Robust Design of a Control System Instrumentation

Using Structural Analysis and ANFIS Neuro-Fuzzy Logic Approaches

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***Abstract*-This paper focuses on the robust design of control system instrumentation; it proposes a design approach for determining the best hardware architecture of a control system. This method is based on Structural Analysis which consists of selecting the most relevant input variables of the system, and constructs the model Adaptive Network Fuzzy Inference System ANFIS for modelling the system that is used to quantify the dependability constraints according to Quality of Performance QoP based on the uncertainties measures from the sensors, and actuators implemented in the design phase of the control system. In this work, the speed control system $v_{t+\delta t}$ of an electrical vehicle is used as an illustrative example. A method to optimize the instrumentation is presented; it uses financial cost and dependability as criteria.**

Keywords- Design of a Control System Instrumentation, Structural Analysis, Quality of Performance, ANFIS Model

I. INTRODUCTION

Several recent studies [1-4] have proposed the possibilities for more dependable control of development autonomous vehicles by using knowledge of road slope data additional sensors. Drivers today drive on the road slope making fuel costs a major expense. The multitasking control systems propose the orientation to several ways of the concepts robust design of vehicles.

There has been much research on the robust design of control system [5, 6]. The design of fault tolerant control system using structural model is given in [7]. Reference [8] shows an approach to optimize the instrumentation using financial cost and dependability as criteria. In [9], the problem of co-design of distributed Bayesian networks for the control loop was addressed which influences the Quality of Control (QoC) and the Quality of Service (QoS) for the wireless network. For our case study of quality of performance QoP, it concerns the ability to guarantee the performance and robustness of a system of the vehicle in design phase; it essentially depends on the control. Before study the quality of performance, we will give the specification of parameters that influence the QoP (which are the sources of disturbances: the slope of the road αt and the uncertainties of the sensors). To study the influence of disturbance on the performance of the control, we need to set different intervals of states for QoP using the quantization of unknown physical quantities using AN F IS model.

In the last decade, there has been significant research effort in the structural analysis [3-8, 10-14]. The step of design in the reference [3] concerns the ability to guarantee the performance and robustness of a system of the vehicle in design phase using the Fault Tolerant Level (F T L) as criteria; it essentially depends on the control algorithm which consists in finding all paths of the control u(t) based on a structural model that link the physical variables for electrical vehicle. The structural analysis model is presented in [4] in order to take into account different states cases of system for example, the slope of the road constant and variable, also the problem of reject disturbance using graphical tree techniques from approach structural analysis is given. References [5] and [6] present an extension of the structural modelling according to different behavioural modes for a tank process. The reference [10] defines that the structural modeling is an important tool in the immense stage of control system design using a poor knowledge of the system.

The criterion of quality of performance can be judged from the overshoot in the case of a step response, the accuracy, phase margin, response time. A criterion of QoP could be a combination of these criteria [15]. The criterion of QoP can also be defined as a function of the position error, as is the case in reference [16].

Adaptive Network Fuzzy Inference System (AN F I S) is based on order Takagi Sugeno (T S) fuzzy model using a network adaptive capabilities and the fuzzy logic approach [17, 18]. It is useful in many applications demonstrating the good performance and robust of ANFIS in approximation of nonlinear relations with multiple inputs and multiple outputs. The reference [19] gives the numerical validation performance of three AN F I S models for a complex water treatment process. In [20] the ANFIS model has been used to assess the quality of water and its goal is to approximate the water quality status in function known characteristics of the process.

This work is an extension of results presented in [4], it focuses on the robust design of instrumentation for determining the best hardware architecture of a control system according to these main contributions:

• The interest of the use the structural analysis is to model qualitatively the links between variables and constraints and deduct relations between variables, more especially select the influential input variables on the system thanks to graphical tree, this method is applicable despite imprecise knowledge of the system; particularly the behavior of the system for the case of the electrical vehicle moves on the variable road slope as illustrated in the Fig. 2 in the reference [4].

• Use the ANFIS neuro-fuzzy to quantify the quality of performance QoP based on selected data parameters by the structural analysis (graphical tree) which are most influential in the control of the unknown physical quantity. The speed control system $v_{t+\delta t}$ of an electrical vehicle on road slope is used as an illustrative example application.

• To obtain optimal instrumentation that takes into account the criteria of dependability relative to QoP with low cost, despite the influence of disturbance following: the slope of the road and uncertainties sensors.

In this paper, the first step of robust design approach of control system aims essentially at selecting the parameters of instruments that has influence on the system, using the structural analysis and also it is possible to use another method for example the correlation between the variables like the Principal Component Analysis (PCA) from data provide by actuators and sensors. Secondly a controlled system can be modeled by ANFIS model, that is to say, taking advantage of the architecture of ANFIS model in order of T S structure.

After finding a first global vision of potential hardware architecture, the designer assesses its characteristics(costs, reliability, quality of performance, fault tolerance level) in order to determine its points and possible improvements in design phase. More especially, its aim is to provide a help to the designer for finding the hardware architecture of this system. The designer searches to find the best architecture, that is to say the number and the type of sensor and actuator. In this context, two criteria's will be used to define the best set hardware architecture instrumentation:

• The dependability of the system according to the quality of performance QoP.

• The financial cost of the whole system that has to be as low as possible.

After the designer will choose the best set of architecture that has the best ration cost/dependability as shown in Fig. 1 where the value of dependability desired is defined par designer in the phase of objectives and specifications for design control system.

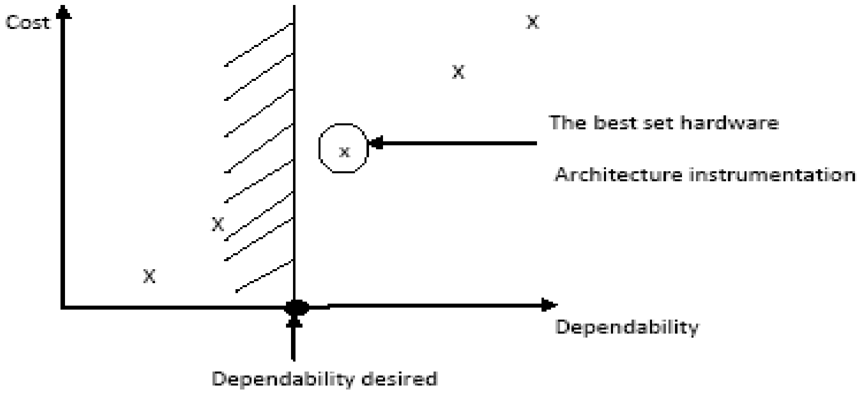

Fig. 1 The design approach concept using the dependability constraints and cost criteria for the control system

II. STRUCTURAL ANALYSIS AND MODELLING

Structural modeling requires a set of physical variables linked by a set of relations. It is used to qualitatively represent the interaction between the variables without explicitly knowing the constraints. The structural analysis allows some properties such as observability, controllability and monitor ability properties to be determined, despite the little information in the model [4, 10, 12].This article shows that the structural analysis is a good tool to select the inputs for ANFIS model, despite a lack of precise model of the control system.

A. General Principle

A structural analysis can be represented by a bipartite graph [4], [13], which gives a representation of the links between the physical variables Z and constraints F of the process as follows:

$$S : \{F\} X \{Z\} \rightarrow \{0, 1, -1\}$$

• $S(f_i, z_i) = 1$ if and only if the variable z_i appears in the constraint fi and if its value can be deduced from the others variables appearing in f_i .

• $S(f_i, z_i) = -1$ if and only if the variable z_i appears in the constraint f_i but its value cannot be deduced from the others variables appearing in f_i .

• $S(f_i, z_i) = 0$ if the variable z_i does not appears in the constraint fi .

This modeling can be represented by an incidence matrix where each row is associated with a constraint and each column with a variable [4]. For example, the matrix on Table 1 corresponds to a process of electrical vehicle as shown in Fig. 2. The available instruments for this vehicle are: Electrical motor, Speed sensor C_V, GPS. The considered variables are the following ones: a is the acceleration of the vehicle, v is the speed of the vehicle, x is the position of the vehicle, U is the control signal of the motor, C_V is the measure given by the speed sensor. The variables x, v and a are linked by the constraints in equations (1) and (2):

$$v(t) = \frac{dx(t)}{d(t)} \tag{1}$$

$$a(t) = \frac{dv(t)}{d(t)} \tag{2}$$

We put the value 1 between GPS and x in incidence matrix because x is the measure of the position from GPS, the same principal for Cv and U. The two constraints are not an invertible function if the initial state is unknown. Consequently, the value of x cannot be deduced knowing only the value of v, while the contrary is true (this is valid in constraint 1), the same principal for second constraint, for this reason, we put the value −1 in incidence matrix. Finally, a brief note on how time differentiation in dynamic systems is handled here. There are at least three different ways to represent time differentiated variables:

• To extend the model with equations describing how, for example, x(t) is related to $\dot{x}$ (t)through the differentiation operator. This means that relations who is added for each variable that appear differentiated in the original model [21].

• To consider x and $\dot{x}$ are separate variables and perform structural differentiation of the model [22].

• To consider the variable x and the derivate operator dx/dt are the variables and to treat dynamic equations in the same way as static equations.

All three are possible choices, but for the structural analysis used here we select the second approach.

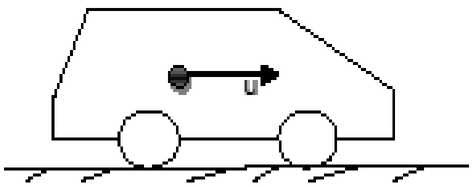

Fig. 2 The electrical vehicle moves on flat road

The studied model is represented by an incidence matrix, in which each row corresponds to an equation and each column to a variable. An x in position (i, j) indicates that variable j appears in equation i

TABLE 1 INCIDENCE MATRIX FOR VEHICLE ON FLAT ROAD

sensors		actuators	physical quantities		
GPS	C_v	U	x	v	a
1			1		
	1			1	
		1			1
			-1	1	
				-1	1

B. Structural Analysis

The reason for the choice of structural analysis approach is that this analysis uses a poor knowledge of the system; it uses only the relation between constraints and variables. Structural analysis is concerned with properties of the system structure. Structural information here means which variables appear in which equations and constraints [14]. Now it will be briefly outlined how an analysis of the structural model can provide, a means to represent the different constraints that link physical quantities to know if a physical quantity may be evaluated according to the other variables. Another interest of this modeling is that it does not need the exact establishment of physical equations. Consequently, this model is easily constructed and the design phase is accelerated faster. The types of variables in a structural model can in a diagnosis context be divided into [4, 8]:

• Known physical variables, from the sensors and actuators.

• Physical variables are supposed unknown.

• Modes or states of the system for which the relations are considered valid.

The types of relation of constraints in a structural model can in a diagnosis context be divided into:

• Those related to physical constraints verified whatever the operating mode.

• Those linking physical quantities and measurement capabilities.

• Those specific to particular modes or states of the system.

III. ANFIS A HYBRID TOOL FOR QUANTIZATION

A strong focus of the neuro-fuzzy ANFIS model research has shifted towards the quantization of nonlinear functions, especially for modeling and system identification [23]. The main application area of neuro-fuzzy systems is in control and decision support systems. In control, in the context of fault diagnosis, however, the ability to build decision support systems is more important. In this work, the ANFIS is the tool of quantizing unknown physical quantity based on data selected by the structural analysis.

A. T S System

AN F IS system performs a linear approximation of the output variable by decomposing the input space in different spaces, consider Fig.3 to describe the architecture of an ANFIS system and briefly explain the inference mechanism of such a system. [25] proposed a more detailed network has three inputs and one output, a system ANFIS consists of five layers, and each layer may contain several nodes. To ease the writing, this system is not fully connectionist (partial links between layers 1 and 2) but the principles described below are generalizable.

The overall output is then determined as the weighted sum over all consequences. A Frequently employed learning algorithm is the AN F IS proposed by [24]. The inputs are used twice: They are inputs of the fuzzification layer and at the same time inputs of the consequences. The membership functions are triangular functions trimf and t-norm is a product operator. An important step is the normalization of the membership functions performed in the layer 4. A very similar structure is present in the Local Linear Model Tree (LLMT) approach presented by [23]. The only difference to the ANFIS structure is the use of multi-dimensional membership functions whereas ANFIS uses a grid-based structure of membership functions with explicit AND-operator. The two approaches further differ in their learning algorithms [23].

The architecture of ANFIS consists of five layers for a first order Sugeno fuzzy model, then the system presents 8 inference rules, a typical rule if then rules can be expressed as:

R_j : If x_1 is A_i^j and x_2 is B_i^j and x_3 is C_i^j , then

$$y_j = p_i^j x_1 + q_2^j x_2 + g_3^j x_3 + r_i^j \tag{3}$$

For simplicity, we assume the fuzzy inference system under consideration has three inputs x_1, x_2 and x_3 and output y; a brief introduction of the model is as follows. In the layer 1 allows the “fuzzification” of the variables x_1, x_2 and x_3. The parameters used in the activation functions (typically, it is Gaussian or triangular) are called parameters “premises”. The value obtained while μ_{A1} represents the degree of membership of the value of x_1 for all A_1.

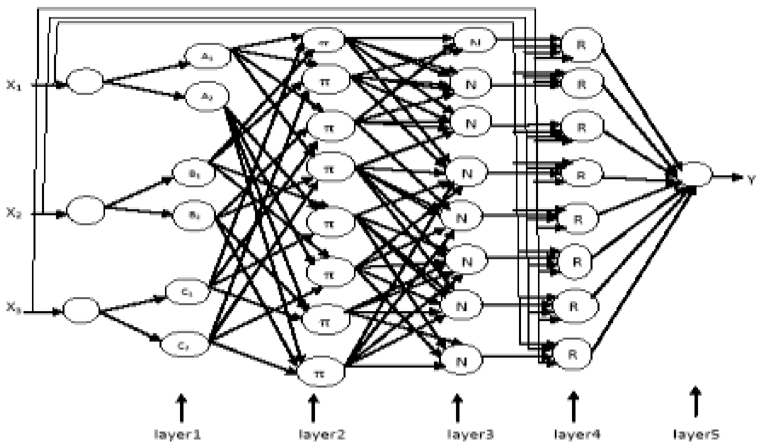

Fig. 3 The ANFIS architecture (for 3 inputs and one output)

In the layer 2 each node corresponds to a T-Norm fuzzy (T-Norm operator allows realize the equivalent of "AND" Boolean). It receives the output nodes of fuzzification and calculates its output value produced by the operator (this operator is generally used but there are others: max, min...).

$$\mu_j = \mu_{A_i^j}(x_1)\mu_{B_i^j}(x_2)\mu_{C_i^j}(x_3) \quad i = 1,2,3 \tag{4}$$

In layer 3 normalizes the results provided by the previous layer. The results represent the degree of implication of the value in the final result. Each node in layer 4 is linked to initial input. We calculate the result according to their input and a linear combination of the first order of the initial inputs (Approach Takagi-Sugeno). The output of this layer 5 computes the overall output as the summation of all incoming signals:

$$Y = \sum_{j=1}^{8} \mu_j \left(p_i^j x_1 + q_2^j x_2 + g_3^j x_3 + r_i^j \right) \Big/ \sum_{j=1}^{8} \mu_j \tag{5}$$

B. *Numerical Validation of AN F IS Model*

RMSE is a global measure of the total number of points cases of instrumentation of the differences between values predicted by an estimator AN F IS and the values desired by operator. ANFIS model has the greatest potential to achieve a lower Mean Square Error RM SE after learning completed. This criterion is defined by the expression, Where:

$$RMSE = \sqrt{1 \Big/ N \sum_{K=1}^{N} \left(y_k - \hat{y}_k \right)^2} \tag{6}$$

RMSE consists to assess the performance of estimator AN F IS for K case of instrumentation, where $1 \leq k \leq N$.

IV. CONCEPT OF THE STEPS DESIGN FOR A CONTROL SYSTEM

A. *Instrumentation and Dependable Control System*

The instrumentation of a control system is composed of actuators and sensors that allow one given instrument to take part in several tasks in different operating modes or states of system. In this context, finding instruments that are common to several tasks along the process life, permits to reduce the global system cost [7]. However, the use of common resources can lead to faults that can disturb different tasks of the control system. Therefore, the design of an instrumentation system can be expressed as an optimization problem and consists in finding a good balance between instrumentation cost, quality of performance QoP. In this work, the quality of performance QoP presents the interaction between three disciplines as given in Fig. 4 robust control, dependability analysis and optimal control and robustness in different operating modes or states of system

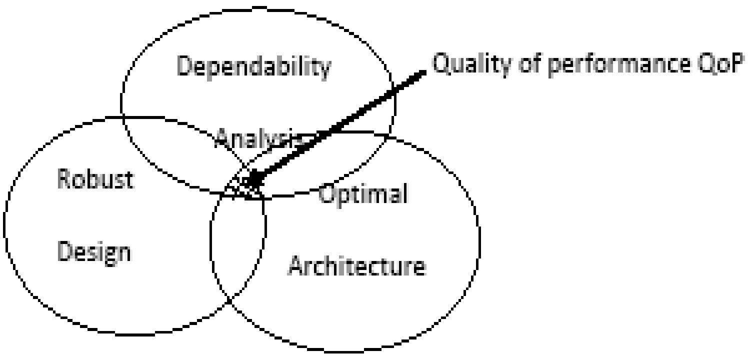

Fig. 4 The three disciplines of QoP

B. *First Steps of Control System Design*

The first steps of control system design aim essentially to find the hardware architecture. The designer has to determine the places where sensors or actuators can be implemented, then for each of them, the number and the type of instruments among those available. The choice is made in order to obtain hardware organizations that can properly perform the mission according to the objectives in terms of financial cost, reliability and safety [7]. Different strategies of control are sometimes proposed to the designer. In this paper, the designer has to determine for each strategy, various control systems whose different characteristics (cost, dependability) are compared with respect to the interests of each strategy.

Moreover, the design of hardware control systems is characterized by a weakness of available information to the designer. Indeed, since this activity takes place early in the design process, a lot of choices are not fixed, such as the maintenance policies, the final choice about the suppliers, device sizing. The precise and accurate dependable characteristics of the instrument are often unknown, imprecise or would require a disproportional investment compared with the current objectives. In this context, an accurate estimation of the cost and the dependability of the system are not required. The designer needs rather relative size orders which are only used to compare the different solutions.

V. FORMALIZING AND RESOLVING THE OPTIMIZATION PROBLEM

A. Design and Optimization Process

The design process of a control system consists of finding a first solution of potential hardware architecture; the designer assesses its characteristic (costs, reliability) in order to determine its weak points and the possible improvements. From that, new potential hardware architecture is deduced and the cycle goes on until a satisfactory solution is found according to the several technical and economic criteria [13].

The final solution results in a great number of cycles, a nonlinear process is proposed. It consists of providing a description of the physical system from which all hardware architecture can be deduced indirectly and automatically, thanks to the structural analysis. Then, by integrating the constraints about the quality of Performance QoP and the cost criteria and finally, by solving the optimization problem, the designer obtains the optimal hardware architecture that satisfies the dependability constraints with the lowest cost.

B. Specification of Dependability Constraints

Structural modeling to describe a controlled system, and after analysis to determine for each control or unknown quantity, good QoP for process instruments (sensor and actuator) implanted. In the case of designing a control system, the objective is to determine the instrumentation providing a minimal economic cost provides a level of dependability required. This level set by the criterion level of QoP must be specified for each mission or task control system design and assigned to each physical variable and each actuator required for accomplishment of the assignment.

In this paper, the QoP is defined as the difference between the reference quantity $q_{desired}$ that we want to achieve, and real value of the physical quantity to be controlled q_{real} using AN F IS model.

$$QoP = \left| q_{real} - q_{desired} \right| \tag{7}$$

The function QoP is used in terms of dependability to set desired quality of performance n. If a physical quantity q is required by a task whose quality of control is set to the value of n for the whole process instrumentation, the corresponding constraint is:

$$QoP(q) \le n \Rightarrow \begin{cases} QoP(q_1) \le n_1 \\ QoP(q_i) \le n_i \end{cases} \tag{8}$$

$$\Rightarrow \begin{cases} \left| q_{real_1} - q_{desired_1} \right| \le n_1 \\ \left| q_{real_i} - q_{desired_i} \right| \le n_i \end{cases}$$

C. Building and Solving of the Optimization Problem

The final optimization problem is obtained by adding the cost criterion to the quality of performance QoP constraints which are deduced from the specification. This criterion corresponds to a financial cost of the system and it is associated with the sum of the individual costs of the instruments (denoted Ci). The optimization problem is consequently defined by:

$$\begin{cases} Min\left(\sum_1^k C_{qi}\right) \\ \left| q_{real_1} - q_{desired_1} \right| \le n_1 \\ \left| q_{real_i} - q_{desired_i} \right| \le n_i \end{cases} \tag{9}$$

This problem interests to an Integer Linear Programming (ILP) problem which is a standard optimization problem [26]. For medium systems (about 100 instrumentation points), this problem can be exactly solved by current computation capacity. Branch and Bound or Branch and Cut algorithms are enumeration techniques that are well suited to solve this problem and that provide the optimal solution. For larger systems, stochastic algorithms such as genetic algorithms can be used [26]. The final result of the optimization phase is a set of instrumentation systems which all satisfy the dependability constraints imposed by the designer and with the lowest cost.

VI. STRUCTURAL MOLDING OF ELECTRICAL VEHICLE DYNAMIC

A. *Structural Modeling*

The aim of structural representation is to identify structural properties of the system. These will serve to guide for complete implementation using the model of behavior. We only keep the model of behavior that expresses information about existence of relationships between variables without taking into account their particular form. The results obtained are independent of models of behavior for each activity. No restrictions will be to do about the type of modeling to use. A structural analysis is used to describe the system and the global incidence matrix for the whole system is given in Table 2 and the global vision of the electrical vehicle is showed in the graphical tree in Fig. 6. Where the algorithm of research is used to search the different ways to evaluate an unknown variable, its principal aim is to find an unknown variable according to known variable and disturbance [3], the result of this algorithm is given in Fig. 6.

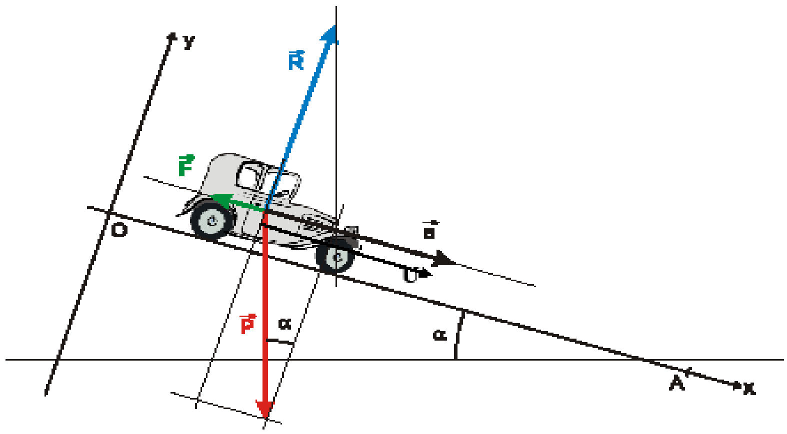

Fig. 5 Dynamic model of an electrical vehicle moving on a sloppy road [4]

TABLE 2 THE GLOBAL INCIDENCE MATRIX FOR ELECTRICAL VEHICLE

	α_t	$\alpha_{t-\delta t}$	R	a_t	$v_{t+\delta t}$	v_t	x_t	δt	$t_{descent}$	a_y	$\Delta\alpha_t$	u_t	cv_t	GPS	Ch	I_t	m_t	Δm_t	case of slope
f_1				1	1	1		1											variable
f_2	1			1								1							
f_3						1							1						
f_4							1							1					
f_5	1															1			
f_6	1		1							1									constant
f_7				1			1		1										constant
f_8	1	1									1								variable
f_9						1	-1												constant
f_{10}									1						1				constant
f_{11}								1							1				variable
f_{12}																	1	1	

B. *Description of the Process*

Consider the following variables used in this electrical vehicle, as shown in Fig.5. : α_t, $\alpha_{t-\delta t}$ are the angle of slope, a_t is the total acceleration of the vehicle, a_y is the acceleration of the vehicle projected on the axis y, X_t is the position of the vehicle, $V_{t+\delta t}$, V_t are the speed of the vehicle, $t_{descent}$ is the time of descent the road slope, δt is the period of sampling, u_t is the control signal of the motor, and I_t is the measure given by the inclinometer, Ch the measure given by the chronometer, cv_t is the measure given by the sensor speed, GPS is the measure given by the GPS sensor.

The parameters are defined by:

M is a fixed parameter used in the model and corresponding to the assumed mass of the vehicle, m_t is a real mass quantity of the vehicle, Δm_t is the variation of the mass due to the various transported loads at each trip, ε^t_V is the uncertainty of the measurement error while V_t is the real speed, ε^t_I is the uncertainty of the measurement error of inclinometer, $\Delta\alpha_t$ is the variation of the slope [4], R is external force of the electrical vehicle: reaction of the road.

The instruments that are available for a vehicle are: Electrical motor, speed sensor, GPS sensor, inclinometer to measure the angle of slope, chronometer to measure time.

VII. STUDY OF QUALITY OF PERFORMANCE QOP

We define QoP as the ability to guarantee the performance, and robustness of a system. Before studying QoP, we cite the parameters that influence the QoP:

- The slope t of the road (especially in the case of roads that have high slope)

- The measurement uncertainties of the instruments.

In this work, we will evaluate the quality of performance QoP, for this reason a set of parameters is necessary to allow the evaluation criteria, and we must know:

-The agreed measures for the instruments used: This is the domain of possible variation of the physical quantity to be measured. It is defined by a minimum value and a maximum value. These two extremes are called the minimum and maximum range.

-The cost of the instrument, which defines the overall cost of use of the instrument (installation, maintenance, uncertainty) and use in the quantitative criterion of the cost of the system.

A. Evaluation of a Single Physical Quantity Using Multi-Criteria:

The overall evaluation of a system matches the following functions:

-The cost of instruments in equipment.

-Measuring range (equipment availability).

-Reliability in terms of uncertainty of measurement instruments.

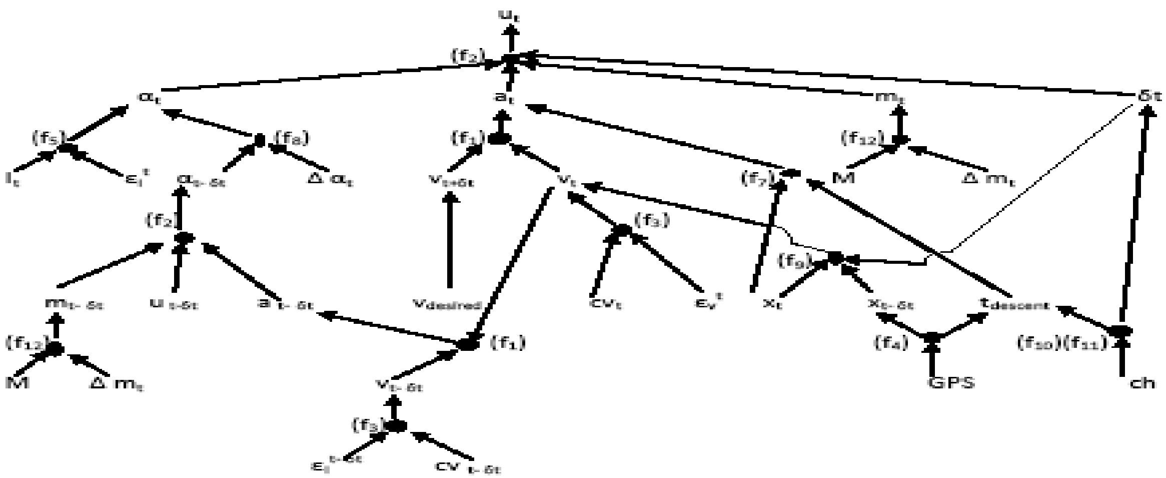

Fig. 6 The graphical representation for different paths of the control u_t with several disturbances

VIII. THE APPLICATION ON OUR CASE STUDY

To study the influence of disturbances (the slope, the uncertainties of the instruments) on the performance of the control system, we will determine the different interval of different states of QoP according to a criterion:

$$QoP = \left| v_{t+\delta t} - v_{desired} \right| \tag{10}$$

The classification of variables used in the application:

-Two disturbances, the first is the road slope αt and the measurement uncertainties provided by the instruments.

Table 3 summarizes the measurements from different instruments cv_t, I_t, u, GPS, Ch for 13 cases. Knowing that the data presented in this table are obtained from simply specification parameters, where cv_t is the measured speed provided by speed sensor, it is the measured slope provided by inclinometer, u is the control signal for electrical motor, Ch is the measured time from chronometer and GPS coordinates: GPS Latitude, GPS longitude, GPS elevation. We chose arbitrarily the values of the costs associated with sensor and actuator, Ci_u for the cost of motor, Ci_{Cv} cost for the speed sensor, Ci_I for the cost of inclinometer.

TABLE 3 THE DIFFERENT POSSIBILITIES INSTRUMENTATION: DATA PARAMETERS, COST

Number of instrumentation		1	2	3	4	5	6	7	8	9	10	11	12	13
Data parameters	cv_t	14.999	9.999	7.999	13.999	12.999	16.999	17.999	5.999	15.499	16.999	16.199	15.899	16.009
	I_t	4.398	8.798	9.998	2.198	3.998	5.998	8.998	0.998	3.298	3.998	3.498	2.999	3.998
	u	210	240	250	150	170	200	240	270	200	240	230	240	240
	Ch	13.4210	8.2130	6.9990	14.5460	12.1130	14.8770	16.9990	6.0000	16.9990	18.1110	16.0000	14.1110	17.9990
	GPS latitude	13.4440	7.9990	8.1110	15.0000	10.9990	17.3210	16.0000	6.9990	13.9990	18.0000	15.0000	13.0000	14.0000
	GPS longitude	12.2220	8.9990	6.5550	16.1110	11.9990	15.0000	15.9990	5.0000	14.9990	17.1110	17.1110	16.0000	16.9990
	GPS elevation	2.1999	5.8650	6.2480	1.2920	2.4980	3.3320	8.9980	0.5870	2.9980	2.3510	1.7490	1.8740	1.8170
costs	Ci_{Cv}	3	4	2	3	4	5	6	3	5	4	5	3	4
	Ci_I	2	3	2	3	2	4	5	4	4	3	4	4	4
	Ci_u	10	11	10	10	11	14	13	20	10	11	12	15	15

According to the graphical tree representation in Fig. 6, and by translating this branch (Fig. 7) that link relations of system electrical vehicle, there exists a relationship f between the speed and slope and signal control. Consequently, to control the speed $v_{t+\delta t}$, it needs to measurement of speed sensor and motor, inclinometer; that is to say, from structural analysis, there is qualitative relation f as following:

$$v_{t+\delta t} = f\left(I_t, u, cv_t\right) \tag{11}$$

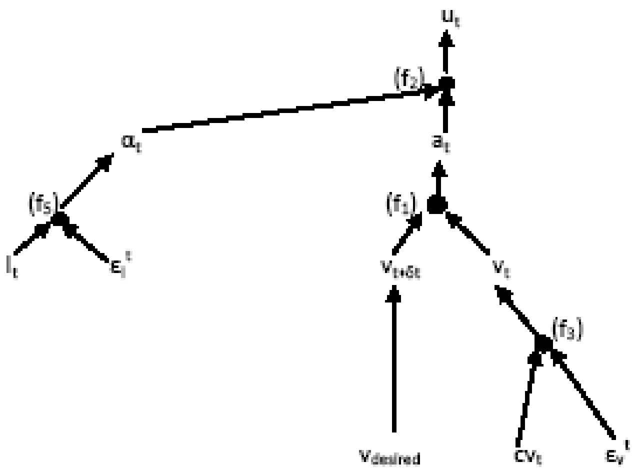

Fig. 7 Branch of $v_{t+\delta t}$

IX. ROBUST DESIGN BASED ON THE ANFIS

The neuro-fuzzy model is constructed from input-output data obtained by system simulation using Matlab software. The multi-variable dynamic system is represented as a model thus based on rules behavior that approximates the nonlinear dynamics as a concatenation of a set of locally linear sub-models.

We consider the following data set of the control system instrumentation as well as the use of hybrid system combining ANFIS fuzzy logic, neural networks, expert systems and prove their effectiveness in a variety of real world problems and the industry. Each intelligent technique has particular properties (learning ability, decisions explanation).

A. Elaboration of the Data Input –Output

Thanks to the structural modeling and the graphical tree representation which allow the selection of parameters that has influence on the system to approximate the speed $v_{t+\delta t}$ of electrical vehicle that used to quantize the quality of performance QoP. We have the measurements from different case of instruments implemented in the electrical vehicle which are a set of three descriptors instrumentation selected by structural analysis as shown in Fig. 8: the control signal of the motor (u_t), measured speed provided by speed sensor (cv_t), measured slope of the road provided by inclinometer (I_t). In addition, we have the value of the desired speed $v_{desired}$. We assume the fuzzy inference system under consideration has three inputs: u, cv_t, I_t and one output: $v_{t+\delta t}$ where p^j_i, q^j_i, g^j_i, r^j_i are consequent parameters. From equation (5), the speed of electrical vehicle is defined as follows:

$$v_{t+\delta t} = \sum_{j=1}^{8} \mu_j \left(p_i^j u + q_i^j cv_t + g_i^j I_t + r_i^j \right) \Big/ \sum_{i=1}^{8} \mu_j \tag{12}$$

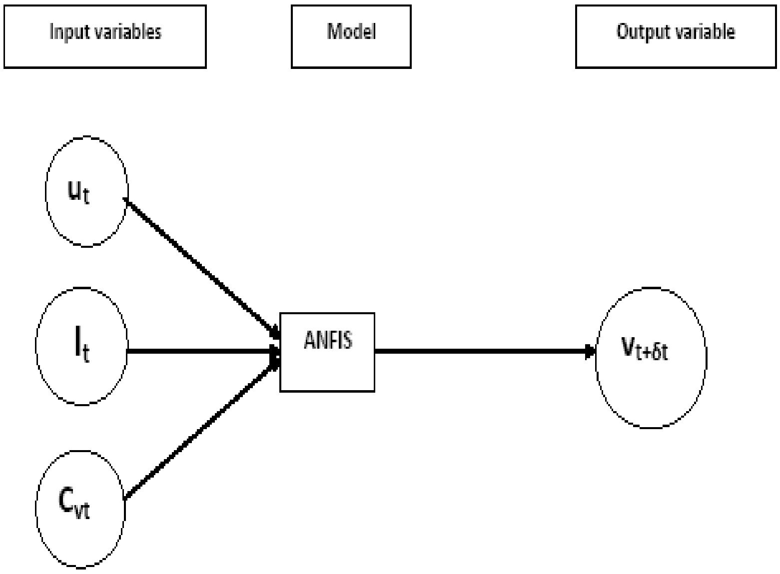

Fig. 8 The architecture of ANF IS model for three inputs and one output

The computing flowchart of robust design approach was constructed as shown in Fig. 9, where the original database of the system was first normalized and the parameter of approximation was obtained by applying hybrid learning and the validation of the model. More especially, the designer chooses the best hardware architecture of the control system according to the dependability criteria in function to the quality of performance QoP and the financial cost.

B. Results of Simulation

The first step to construction the ANFIS model consists of taking advantage of the structure of T S; In order to achieve a set of tests, different parameters must be fixed in advance, for example the type of membership function was gbellmf after using the triangular membership function trimf that is the faster, learning algorithm: hybrid Learning. The approximation of speed of electrical vehicle $v_{t+\delta t}$ is based on the hypothesis that ANFIS model has the greatest potential to achieve a lower Mean Square Error RM SE after learning completed. Where:

$$RMSE = \sqrt{1/N\sum_{K=1}^{N}\left(v_{desired} - v_{t+\delta t}\right)^2} \tag{13}$$

The information of ANFIS model:

-Number of nodes: 78

-Number of linear parameters: 36

-Number of nonlinear parameters: 54

-Total number of parameters: 90

-Number of training data pairs: 13

-Number of fuzzy rules: 9

-ANFIS training completed at epoch 20.

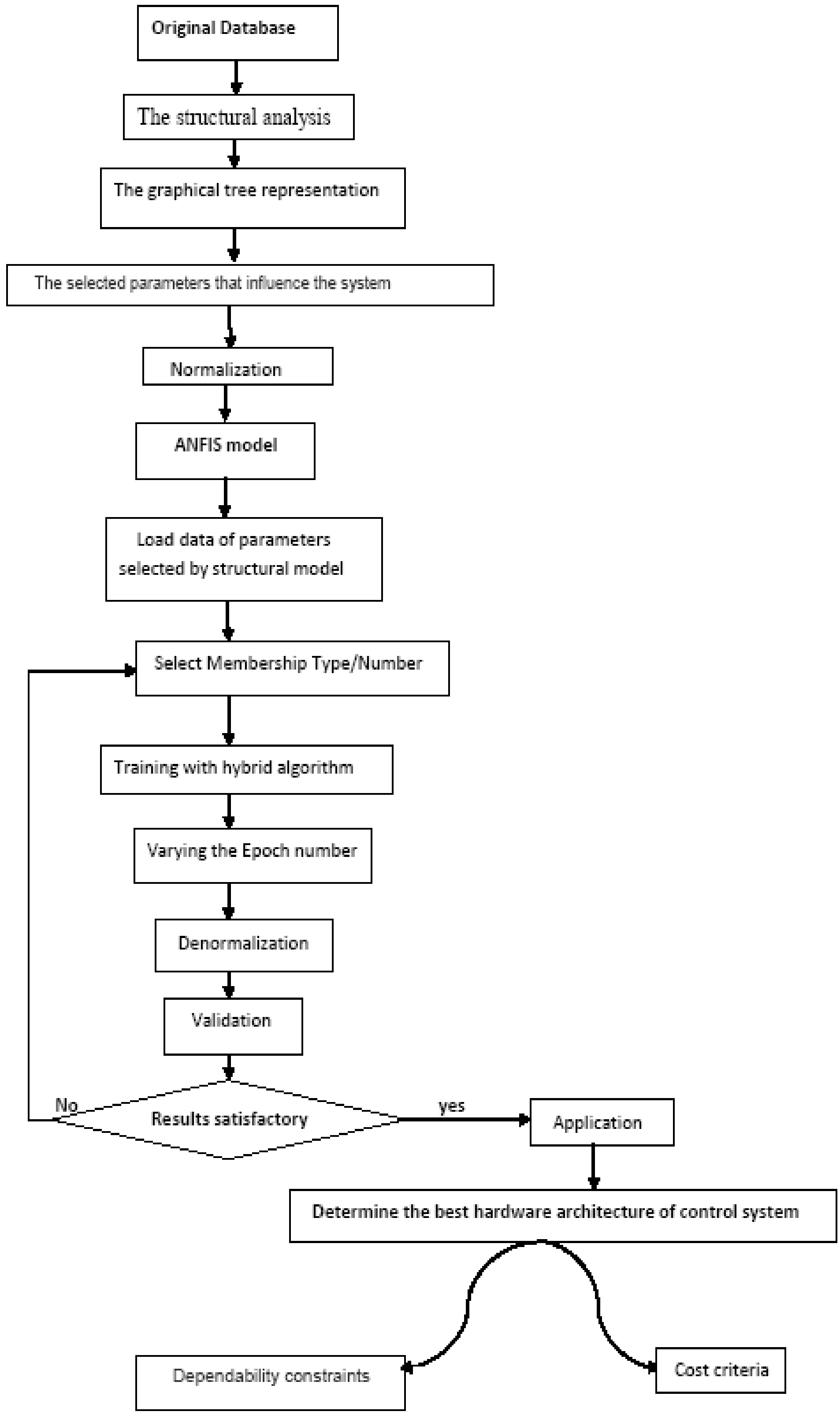

Fig. 9 The organization flowchart describing robust design based on the ANFIS model

From the simulation results in Fig. 10, it can be seen at defining an ANFIS tool that is able to approximate and predict unknown variable. In this way, a neuro-fuzzy system for prediction unknown variable $v_{t+\delta t}$ to control based on data measurements from the sensors measurements and thanks to the available actuators. As ANFIS demonstrated its ability to construct any nonlinear function with multiple inputs and outputs in many applications, its estimating performance was investigated for a complex vehicle electrical system.

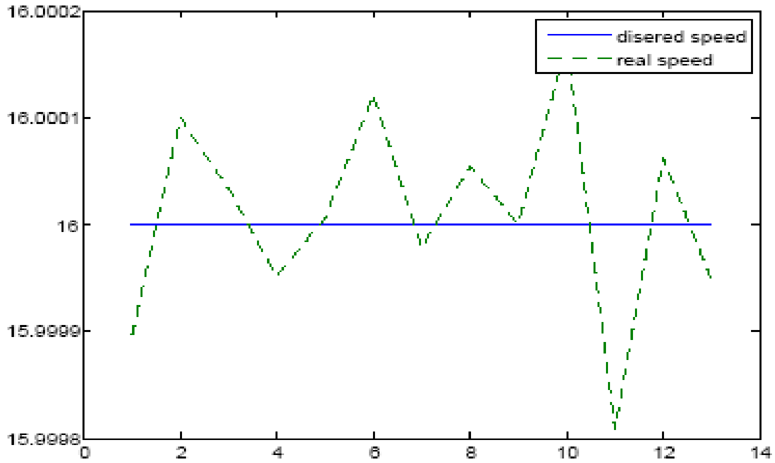

Fig. 10 The approximation of the speed $v_{t+\delta t}$ by ANFIS model according 13 case of instrumentation

Applying the optimization problem in the system of equations 9, and the threshold value of the quality of performance desired QoP equals 9. 10^{-5}. We obtain:

$$\begin{cases} Min\left(Ci_{final}\right) = Min\left(Ci_{C_\upsilon} + Ci_I + Ci_U\right) \\ \left|v_{t+\delta t_1} - v_{desired_1}\right| \le 9\cdot 10^{-5} \\ \left|v_{t+\delta t_i} - v_{desired\, i}\right| \le 9\cdot 10^{-5} \end{cases} \tag{14}$$

We have been able tracing the evolution of criterion of final cost (Ci_{final}) and criterion of the quality of performance QoP, is shown in Fig. 11:

We discuss the state of quality depending on the value of QoP as follows:

-QoP is good, if QoP $\in [0 , \ 9 .10^{-5}$ [

-QoP is degraded, if QoP $\in [9.10^{-5}, 20.10^{-5}$ [

-QoP is bad, if QoP $\in$ [20.10^{-5} , 120.10^{-5}[

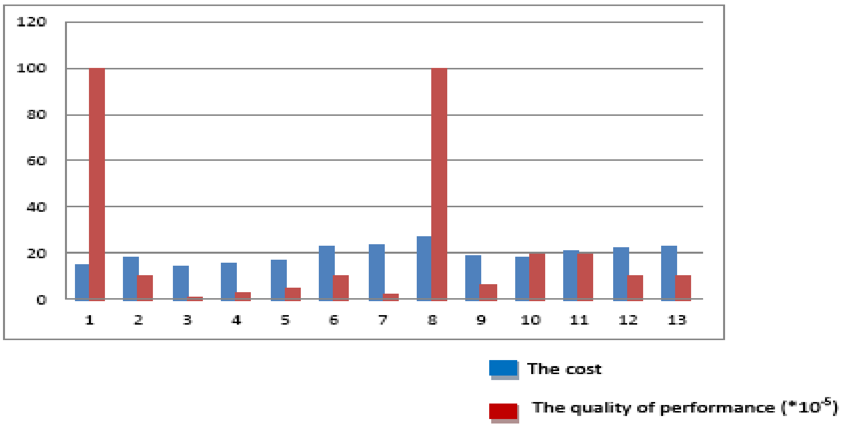

Fig. 11 The histogram of quality of performance QoP and cost using model ANFIS according to 13 case of instrumentation

From the result shown in Fig. 11, we obtained 13 pairs that are composed by two columns of colors red and blue which represent respectively the cost of instruments and quality of performance QoP obtained by AN F IS model. The pair 3 shows as an ideal case where the value of the cost is (14), with good quality of performance 1.10^{-5} near zero, QoP $\in [0, \ 9 .10^{-5}$ [.

The approximation of the ANFIS models was validated using the criteria of quality of performance QoP. Accurate prediction of the speed control is crucial. A neuro-fuzzy hybrid approach was used to construct a speed control system. In particular, we used the ANFIS to build a prediction model, to illustrate the applicability and capability of the ANFIS. The results demonstrate that the ANFIS can be applied successfully and provide high accuracy and reliability for electrical system.

X. CONCLUSION

The use of structural analysis is shown in this work to help a designer to select the relevant sensor and actuator in the instrumentation. Moreover, the used method is relatively easy to use and requires a reduced amount of data, that is to say, an incidence matrix built by a structural modeling. It is an important tool to model the system which has little information.

The robust design approach of the control system is presented using ANFIS model to study QoP with the cost criterion using the variables selected by graphical trees of structural analysis approach. The focus is to determine optimal instrumentation with lower cost for the system of the electrical vehicle which provides good QoP, despite the influence of disturbance following the slope of the road and uncertainties of sensors and actuators of the vehicle.

In our future work, we foresee to compare the existing results with the results in this reference [27]; where the difference between these two references is relative to the criteria of the quality of performance QoP. Here, the QoP is quantized by ANFIS model but in the reference [27], it quantized by the properties of the structural analysis.

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