A NEURAL NETWORK CONTROLLER OPTIMISED WITH MULTI OBJECTIVE GENETIC ALGORITHMS FOR A LABORATORY ANTI-LOCK BRAKING SYSTEM

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Résumé

Dans ce travail, nous considérons la conception d'un réseau de neurones pour contrôler un système de freinage Anti Blocage des Roues ABS qui est un système fortement non linéaire. L'objectif est de contrôler le dérapage ou bien le patinage des roues. Le contrôleur est conçu en hors-ligne en utilisant un outil d'optimisation puissant qui est les algorithmes génétiques multi objectifs. L'objectif du processus de la conception du réseau de neurones est de trouver le meilleur contrôleur avec une structure raisonnable. La structure est définie par le nombre de variables d'entrées et le nombre de neurones dans la couche cachée. Ainsi l'algorithme génétique multi objectifs doit minimiser trois objectifs: le nombre de neurones dans la couche cachée, l'erreur qui est la différence entre le coefficient de patinage de roue "slip" désiré et le coefficient de patinage de roue réel et le troisième objectif est le nombre de variables de l'entrée du réseau de neurones. Les résultats de simulation trouvés sont satisfaisants et encourageants.

Mots clés ***:*** *Système de freinage antiblocage des roues ABS, réseaux de neurones, algorithmes génétiques multi objectifs.*

Abstract

In this work, we consider the design of a neural network controller for the ABS laboratory system witch's highly non linear. The objective is to control the wheel slip. The controller is designed off-line using a multi-objective optimisation process solved using a multi objective genetic algorithms. The objective of the design process is to find a satisfactory controller with a reasonable structure. The structure is defined as the number of input variables and the number of neurons in the hidden layer. Thus the multi objective genetic algorithms has to minimize three objectives: the number of neurons in the hidden layer, the error which is the difference between the wheel slip reference and the real wheel slip and the third objective is the number and type of inputs to the network. The results of simulation are encouraging.

Key words ***:*** *ABS systems, Neural Network, Multi Objective Genetic Algorithms*

ملخص

في هذا العمل، نصمم نضام تحكم و مراقبة باستعمال الشبكات العصبية للتحكم في نظام كبح ضد تقييد العجلات و الذي هو نظام غير خطى بدرجة عالية المعروف بنظام "أ بي أس". و الهدف هو التحكم في انزلاق العجلات و السيطرة عليها. نظام التحكم المصمم تم تصميمه خارج الخط باستعمال طريقة فعالة في التحسين و هي الخوارزميات الجينية متعددة الأهداف . و الغرض من هذه عملية تصميم نظام التحكم بالشبكات العصبية بالخوارزميات الجينية متعددة الأهداف هو إيجاد أحسن شكل و هيكل للشبكة العصبية. هيكل الشبكة تجدده عدد المتغيرات عند مداخل الشبكة العصبية، عدد الخلايا العصبية في الطبقة المخفية للشبكة. و بالتالي فإن دور الخوارزميات الجينية متعددة الأهداف هو وجوب تصغير و تحسين الأهداف الثلاثة التالية: عدد الخلايا العصبية في الطبقة الخفية للشبكة، الخطأ و الذي يتمثل في الفرق بين عامل انزلاق العجلة المراد أو المرجعي و عامل الانزلاق الفعلي و الهدف الثالث هو عدد و نوع المدخلات للشبكة. النتائج المتحصل عليها مشجعة جدا.

الكلمات المفتاحية ***:*** *نظام الكبح ضد تقييد العجلات، الشبكات* العصبية، الخوارزميات الجينية متعددة الأهداف.

The Anti-lock Braking System (ABS) is designed to optimize braking effectiveness while maintaining car controllability. Nowadays it is implemented in most cars. The objective of the control system of the ABS is to prevent wheel lock during braking. The design of the control system is complicated by the fact that the model of the system is highly non linear and it is thus difficult if not impossible to use linear design methods, A several researchers working for the study and the improvement of these systems [1,2,3,4,5,6]. In this work, we consider the application of a neural network controller for a laboratory ABS system. Due to their approximation capabilities [7, 8], neural networks, NN, have been used mainly in the control of nonlinear systems [9].

The basic idea is to adjust the weights of the neural network. The weights adjustment process is carried out until satisfactory control is obtained. It can be performed off line, if a good, reliable model of the process is available or on line in the context of adaptive control if the model is poorly known or time varying. In this work, we consider the design of a NN controller for the ABS laboratory system. The controller is designed off line using a multi objective optimisation framework solved using a multi objective genetic algorithms.

The objective of the design is to find a satisfactory controller of the wheel slip with a reasonable structure. The structure is defined as the number of input variables and the number of neurons in the hidden layer. This paper is organised as follows, in the next section the laboratory ABS system is described, section 3 presents the neural network design procedure and section 4 is devoted to the results of simulation.

1. THE LABORATORY ABS SYSTEM

Anti-lock Braking Systems are closed-loop control devices that prevent wheel lockup during braking and as a result vehicle stability and steering is maintained. In the past few decades, anti-lock braking systems and electric control unit controllers of many different designs have been mounted in many types of vehicles. A typical ABS is composed of a central electronic control unit ECU, four wheel speed sensors (one for each wheel), and two or more hydraulic valves within the vehicle brake circuit. The sensors measure the position of the tires, and are generally placed on the wheel-axis. The sensor should be robust and maintenance free, not to endanger its proper working. These position measurements are then processed by the ECU to calculate the differential wheel rotation. The ECU constantly monitors the rotational speed of each wheel. When it senses that any number of wheels are rotating considerably slower than the others (a condition that is likely to bring it to lock), it actuates the valves to decrease the pressure on the specific braking circuit for the individual wheel, effectively reducing the braking force on that wheel. The wheels then turn faster; when they turn too fast, the force is reapplied. This process is repeated continuously, and this causes the characteristic pulsing feel through the brake pedal. The ECU needs to determine when some of the wheels turn considerably slower than any of the others because when the car is turning the two wheels towards the center of the curve inherently move slightly slower than the other two. In general, there are two major advantages of an anti-lock braking system over conventional brakes: shorter stopping distances on most road surfaces, and steering control enhancement during hard braking manoeuvres [4,10].

The laboratory ABS system considered here consists of two rolling wheels (figure 1). The lower car-road wheel simulating relative road motion and the upper car wheel, equipped with a tyre, remaining in a rolling contact with the lower wheel.. The surface of the lower wheel is smooth and can be covered with a given material to simulate various road conditions.

The main objective of the control system is to prevent wheel-lock during braking. This is performed through the control of the wheel slip to maximize the coefficient of friction between the tire and road for any given road surface while the car is controllable. If this wheel becomes motionless either the car velocity is not equal to zero which means that it remains in slip motion or the car velocity is equal to zero and is thus absolutely stopped. In the first case the ABS algorithms has to unlock the wheel to stop its slipping. The wheel starts to rotate and after a short time period it is stopped again. This process is repeated until the car is stopped.

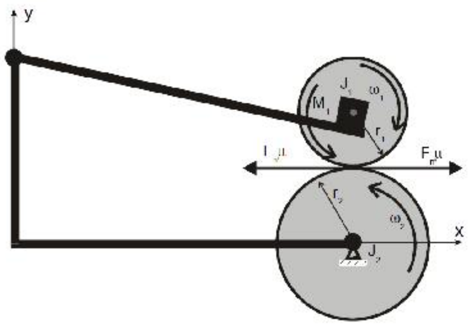

Figure 1 : Schematic diagram of ABS

In order to simulate the braking process, we use a model of the laboratory ABS system given in [11]. Let x_1 and x_2 be respectively the angular velocity of the upper and lower wheel, and ª be the slip defined as the relative difference of the wheels velocity. The equations of motion can be put in the form :

$$\dot{x}_1 = F_1(x_1, x_2, \text{ª}) + G_2(\text{ª})(sign(x_1))M$$

$$\dot{x} = F_2(x_1, x_2, \text{ª}) + G_2(\text{ª})(sign(x_1))M$$

$$\dot{M} = c(b(u) - M) \quad (1)$$

$$b(u) = \begin{cases} b_1 u + b_2 & u > u_0 \\ 0 & u < u_0 \end{cases}$$

Where u is the control signal, M is the braking torque, x1 and x2 are the angular velocity of the upper and lower wheel, λ "slip" the relative difference of the wheel velocities. These equations are highly non linear and complicated by the sign function which also intervene in F_i and G_i. It is difficult to obtain a linear model for designing a linear controller or even to use non linear design techniques [12]. It would be interesting to try some alternative approach that do not rely on the structure of the model such that neural controller. This is described in the next paragraph.

2. THE DESIGN OF THE NN CONTROLLER

2.1. The NN controller

In this work, we consider a single hidden layer multi layered perceptrons, MLP [13]. When designing such a neural network for control, one is first confronted with the choice of the structure of the network. For single hidden layer networks, it consists in deciding what variables to input to the controller and in fixing the number of neurons in the hidden layer. Once the structure is decided upon, optimisation of the weights of the connections, otherwise known as the learning process, can start.

The structure of the networks influences the learning process and the quality of control since the approximating error depends on the number of neurons in the hidden layer and on the information input to network [14]. Clearly, it is not possible to consider simultaneous design of the structure and weights in an on line learning procedure. However, this is a feasible alternative in the case of off line learning. In this work, we consider an off line simultaneous design of the structure and the connection weights of a neural network.

A multi-objective genetic algorithm, MOGA, is used for finding a good solution. Optimisation is performed in closed loop with the controller in the loop. In the next paragraph we describe the multi-objective genetic algorithms.

2.2. The solution procedure with a Multi objective genetic algorithm:

A Multi objective optimisation problem consists in optimising a vector valued objective function. An n objectives problem is defined as:

$$\min\,(f_1(x),\, f_2(x) ... f_n(x))$$

A solution z is said to dominate a solution y if : $f_i(z) \le f_i(y)\ \forall i$ and there exits at least one i such that $f_i(z) < f_i(y)\ \forall i$. The non dominated solutions form the Pareto front. The multi-objective genetic algorithm is used to find solutions close to the Pareto front.

The main elements of the multi objective genetic algorithms are:

(a) *The individuals of the populations* : Each individual represents an NN controller. Its chromosomes comprise three sub-chromosomes: the first encodes the input variables, the second the number of hidden neurons and the third the weights of the networks.

(b) *Fitness function :* The fitness function gives the quality of the solution associated with the chromosome. Since our objective is not only to find a controller that gives satisfactory closed loop performance but also one with a structure as simple as possible that is with a reasonable number of input variables and a reasonable number of neurons in the hidden layer, in this work, the fitness is based on the concept of non dominance using the following three objectives: the number of input variables, the number of neurones in the hidden layer, the cumulated error made by the controller when controlling the system for a sufficiently long period of time.

This error which is the most important element in the design procedure is computed as follows. Each chromosome in the population represents an NN controller with its input variables, the number of neurons in the hidden layer and the values of the connections weights. In order to compute the error, the controller is applied in closed loop for controlling the laboratory ABS system represented by the model (1).

The simulated control system is carried out for sufficiently long period of time. The controllers that give an unstable closed loop are affected a very high cost. The procedure can be seen as looking for a stable optimal NN controller in the sense of the cumulated output error. The steps of the MOGA used here are as follows [15] :

Step 1 Initialisation

An initial population of N individual is created. An individual is a NN controller represented by a chromosome that contains its input variables, its number of neurons and the values of the connection weights. For each individual the vector valued objective function is formed as follows: $f_i = (N, L, E)$ where N is the number of input variables, L is the number of neurons and E is the cumulated output error.

Step 2: Ranking

For the current population we determine the non dominated individuals. We allocate the same dummy fitness for all these non dominated individuals generally f_0=1. In order to maintain some diversity in the population, this dummy fitness is scaled by a factor proportional to the number of individual in this front. This quantity is called a niche. Each individual in the front will have a dummy fitness $F_i = f_0 m_i$, m_i is the niche. With the remaining individuals of the population we determine the new non dominated front to which we allocated the dummy fitness $f_1 = f_0 m_s$ where m_s is the smallest niche in the previous front. This dummy fitness is then scaled as in above. This process of sorting and allocating dummy fitness is continued until the last individual of the front sorted.

At the end of the step, the three objectives are transformed into a single objective according to the concept of non dominance.

Step 3: Application of a simple genetic algorithms

In this step we apply the simple genetic algorithms with single objective to the current population each individual having its dummy. A new population is generated with all individuals having a vector valued objective function computed as in the initialisation step.

Step 4 Stopping

If the maximum number of generations is reached stop otherwise go to step 2.

3. SIMULATION RESULTS

The approach described above is applied to the simulated model of the laboratory braking system. The simulation scenario consists in accelerating the two wheels until they reach 240 rad/s for the upper wheel and 220 rad/s for the lower wheel, which corresponding to speed of nearly 86 km/h. Braking is then started in order to prevent wheel lock. The slip reference is λ^*=0.2. An MLP controller with sigmoïdal activation functions for the hidden neurons is chosen. After running the MOGA algorithm, an NN controller is extracted from the best individuals from the last generation, (pareto front).

The controller has three inputs: $e(t) = \lambda^* - \lambda(t)$, $\lambda(t-3)$ and $u(t-3)$. It has 12 neurons in the hidden layer. The controller is then applied to control the simulink model of the ABS laboratory provided by the vendor. The sampling time is 0.01 seconds. The time for computing the control signal in an ibm PC compatible with a clock at 1.4 Ghz is less than this sampling time.

Figure 2 to 5 shows the results of the simulation. The wheel sleep reaches its reference smoothly and very quickly. The control signal is also smooth. The braking time, i.e. when both wheels are stopped, is around 0.3 seconds, this results are very encouraging.

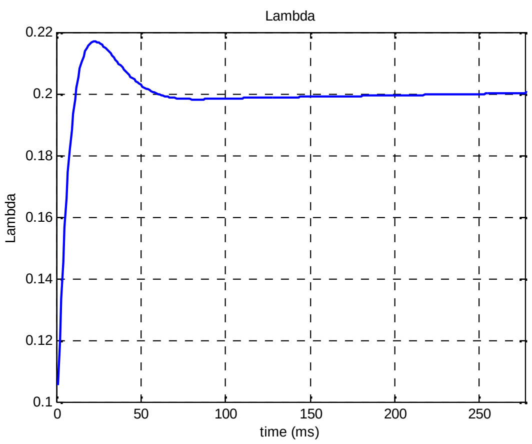

Figure 2 : The slip

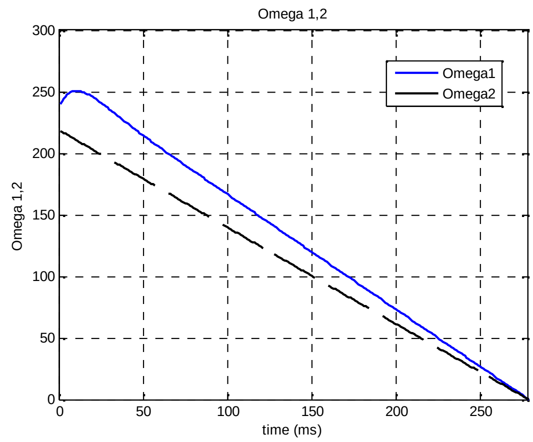

Figure 3 : Angular velocities

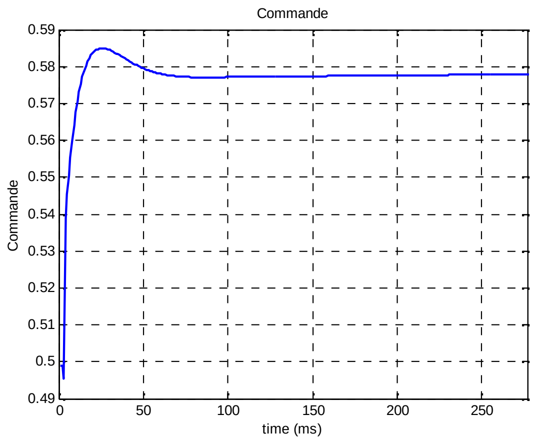

Figure 4 : The control signal

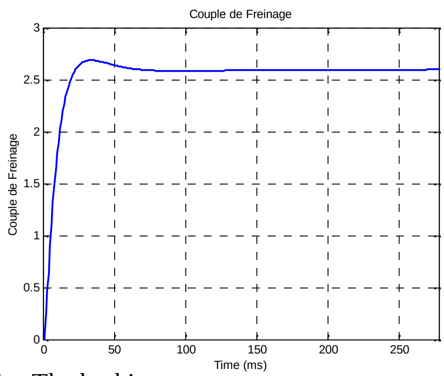

Figure 5 : The braking torque

CONCLUSION

Given the required reliability, it is illustrative to see the choices made in the design of the ABS control system. Correct functioning of the ABS system is considered of the utmost importance, for protection and safeguarding both the passengers within, and person outside of the car. The system is therefore built with some redundancy, and is designed to monitor its own working and report failures. The general working of the ABS system consists of an electronic unit, known as electronic control unit, which collects data from the sensors and drives the hydraulic control unit, mainly consisting of the valves that regulate the braking pressure for the wheels.

In this paper, a neural network controller is design for a highly non linear system which is an ABS laboratory system. The design is based on three objective representing quality of control and structure of the NN controller. The solution procedure utilises a multi-objective genetic algorithms. The obtaining results are encouraging.

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