural network estimated speed. But when the shunt presents some issue, safety decisions are made until the sensor maintenance is done. In [17] the sensors faults detection requires a real time digital signal processing system, while the approach of the present study allows to clearly discerning each sensor fault through testing circuits, with minimal digital signal processing effort.

2.2.1. The Self-Validating Implementation

The shunt test is done by the scheme detailed in Fig. 3. The shunt resistor measures the current and it is connected to a DPDT relay. The relay switches between the shunt resistor connection with the DC motor (normally closed position) and the validation circuit (normally open position). The microcontroller controls the switch. The voltage over the shunt resistor, when the validation circuit is active, gives information about the shunt condition. So, when the switch is in the validation circuit position, the following conditions of the shunt resistor can be identified:

- The shunt resistor has a short circuit - in this case, the voltage presented in the signal amplifier is close to 0 V;
- The shunt resistor may be disconnected - in this case, the voltage presented in the signal amplifier will be the saturation voltage;
- The shunt resistor presents a different value of voltage than expected - in this case, according with the tolerances and uncertainty of the circuit, the shunt status can be decided to an over range or under range condition;
- The shunt normal operation – the measured voltage is in an expected value, according with the uncertainty.

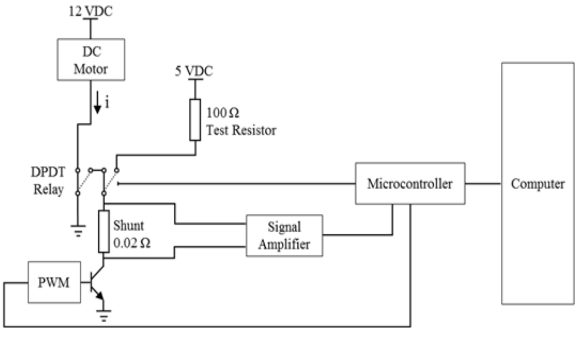


Fig. 3. Shunt resistor validating elements.

2.2.2. Uncertainty of Current Measurements

The Equation (1) clarify that the uncertainty of current measurement is given by a system which has the shunt resistor, the motor current and the instrumentation amplifier with resistor R_G for signal gain.

$$V_{out} = R_{shunt} \cdot i_{motor} \cdot \left(5 + \frac{200\ \text{k}\Omega}{R_G}\right) \tag{1}$$

Table 1 presents the sources of uncertainty considered in the evaluation. The parasite resistances were considered null and the operational amplifier was considered ideal.

Table 1. Uncertainty sources for current.

Source of uncertainty	Description	Value	Distribution	Standard uncertainty	Degrees of Freedom
$u_{R_{shunt}}$	R_{shunt} tolerance	$0.56\ \Omega\ \pm\ 5\ \%$	Rectangular	$\frac{0.028\ \Omega}{\sqrt{3}} = 0.016\ \Omega$	∞
u_{R_G}	R_G tolerance	$R_G = 6.8\ \text{k}\Omega\ \pm\ 1\ \%$	Rectangular	$\frac{68\ \Omega}{\sqrt{3}} = 39.259\ \Omega$	∞

Considering the motor current as $i_{motor} = 0.25\ A$, which is the current of the motor under the maximum applied voltage (12 V), the sensibility coefficients for Equation (1) are:

$$c_{R_{shunt}} = i_{motor}.\left(5 + \frac{200\ \text{k}\Omega}{R_G}\right),$$

$$c_{R_G} = -\frac{200\ \text{k}\Omega.R_{shunt}.i_{motor}}{{R_G}^2}$$

And the combined uncertainty is:

$$u_c = 0.141\ V$$

And the final result with 95 % confidence interval for the voltage of measured current:

$$V_{out} = 4.81\ \pm 0.28\ V$$

2.2.3. Uncertainty of the Shunt Resistor Validation Circuit

The uncertainty of the shunt resistor validation circuits given by a system which has the shunt resistor, the test resistor (100 **Ω**), the instrumentation amplifier with resistor R$_G$ for signal gain, the DC motor and the transistor used for PWM switching. Equation (2) presents the voltage over the shunt resistor during the validation test. The voltage over the transistor (collector to emitter voltage) when it is switched on is given by V_t.

$$V_{shunt} = (V - V_t)\frac{\text{R}_{\text{shunt}}}{R_1 + \text{R}_{\text{shunt}}} \qquad (2)$$

Equation (3) presents the voltage output of the signal amplifier, according to the other components.

$$\text{V}_{\text{out}} = \left(5 + \frac{200\ \text{k}\Omega}{\text{R}_\text{G}}\right).(\text{V} - \text{V}_\text{t}).\frac{\text{R}_{\text{shunt}}}{\text{R}_1 + \text{R}_{\text{shunt}}} \qquad (3)$$

Then, the Analog to Digital (AD) converted value is:

$$\text{AD}_{\text{value}}=\text{V}_{\text{out}}.\frac{2^\text{N}}{\text{V}_{\text{ref}}}=\text{A}_\text{V}.\text{V}_{\text{shunt}}.\frac{2^\text{N}}{\text{V}_{\text{ref}}}=$$
$$=\left(5+\frac{200\ \text{k}\Omega}{\text{R}_\text{G}}\right).(\text{V-V}_\text{t}).\frac{.\text{R}_{\text{shunt}}}{\text{R}_1\text{+R}_{\text{shunt}}}.\frac{2^\text{N}}{\text{V}_{\text{ref}}}$$

The sources of uncertainty considered in the evaluation are presented in Table 2. Values and uncertainties of V_t and $V_{ref} = V$ were measured using a digital voltmeter with precision of 0.5 % of displayed value + 2 digits.

The combined uncertainty of the system is:

$$u_{c_{AD}} = 4.91$$

The final result with 99 % confidence interval for voltage and measured current, the normal shunt validation voltage, expressed in AD units, is:

$$AD_{value} = 165\ \pm 15$$

Table 2. Sources of uncertainty for current.

Source of uncertainty	Description	Value	Distribution	Standard uncertainty	Degrees of Freedom
$u_{R_{shunt}}$	R_{shunt} tolerance	$0.56\ \Omega\ \pm\ 5\ \%$	Rectangular	$\frac{0.028\ \Omega}{\sqrt{3}} = 0.016\ \Omega$	∞
u_{R_G}	R_G tolerance	$6.8\ \text{k}\Omega\ \pm\ 1\ \%$	Rectangular	$\frac{68\ \Omega}{\sqrt{3}} = 39.259\ \Omega$	∞
u_{R_1}	R_1 tolerance	$100\ \Omega\ \pm\ 1\ \%$	Rectangular	$\frac{1\ \Omega}{\sqrt{3}} = 0.577\ \Omega$	∞
u_{ADC}	ADC resolution	1 ADC count	Rectangular	$\frac{1}{\sqrt{12}} = 0.288$	∞
u_{Vt}	Transistor collector-emitter voltage	$780\ \text{mV}\ \pm 5.9\ \text{mV}$	Rectangular	$\frac{5.9\ \text{mV}}{\sqrt{3}} = 3.4\ \text{mV}$	∞
u_{Vref}	Source voltage	$4.97\ \text{V}\ \pm\ 44.9\ \text{mV}$	Rectangular	$\frac{44.9\ \text{mV}}{\sqrt{3}} = 25.9\ \text{mV}$	∞

Thus, in the validation test, we consider that values obtained in the AD that are out of the confidence interval indicate that the shunt is out of the normal operation range and may present problems or be damaged.

2.2.4. Uncertainty of Speed Measurements

The uncertainty of speed measurement is given by a system which has the microcontroller and its internal oscillator. The motor speed in rotations per minute (RPM) is given by the number of pulses of the encoder during a period of time T in minutes, $P_{encoder}$. The number of segments per revolution of the incremental encoder PPR. The clock multiplier of the microcontroller, PLL_{mul}. The external crystal oscillator frequency, $\mathrm{f_{osc}}$. The number of counts for the microcontroller timer to overflow, $\mathrm{T0_{ovr}}$. The crystal oscillator frequency divider, $\mathrm{PLL_{div}}$. The processing unit clock divider, $\mathrm{CPU_{div}}$. The microcontroller timer clock divider, $\mathrm{T0_{div}}$ and the time scale factor, k. These elements are constants in the current configuration of the microcontroller: $\mathrm{PLL_{div}} = 5$, $\mathrm{CPU_{div}} = 2$, $\mathrm{T0_{div}} = 32$, $\mathrm{T0_{ovr}} = 2^{16}$, $\mathrm{PPR} = 4$ pulses/revolution, $\mathrm{PLL_{mul}} = 24$, $\mathrm{k} = 60$ seconds/minute. Equation (4) presents the speed according to these parameters:

$$Speed=\frac{P_{encoder}}{PPR.\ T}.k=\frac{P_{encoder}.PLL_{mul}.f_{osc}}{PPR.PLL_{div}.CPU_{div}.T0_{div}.T0_{ovr}}.k \tag{4}$$

Table 3. Speed uncertainty considerations.

Source of uncertainty	Description	Value	Distribution	Standard uncertainty	Degrees of freedom
u_{osc}	Crystal tolerance	20 MHz $\pm$ 20 ppm	Rectangular	$\frac{400\text{ Hz}}{\sqrt{3}} = 230.9\text{ Hz}$	∞
u_{enc}	Encoder resolution	1 pulse	Rectangular	$\frac{1}{\sqrt{12}} = 0.2886\text{ pulse}$	∞

Considering a given number of $P_{encoder} = 36\,pulses$ and a given period, $T = 145\,ms$, the combined uncertainty is:

$$u_c = 24.777\,RPM$$

The final result with 95 % confidence interval is:

$$\text{Speed} = 3724\ \pm 50\,RPM$$

2.2.5. The SEVA Details

The SEVA status definitions for this application are detailed in the following paragraphs:

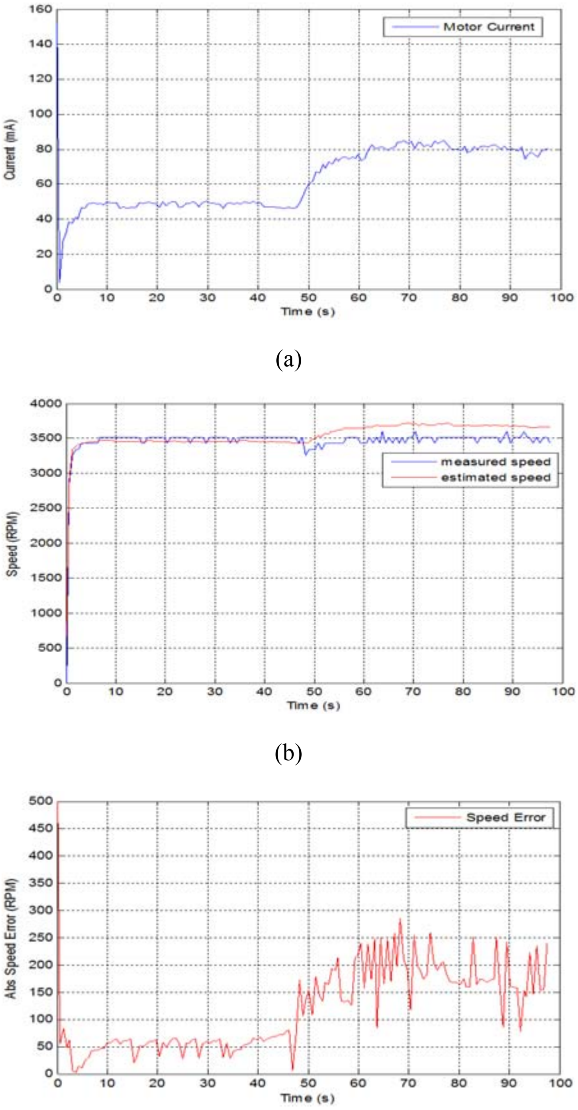
- CLEAR, when the measurement value is obtained from the encoder, which is in good condition and no fault is detected. The control operates normally;
- BLURRED, when an instantaneous encoder fault occurs and the shunt test result is in a normal operating range. In this case, the sensor output is the speed estimation, from compensation and correction methods, through the neural network. VU is enlarged, corresponding to the encoder fault condition and the speed estimation through secondary variables. The control operates with the estimated speed;
- DAZZLED, when the encoder is in good conditions but the shunt test result deviates from the normal operating range. This is an awkward situation because if an encoder failure occurs, the speed estimation will be degraded because the abnormal shunt condition. The control is maintained in the last valid value, calculated in a past moment when a measurement was done in a CLEAR or BLURRED sensor conditions;
- BLIND, when an encoder fault occurs and the shunt test translates a fail. In this case, even the measured or the estimated speed will be wrong and there will not have a system reliable parameter that would allow any correct control action. Therefore the control stops and the motor is stopped too.

3. Results and Discussion

From the artificial neural networking basic theory, the sensors self-diagnosis idea, and the virtual sensor concept, it is possible to evaluate the obtained results and to discuss about it. At first, it was analyzed the effect of load variation in the motor. After that, it was realized the neural network training data acquisition and then the experiments with neural network operation.

3.1. Evaluation of Load Effect in the Measured Motor Current

If a load is connected to the motor axis, the motor current grows to maintain the same speed in a closed loop system. This occurs with a current elevation in the motor drive circuit and if the network was not trained to manage this current variation, it will miss the estimated speed. This can be noted in Fig. 4 below, where about the time of 50 seconds a constant load is applied to the motor and the motor current grows from about 50 mA to 80 mA (a). The consequence is the wrong ANN estimated speed (b) and the difference between the measured and estimated speed goes near to 200 RPM (c).



(a)

(b)

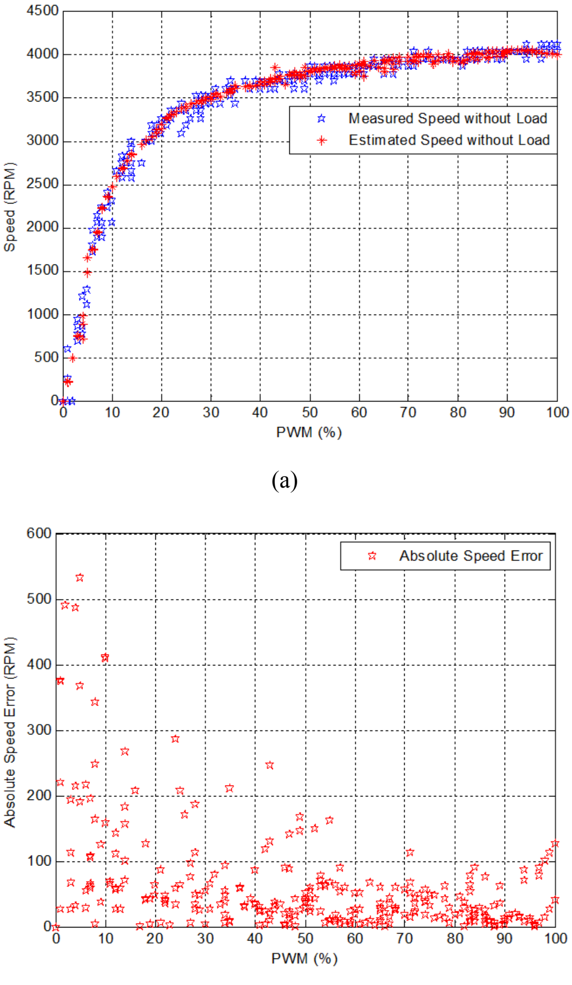
(c)

Fig. 4. (a) Motor current showing the load effect.
(b) PID measured and estimated speed.
(c) Absolute speed estimated error.

3.2. Evaluation the Speed Estimation

In this experiment, the trained network was used to estimate the rotation of the motor and the estimation was compared with the measured rotation. The duty cycle was randomly changed, we waited the speed stabilization, and after 500 milliseconds a speed estimation and the speed measurement sample was collected. We compared the results of 300 samples without load applied (Fig. 5) and with load applied (Fig. 6).

Without load applied, Fig. 5(a) shows the measured and estimated speeds for different duty cycles, while the Fig. 5(b) illustrates the speed differences. In this situation, the mean error stays about 61 RPM. When the load is applied, Fig. 6(a) shows the measured and estimated speeds for different duty cycles, while the Fig. 6(b) illustrates the speed differences. In this case, the mean error stays about 67 RPM.



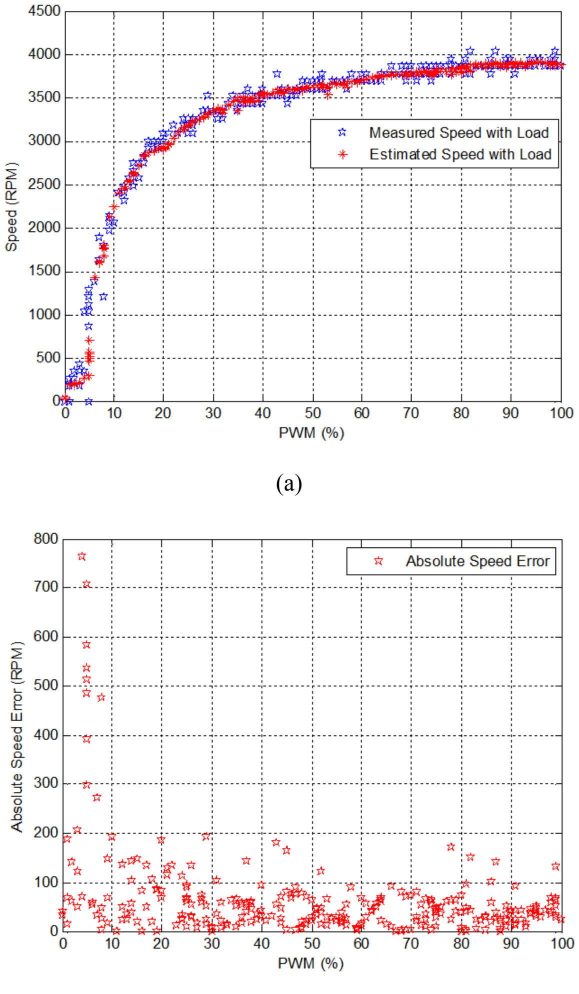
(a)

(b)

Fig. 5. (a) Measured and estimated speed without load.
(b) Estimated speed error without load.

3.3. Operation with Events

With the results obtained, it is possible to progress for an experiment closest to the real system operation. Therefore, a test was executed (Fig. 7) for a setpoint of 3500 RPM, exciting the system with probable events that could happen. The experiment begins with a load free situation, after that an encoder fail is simulated (t = 10 s) and during this fail a load is applied to the generator (t = 22 s). Passing some seconds, the encoder is recovered (t = 40 s) and then the load is removed (t = 52 s).



(a)

(b)

Fig. 6. (a) Measured and estimated speed with load. **(b)** Estimated speed error with load.

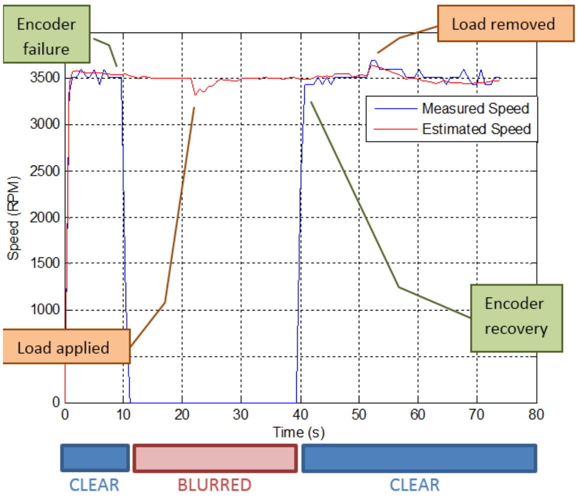


Fig. 7. System operation in 3500 RPM setpoint with events.

According to [7], changes in the measure used to realize the control could degrade or even cause instability in a closed loop system. However, the Fig. 7 shows that the system can deal with an encoder fail without problems. The system operates normally even under a motor load variation, which increases the motor current but do not affect the network speed estimation. Also, the load removing event was identified by the system and thus the properly speed estimation was done. During this test the status of the sensor was showed to the user as presented in Fig. 7, below the speed graphic.

4. Conclusions

As seen in this work, the addition of new features to the traditional transducer is a manner to increase the system robustness, efficiency and safety. Some features may allow that eventual sensor maintenances or failures can occur without the need of stopping the system. In the proposed speed sensor, if an encoder fail occurs the system will continue operating using an estimated speed by an artificial neural network. In case of measurement deviations the system will maintain a safety operation.

If an encoder and the shunt resistor used for current measurement fail occurs together, then the system will stop as a security decision. All these situations are translated into SEVA status and show the virtual sensor relevance in speed systems control. The next research ideas are related to self-identification and self-adaptation methods besides the system integration and tests in more elevated power motors. These procedures are all in a way to ease the sensor integration to the system, reducing the errors and growing the plant controllability.

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