PRACTICAL ASPECTS FOR DESIGN OF INDIRECT MEASUREMENT IN DYNAMIC SYSTEMS

L.F. Mouzinho[1], J.V. FonsecaNeto[2], B.A. Luciano[3], R.C.S. Freire[3] and J.F. CarneiroJr.[4]

[1] Department of Electronic and Electrical Engineering - CEFET/MA, São Luís-MA, Brazil
e-mail: mouzinho@dee.cefet-ma.br.

[2] Department of Electrical Engineering, UFMA, São Luís-MA, Brazil
e-mail: jviana@dee.ufma.br.

[3] Department of Electrical Engineering, UFCG, Campina Grande-PB, Brazil
e-mail: benedito@dee.ufcg.edu.br, rcsfreire@dee.ufcg.edu.br.

[4] Redentorista Technical School, Campina Grande-PB, Brazil
e-mail: joaquimfcj@yahoo.com.br.

*Abstract – In different areas of science and engineering are used different indirect measurement procedures that lead to obtaining the quantity desired. In this paper is described the considerations about indirect measurement system (IMS). Is realized the analysis between direct measurement and indirect measurement, presenting the limitations of the estimator. The **IMS** are classified under the methodological point of view. Practical considerations for design of **IMS** in dynamic system are specified, as clock cycle, time of hardware execution and software, size of the memory of data and program, represented for quality; system modelling; error estimations and uncertainty in indirect measurement.*

Keywords – error estimation, indirect measurement, dynamics systems.

I. INTRODUCTION

In a indirect measurement system, **IMS**, the process to obtain the value of a indirectly measured quantity, takes into account that the values specified as input are originating from a direct measurement. The criteria to use a **IMS** is related with the impossibility of direct measurement. The **IMS** is useful in situations in which is had difficulties to accomplish a direct measurement. Some of those situations can be for safety, time, access or still due to no existence of sensor or transducer to obtain the value of one certain quantity. To indirect measurements can be, also, used when is desired obtain more reliable results than those obtained by conventional methods or still to reduce one group of way procedures for if know the value of one quantity. In the indirect measurement is necessary to have, previously, the knowledge of some quantities and, starting from the relationship among those quantities and that one desire to know, it can be obtained the value of the unknown quantity. The relationship among the known quantities and that one desire to know is realized through the techniques of indirect measurement.

In identification of systems, mathematical models in systems dynamic can be realized and implemented starting from measures observed. The information obtained starting from observations is fundamental for model of dynamic systems. These observations can be the measures of signals obtained through direct measurement systems or indirect measurement systems, depending of the form as is obtained mesurand. If the device generates a electric signal starting from a sensor one that has for objective to detect variations of the quantity of the interest, the measurement system is denominate direct measurement. If the mesurand is obtained starting from quantity that are not directly related with the variations of the quantity to be measured, the system is called of indirect measurement system. Some solutions of isolated problems is used of several algorithms of estimate, as in [1]-[25]. The knowledge of process is possible through the measurement in that are verified amounts of interest that contribute to the control and the optimization of a system. The **IMS** is the link between the plant and the control system or supervision.

Each technique should be used conformable the application, could be used separately or together to obtain the quantity that interest is had so that the execution time of a certain algorithm it is reduced and the result be more exact. The evaluation of the performance global of the **IMS** it takes into considerations the different types of applications. In each one application is used different metric for the performance. The problem of the chosen technique constitutes one of the limitations for the development of **IMS**. The indirect measurement systems in real time, **IMS-RT**, present necessary characteristics to provide support enough to the applications in which the indirect measurement possesses temporary restrictions. These restrictions can be subject to the open and unexpected environment, as example, in industrial automation (verification of the speed of an induction machine) and in the aviation (supervision of the aerospace vehicles path).

II. SYSTEM DEVELOPMENT

The conception of **IMS** is based on finding answer for the estimate of a quantity of interest starting from one or more observers [38]. The objective is obtain a system, where the output to be related to the quantity of interest. The quality of **IMS** can be evaluated conformable the application and the function of developed estimator. The acting of the estimator, however, it presents some limitations, as: information initial of observer about the quantity of interest; experience in obtaining those information (chooses of the technique of indirect measurement) and algorithm developed to extract in an efficient way such informations. Among the mentioned requirements, what possesses a larger impact in the development of system is the choice of the technique of indirect measurement to be used to that it is possible to extract the information from the input quantities appropriately. In Fig. 1 is shown the diagram in blocks of the one or more quantities direct measurement as intermediary for the indirect measurement with base in model. The computational calculation based on model requests values of quantities that are measured directly and, starting from these, the development is proceeded.
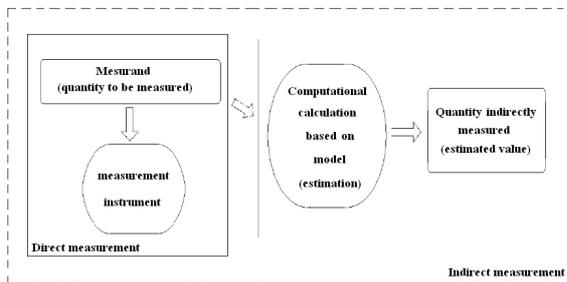

Fig. 1. Indirect measurement process of a quantity starting from the direct measurement of another quantity

Usually, the measurements present some error type. In the indirect measurements those errors come in the variables used in the computational calculation for determination of the quantities of interest. There be a propagation of the uncertainty of the direct measurement during the computational calculation to determine the quantity interest. If the measure is not exact since the real value of an input quantity is not exact, consequently, the value measured indirectly won't be also. To realize the indirect measurement will be necessary some items that contributes for a good result of the measurement.

Considering the several works in indirect measurement published it is verified that the choice of one or more techniques it requests certain ability and experience in obtain the information of input. When cannot apply directly one or another algorithm already known it is necessary to develop a mathematical modelling of the system to estimate the value of the quantity that is had interest. That mathematical modelling requests detail of the system.

The problem of the choice of the technique constitutes limitations for the development of **IMS**. An inadequate choice can to generate the resulted no desired, time of execution during the processing high and slow answer.

III. INDIRECT MEASUREMENT SYSTEM

When the indirect measurement is associated to complex systems several estimate techniques to solve the problem can exist. Different complexity measures exist, some of them can simply be related with the amount of different elements that compose a system, what is, actually, a partial measure, because it disrespects the relationships among the elements of the system. Another measured are related with the number and intensity (connection degree) of the relationships among the elements of the system, forming an inextricable network of relationships. Another measured can be related with the relationship between the number of different elements of the system and the number of functions accomplished by the system, so that a system with small number of different elements and a larger number of functions is more complex than a system with a great number of elements, but with relatively few functions [27]-[29].

The indirect measurement systems are classified in this paper under the methodological point of view in mathematical modelling, defined algorithms and heuristic.

A. IMS starting from the Mathematical Modelling

In the *Mathematical Modelling* it is looked for to obtain an idealized model of one system usually through differential equations or difference equations [30]. Some restrictions are considered of forms that the mathematical model can be simplified, such as that the linear time invariant system. Due to the simplifications, the development of a mathematical model to adapt a real situation cannot describe one significant mathematics and realist of the system. Although that methodology is used by not having knowledge or a technique that describes the system, is due to take in consideration that other factors as physical phenomena or chemical, external disturbances and inexact values also affect the accuracy of the model. The deterministic and stochastic models are usually used in robust control systems, characterized by taking in consideration disturbances unknown, however with limits or known widths. In stochastic model, as example, it can be increased noises to the signals through stochastic parameters [31].

B. IMS through Well-Defined

In this work the *Well-Defined* are considered as all of the algorithms already developed that are used for applications in indirect measurement. The convergence of an algorithm is related with a good definition, considering the characteristics of the points limits. The optimal choice of an algorithm is associated to the a verification of the system, if is linear or no linear, or it is still possessed restrictions [32], [33]. The list of

some algorithms that were applied in indirect measurement are apresented:

- Genetic algorithms;
- TALUS algorithm;
- Artificial Neural Networks(ANN) algorithm;
- Kalman Filter algorithm;
- others computational methods: evolutionary algorithms, distributed algorithms, quadratic minimization, systems of nonlinear equations, unrestricted minimization and linear resource, unidimensional minimization algorithms, linear restrictions, penalization algorithms, generalized reduced gradient algorithm, methods without differentiation, Lagrange method, homotopy method e global minimization method.

C. Heuristic IMS

Is classified here as *Heuristic SMI* the cases of indirect measurement in that are used methods based in the experience with practical rules and strategies already frequently used to obtain the value of a certain quantity. In this case, the linearity restriction is not more necessary or even relevant, once the function input-output is described point to point. In one *Heuristic SMI* exists the possibility to obtain one function of input versus output, no mathematics, and useful in the description of a plant or process. In this measurement type the tool considered more appropriate, conform [34], is the logic fuzzy.

Several problems in indirect measurement are verified and the solution obtained through of the *Well-Defined*, *Mathematical Modelling* and *Heuristic*, as in [35]-[45].

IV. EXPERIMENTAL ASPECTS OF INDIRECT MEASUREMENT IN DYNAMIC SYSTEMS

In this Section are presented three cases of indirect measurement that were presented in [1], [19] and [20] using the techniques Artificial Neural Network and Kalman Filter. In all those presented cases, the procedures were the same ones, to know: modelling of the system; the choice of the measurement technique; development of the algorithm; execution of the algorithm in MATLAB and in C language; transfer of the algorithm in C language for CPU of an architecture reconfigurable and comparative analysis among the directly measured quantity and the indirectly measured quantity.

A. Indirect Measurement of the Rotor Speed

The indirect measurement of the rotor speed in an induction machine it was presented in [1]. The technique of indirect measurement used was *ANN*. The behavior of the stators voltage and currents, rotor flux and rotor speed in the environment MATLAB it was analyzed. After, *ANN* algorithm was developed so that, starting from the set of input signals, stators voltage and current, the training was realized. The *ANN* estimated value of the rotor flux. The rotor speed it was one of *ANN* three weights and, with the minimization of the error, it was obtained the measurement of the rotor speed.

The good performance of the indirect measurement is verified when compared to the values of the direct measurement (the tachometer) and for the architecture in regime. In this case, in the tachometer $1790.00\ rpm$ was visualized, considering the motor no load. The speed obtained by simulation it was $1798.80\ rpm$ and the speed obtained by the indirect measurement was $1791.94\ rpm$.

B. Indirect Measurement of the Speed of an Aerospace Vehicle

In [19], an algorithm is presented in real time for filtering of trajectories and indirect measurement of the speed of aerospace vehicles. This algorithm was based on filtering type Kalman standard and implemented in an architecture reconfigurable. The algorithm was developed, taking into account the restrictions in real time of the system of acquisition of trajectories signals and the characteristics of the hardware of the filter satisfy the demands of execution time and requirements of memory of the algorithm. The results obtained by simulation and for experiments were compared with trajectories signals of the brazillian center of rocket launching's. The proposed algorithm presented a good acting in relationship to the execution time and a smaller discrepancy 2% after the filter's stability period.

C. Indirect Measurement of the Temperature of an Object Inside an Furnace

The development of an indirect measurement model for electro thermal furnace and its implementation in a reconfigurable architecture are presented in [20]. The proposed measurement system is based on the system model, the principle of conservation of energy and the laws of thermodynamics are applied to build a model of the thermal system and the **Kalman** theory is applied for filtering and prediction of the temperatures inside of a resistive furnace. Three setup are established to evaluate the performance of the indirect measurement system: implementation off-line of the algorithm on a test platform, the indirect measurement system is connected on the furnace hardware for standalone and real time operations.

The algorithm was implemented in a low-cost reconfigurable architecture, an AD Converter block receives the temperature values from sensors located inside the furnace and performs the estimation temperature processing of an object without associated sensors. For monitoring and control requirements match, the proposed indirect measurement device had shown as an alternative for optimal estimation of temperatures.

A comparative analysis performed between those two measurements (direct and indirect measurement) verified that the average error of the indirect measure inside the material is of 1.47, approximately.

V. PRACTICAL CONSIDERATIONS FOR DESIGN OF IMS

As mentioned, in many practical situations quantities that present difficulties to accomplish the measurement exist and

one of the used alternatives is the indirect measurement. In this case, it is necessary to know some quantities and, starting from the knowledge of the relationship among those quantities, it can be obtained the value of the desired value. In practice, the estimate error is one of the important items in that measurement type, this why in most of the indirect measurements, the system in which one want to know the value of the quantity is unknown.

A. Quality and Fidelity of the Indirect Measurement

Besides the appropriate choice of the technique used measurement, the quality of **IMS** is associated the need of fast estimates with metric of quality, such as: clock cycle, time of hardware execution and software and size of the memory of data and program. When it is treated of the specifications and projects of a **IMS** for use in real time is necessary to follow the recommendations of the several references on system in real time, such as: estimation of the hardware, estimation of the software and other metric.

The indirect measurement can be simplified to obtain results faster, however it can be incurred estimate error and low accuracy. The high level of accuracy not always is necessary since the estimated value is obtained with metric of quality, allowing alternatives for realize of decisions. The technique of indirect measurement chosen should present fidelity. Conform [46], the fidelity of the indirect measurement is defined considering $D = D_1, D_2...D_n$ as a set of implementations in,

$$\mu_{ij} = \begin{cases} 1, if & E(D_i) > E(D_j) \text{ and } M(D_i) > M(D_j) \text{ or} \\ & E(D_i) < E(D_j) \text{ and } M(D_i) < M(D_j) \text{ or} \\ & E(D_i) = E(D_j) \text{ and } M(D_i) = M(D_j) \\ 0, otherwise. \end{cases}$$

where E and M represent the estimated and the actual measured values, respectively, of a quality metric for a design implementation D; μ_{ij} for all i, j such that $1 \leq i, j \leq n, i \neq j$ and n an analyze between two estimated and actual measured values. The optimal fidelity of the indirect measurement can be writing as:

$$\max \ 100 \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=i+1}^{n} \mu_{ij} \qquad (1)$$

The indirect measurement, associated to quantity direct measurement accumulates uncertainties in measurements along the estimate process [46], [47].

B. System Modelling

A common practice for the mathematical modelling of dynamic systems is to realize considerations about the system. Should be considered that the system is linear time invariant (LTI), causal, and of finite-dimension. Then, the description in the state-space is given by $\dot{x}(t) = Ax(t) + Bu(t)$, $y(t) = Cx(t) + Du(t)$[51]. From problems involving signals

filtering, it is had: $\dot{x} = Ax + B_u u + B\nu$, $y = C_2 x + D_2\nu + w$, with $x(0) = x_0$. Is added noises to the system and the measure represented by ν and w. The value estimate, z, is obtained starting from noisy measures y. Is show in Fig. 2 a general configuration of filtering, with $z = C_1 x + D_1\nu$. In [51] it is defined that a stable filter presents limited estimate error when for all of the finite initial states of system and of filter the estimation error $\tilde{z}$ is limited where the input of system limited ν and w.
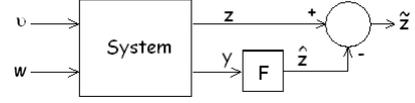

Fig. 2. Filtering Configuration

C. Error Estimations and Uncertainty in Indirect Measurement

The error estimation for an indirect measurement can be divided in two settings: statistical and interval. In the statistical error, is considered that the error of the measures $\Delta x_i = \tilde{x}_i - x_i$ are independent Gaussianas random variables with 0 average and known standard deviations σ_i. In this mode the error estimation is considered optimal. While in the error for interval, only is considered the measurement error Δx_i, $\Delta x_i \in [-\Delta_i, \Delta_i]$, when know Δ_i and, in this mode error estimation, a new algorithm is obtained that until it cannot be great, however it will be better than the previously known [52].

From a Metrology point of view, the measurement process rarely it consists of a direct measurement. To express the result of one indirect measurement with the associated uncertainty, it should be followed the recommendations of the *Guide to the Expression of Uncertainty in Measurement* (GUM). In any method used to obtain the propagation of the uncertainty in indirect measurement is necessary there to be compatibility with the (GUM).

The uncertainty concerning the result of an indirect measure is related with the sensibility of the technique used. In the case of the technique of indirect measurement Artificial Neural Networks, the uncertainty of result of measurement is related with the training type, in other words, how to find the weights w_{ki} in way to approximate the function neuronal of the desired function. Some practical considerations should be verified from way to obtain the better estimate in Artificial Neural Networks, as example, that the number of occult layers it doesn't exceed the number of input, because the vectors of the weights $\vec{w}_k \triangleq (w_{k1}, ..., w_{kn})$ are linelly independent. There are others practical considerations that contribute for that the learning process is more satisfactory, such as [55]-[59]:

initialization of weights - it suggests that the weights are initialized symmetrically around zero, in other words, among $-\frac{1}{2}$ and $\frac{1}{2}$ or -1.0 and 1.0;

activation functions - it suggests that nor all of the functions of activation are lineal;

learning rate (η) and momentum coefficient (α) - good results have been obtained with values of η among 0.1 and 10. And from α, typically values among 0.10 and 0.90 or initializing with small values and during the training that this value is increased;

others - training type and criterion of stop of training.

From the technique of indirect measurement Kalman Filter, the measurement uncertainty can be attributed the choice variance and covariance values.

VI. CONCLUSIONS

It is important to observe, seeking a satisfactory project of indirect measurement systems, that the problem of the chosen technique constitutes one of the limitations for the development of **IMS** and that an inadequate choice can elevate the time of execution during the processing, tends as consequence slow answer. Another important factor is the quality of **IMS** that should be associated to the need of fast estimates with metric of quality, such as: clock cycle, time of hardware execution and software and size of memory of data and program.

It is fundamental that the error estimation are analyzed, because, as mentioned, in most of indirect measurements, the system in which one want to know the value of the quantity is unknown. A filter, for example, is stable when it presents limited estimation error for all of finite initial states of system and of the filter. The error estimation is limited when the input of system are limited. The uncertainty of result of an indirect measurement is related with the sensibility of employed technique together with the uncertainties originating from of direct measurement.

For each technique used in indirect measurement is necessary to know the parameters that contribute to the propagation of the measurement uncertainty, so that is possible to extract the information appropriately, obtaining the result accuracy.

VII. ACKNOWLEDGEMENTS

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