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SOME NEW RESEARCH AREAS AND TRENDS IN TODAY ROBOTICS

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Abstract: In this survey paper some of contemporary research areas and relevant results in robotics are briefly presented. The first research area presented is the approach based on neural networks for learning and improving dynamic models of robots. The second area deals with the possibility of the application of fuzzy logic in robotics. As the third, very topical and widely investigated field in robotics, the problem of position/force control of robots is presented, or more broadly the problem of robotic tasks for robots working in contact with a dynamic environment. The last part contains active systems and constructions as well as problems related to controlling their dynamic performance.

Keywords: Connectionists learning, decentralized control, fuzzy logic, hybrid control, contact tasks, dynamic environment, active system.

1. INTRODUCTION

This predominantly survey paper presents four research areas and tasks of contemporary robotics by the author's choice. The choice of only four research areas has also been determined by the limited paper length, as well as the space needed for each of the chosen topics to be presented.

The neural networks approach was selected as the first research area, which in a certain way has marked the development of robotics during the last decade. It has efficantly supplemented the inherent incapabilities of completely deterministic models of complex robotic mechanisms and systems by providing both an adequate description of their dynamics, and a synthesis of control laws and controller design.

The second area of contemporary research in robotics, involves fuzzy logic control. A potentially powerful alternative for sloving of the complexity problem and model unreliability lies in the techniques of reasonable approximation and knowledge-based control. In this field of investigation fuzzy logic controllers acquired enormous popularity during the last ten years. Unlike "pure" fuzzy logic control which is essentially a nonlinear and coupled system, such as are multi-joint active mechanisms and has not rendered sufficiently good results, a hybridization of the control scheme was proposed. This hybrid control scheme consists of using a satisfactory approximation of the robot dynamic model aimed at weakening the dynamic coupling between robot joints, and further in using heuristics based on fuzzy logic as efficient means for processing the effects uncovered by the approximation model adopted.

The third research area or task in this paper presents the so-called contact task, in which, in fact, one of the most complex control problems in robotics - the position/force control is solved. This part gives the essence of the new approach to control of the manipulation robots interacting with a dynamic environment. Simultaneous control of position and contact force, along with introducing the dynamics characteristics of the environment, proposed by the author of this paper and his coauthors, shads new light on the role of overall system stability during robot-environment contact. This approach to the control of robotic systems interacting with dynamic environments yields extraordinarily broad possibilities for solving the general problem of active system contact, the systems being of different dedications and in contact with specific dynamic environments.

The last topic in this paper logically relies on the problem of contact tasks in robotics, presented in the previous part. Accent is put on active systems, representing specific robotized systems. These systems emerge as a result of the partial or complete automating or robotizing of traditional passive technical objects and systems, which include civil engineering constructions and structures, as well. Robotics thus acquires much in its scope and traditional robots and robotic systems can be understood as a segment of the largest class of active systems. This includes active systems of the most diverse types, from vehicles of various dedications (road, railway, flying and other vehicles) to active foundations of buildings and other civil engineering structures which can be regarded as general contact tasks of active technical systems or active construction, which are in a specific interaction with the dynamic environment.

2. NEURAL NETWORKS IN ROBOTICS

Classic model-based control algorithms for manipulation robots cannot provide the desirable solution because traditional control laws are, in most cases, based on models with incomplete information and partially known or inaccurately defined parameters. Also, as a solution, adaptive model-based control algorithms can tolerate a wider range of uncertainties, but in the presence of sensor data overload, heuristic information, limits to real-time applicability, and a very wide interval of system uncertainties, the application of adaptive control cannot ensure high-quality performance. These facts provide the motivation for robotic intelligent control and emphasize the necessity that efficient robotic intelligent control must be based on the following postulates:

a) robustness and great adaptability to system uncertainties and environmental changes;

b) learning and self-organizing capabilities with generalization of acquired knowledge;

c) real-time implementation on robot controllers using fast processing architectures.

One of the most important problems in the dynamic models of manipulation robots is the high nonlinearity and prominent coupling between the subsystems (mechanical degrees of freedom (DOF) of the robotic mechanism). The dynamic model of the manipulation robot, disregarding the friction force and other perturbations, can be represented in the form:

$$P = f(q,\dot{q},\ddot{q},\theta) = H(q,\theta)\ddot{q} + h(q,\dot{q},\theta) \quad \text{or} \tag{1}$$

$$P = f(q,\dot{q},\ddot{q},\theta) = H(q,\theta)\ddot{q} + \dot{q}^T C(q,\theta)\dot{q} + g(q,\theta) \tag{2}$$

where $P \in R^n$ is the vector of the driving torques or forces; $H(q,\theta): R^n \times \theta \Rightarrow R^{n\times n}$ is the system matrix of inertia; $h(q,\dot{q},\theta): R^n \times R^n \times \theta \Rightarrow R^n$ is a vector, including the Coriolis and gravitational effects; $C(q,\theta): R^n \times \theta \Rightarrow R^n \times R^n \times R^n$ is a matrix, including the centrifugal and Coriolis effects; $g(q,\dot{q},\theta): R^n \times R^n \times \theta \Rightarrow R^n$ is the vector of gravitational moments; $\theta \in R^n$ is the vector of system parameters; n is the number of DOF; nt is the number of system parameters. The classical way of controlling robotic systems is by means of local PID controllers for each DOF of the robotic mechanism [1]:

$$u = u_{fb} = -KP\,\varepsilon - KD\,\dot{\varepsilon} - KI \int \varepsilon \; d\,t \tag{3}$$

where $u \in R^n$ is the control input; $u_{fb} \in R^n$ is the feedback control; $KP \in R^{n\times n}$ is the matrix of local positional gains; $KD \in R^{n\times n}$ is the matrix of local velocity gains; $KI \in R^{n\times n}$ is the matrix of local integral gains; $\varepsilon = q - q_d$ is the error of the feedback ($\varepsilon \in R^n$); q and q_d are the real and nomial (internal) generalized coordinates ($q \in R^n$, $q_d \in R^n$). However, this control law is inadequate for contemporary high precision robots with high working speed. The influence of the coupling between the robot subsystem in this case is an essential factor, so "dynamic" control has to be introduced [1], based on the dynamic robot model, i.e. on feedforward (centralized or local) control and local controllers:

$$u = u_{ff} - KP\,\varepsilon - KD\,\dot{\varepsilon} - KI \int \varepsilon \; d\,t \tag{4}$$

here $u_{ff} \in R^n$ is the nominal centralized or decentralized control, being synthesized off-line in the complete dynamic robot model, or based on the subsystems (local nominal control). Beside these, there are also other solutions for robot control such as the computed torque method:

$$P = \hat{H}(q,\theta)\,[\,\ddot{q}_d + KP(q - q_d) + KD(\dot{q} - \dot{q}_d)\,] + \hat{h}(q,\dot{q},\theta) \tag{5}$$

where $\hat{H}(q,\theta)$ and $\hat{h}(q,\dot{q},\theta)$ are estimates of $H(q,\theta)$ and $h(q,\dot{q},\theta)$.

However, in the process of controller design, we encounter structural uncertainties (inaccuracy of model parameters and supplementary perturbations), unmodelled high-frequency dynamics, such as structural resonant modes, actuator dynamics, sampling intervals, measuring noise, etc. The time variation of robot parameters and the variety of robotic tasks also represent additional difficulties for the control system. In this case classical non-adaptive algorithms are not robust enough, because these algorithms are capable of compensating for only part of the uncertainties. Hence a more suitable approach is found in the adaptive control technique. As an adaptive control technique in robotics the well known reference control model has been used.

Methods based on neural networks (connectionist theory) with distribution processing offer implementation tools for the complex input-output relations of robot kinematics and dynamics. Let us briefly explain the inverse dynamics problem of robot control. There is a causal connection between the driving torques and the resulting time history of the coordinates (trajectories) of a robot. Let $P(t)$ denote the driving torque and $q(t)$ the generalized (internal) robot coordinates. The casual connection between P and q can be defined using the functional F, i.e. $F(P(.)) = q(.)$. If we want the robot to track the desired trajectory q_d, the problem of generating the necessary driving torque P realizing q_d, is equivalent to finding the inverse mapping of the functional F. Hence, the model of the neural network for inverse dynamic mapping can be treated as an example of an autonomous generator of driving torques. Neural controllers can compensate for a very wide spectrum of uncertainties. Also, the learning process in the case of neural networks is based on the properties of generalization and association, enabling high quality tracking of robot trajectories quite different from those on which the learning was performed. On the other hand, the suitability of neural networks for fast computations enables their application in the control of manipulation robots in real time.

It is important to emphasize that the application of neural networks for learning the robot dynamics is not limited to noncontact tasks only, but is also suitable for robot contact tasks such as deburring, grinding, assembly, etc. In this case the inverse dynamic mapping is more complex because the functional F depends on contact forces, too. There are several interesting solutions in this field, from which only [9, 10] will be noted.

As an example, leraning the inverse dynamics of robotic mechanism will be presented, where exact robot dynamics is generally unknown. Therefrom, the proposed methods of neural networks can be considered as autonomous generators of the driving torques (Fig. 1). This connectionst structure is usually used as part of a feedforward controller in a decentralized control scheme. In this case, the feedback controller serves as a robust controller with the aim of achieving low errors and high quality learning.

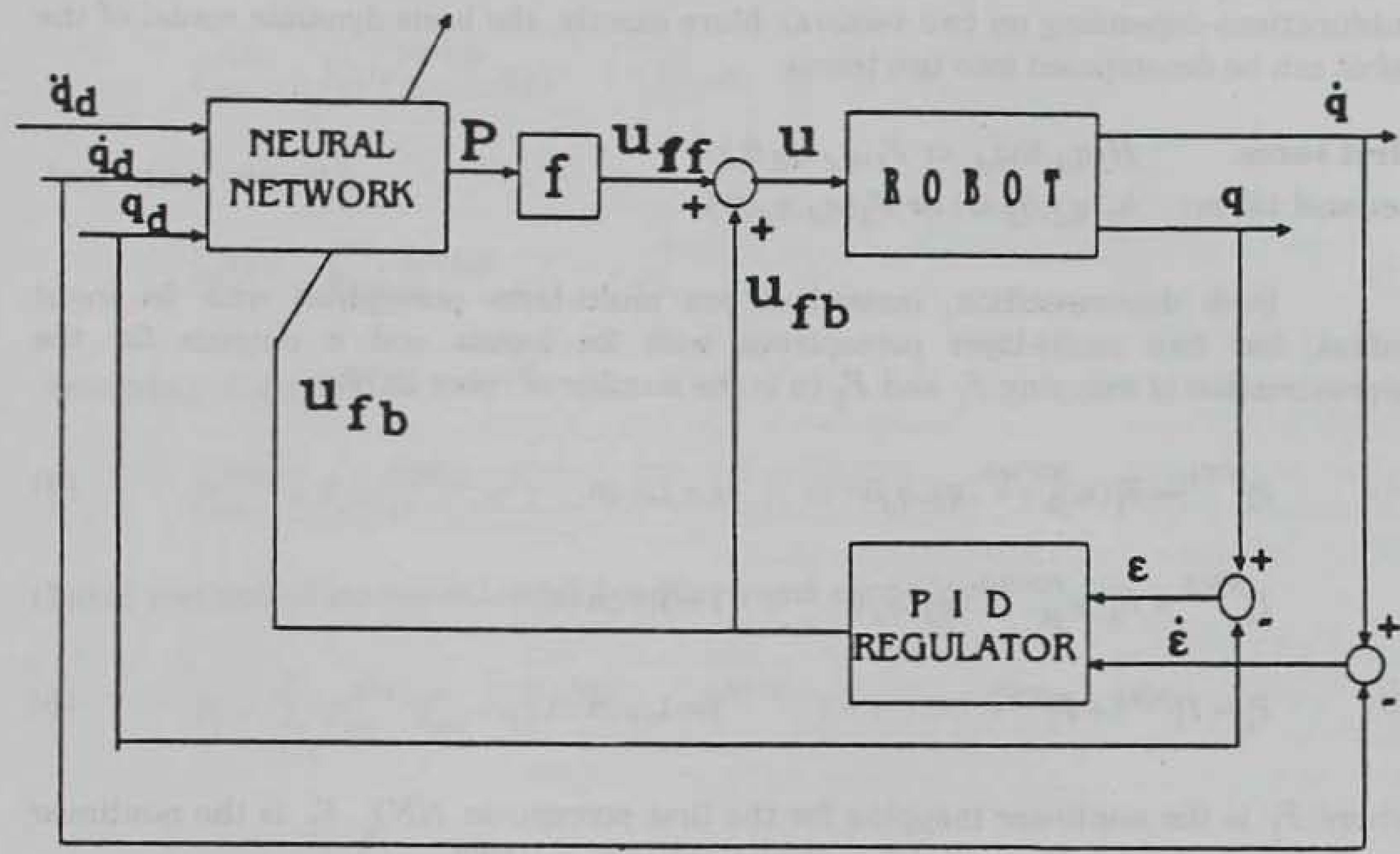

Figure 1: Decentralized control structure with connectionist learning

Training and learning the connectionist structure is accomplished exclusively in an on-line working regime by the learning method based on feedback error [4] (Fig. 1). This method is an exclusively on-line method for robot control but this control structure provides an internal teacher so that the control scheme works in an unsupervised manner. Tuning the network weighing factors during real-time control is much more suitable than other learning as structures specialized or generalized learning [5].

The naive approach that does not use a priori knowledge about the inverse dynamics model can be very impractical from the standpoint of computer implementation due to high dimensionality of the input-output spaces and long learning time. For instance, with standard manipulation robot configurations with 6 DOFs there are 18 input and 6 output variables, so the number of the forms of trajectories (a pair of input-output variables) can be very large (from 100 to 1000). Hence, for robot training it is necessary to use np^{18} pairs, i.e. training using such an approach requires a neural network of impractical size and irrationally large learning epochs number. Hence it can be concluded that such a naive approach is more justified if applied to low-dimensional robotic systems.

The principle of functional decomposition applied to learning systems simplifies the learning procedure by reducing the learning domains and the complexity of functions. The decomposition brings two advantages: first, a more compact data set, requiring less input data than the original approach, and second, the decomposed networks are mutually simpler, by which the necessary learning time is reduced. As a solution for efficient decomposition, two different decomposition methods of the robot dynamics in internal coordinates have been proposed [6]. The first represents the "$3F$ –

$2PF$" decomposition (decomposition of the functional depending on three vectors into subfunctions depending on two vectors). More exactly, the basis dynamic model of the robot can be decomposed into two terms:

first term: $H(q_d,\theta)\ddot{q}_d$ or $F_1(q_d,\ddot{q}_d,\theta)$

second term: $h_1(q_d,\dot{q}_d,\theta)$ or $F_2(q_d,\dot{q}_d,\theta)$.

Such decomposition, instead of one multi-layer perceptron with $3n$ input values, has two multi-layer perceptrons with $2n$ inputs and n outputs for the approximation of mapping F_1 and F_2 (n is the number of robot DOFs):

$$P_i^{NN1} = F_1(w_{jk}^{NN1ab}, q_d, \ddot{q}_d) \qquad i=1,\dots,n \tag{6}$$

$$P_i^{NN2} = F_2(w_{jk}^{NN2ab}, q_d, \dot{q}_d) \qquad i=1,\dots,n \tag{7}$$

$$P_i = P_i^{NN1} + P_i^{NN2} \qquad i=1,\dots,n \tag{8}$$

where F_1 is the nonlinear mapping for the first perceptron $NN1$. F_2 is the nonlinear mapping for the second perceptron $NN2$; P_i^{NN1} and P_i^{NN2} are the parts of the robot dynamic model generated by perceptrons $NN1$ and $NN2$; w_{jk}^{NN1ab} and w_{jk}^{NN2ab} are the weighting factors for perceptrons $NN1$ and $NN2$. P_i is the driving torque at the output of the connectionist structure. Training of both perceptrons is carried out synchronously by the feedback error learning method (Fig. 2). The feedback error signal or the driving torque error signal is transferred as an output back-propagation error to both perceptron outputs.

The second decomposition method includes a still deeper decomposition process. This is the "$3F-1PF$" decomposition (decomposition of a three-vector function into three one-vector subfunctions). The robot dynamic model can be decomposed into three terms:

first term

$$H(q_d,\theta)\ddot{q}_d \text{ or } F_1(q_d,\ddot{q}_d,\theta)$$

second term

$$g(q_d,\theta) \text{ or } F_2(q_d,\theta)$$

third term

$$\dot{q}_d^T C(q_d,\theta)\dot{q}_d \text{ or } F_l(q_d,\dot{q}_d,\theta) \qquad l=3,\dots,n+2$$

Multilevel perceptrons and the output torque are defined according to the following equations:

learning $H(q_d,\theta)$

$$P_{im}^{NN1} = F_1(w_{jk}^{NN1ab}, q_d) \quad i = 1,\dots,n; \quad m = 1,\dots,n \tag{9}$$

learning $g(q_d,\theta)$

$$P_i^{NN2} = F_2(w_{jk}^{NN2ab}, q_d) \quad i = 1,\dots,n \tag{10}$$

learning $C_l(q_d,\theta)$

$$P_{im}^{NNl} = F_l(w_{jk}^{NNlab}, q^0) \quad i = 1,\dots,n_j; \quad m = 1,\dots,n; \quad l = 3,\dots,n+2 \tag{11}$$

total output of connectionist feedforward structure

$$P_i = \sum_{m=1}^{n} P_{im}^{NN1} \ddot{q}_{im}^{d} + \dot{q}_d^T P^{NNl} \dot{q}_d + P_i^{NN2} \quad i = 1,\dots,n; \quad l = 3,\dots,n+2 \tag{12}$$

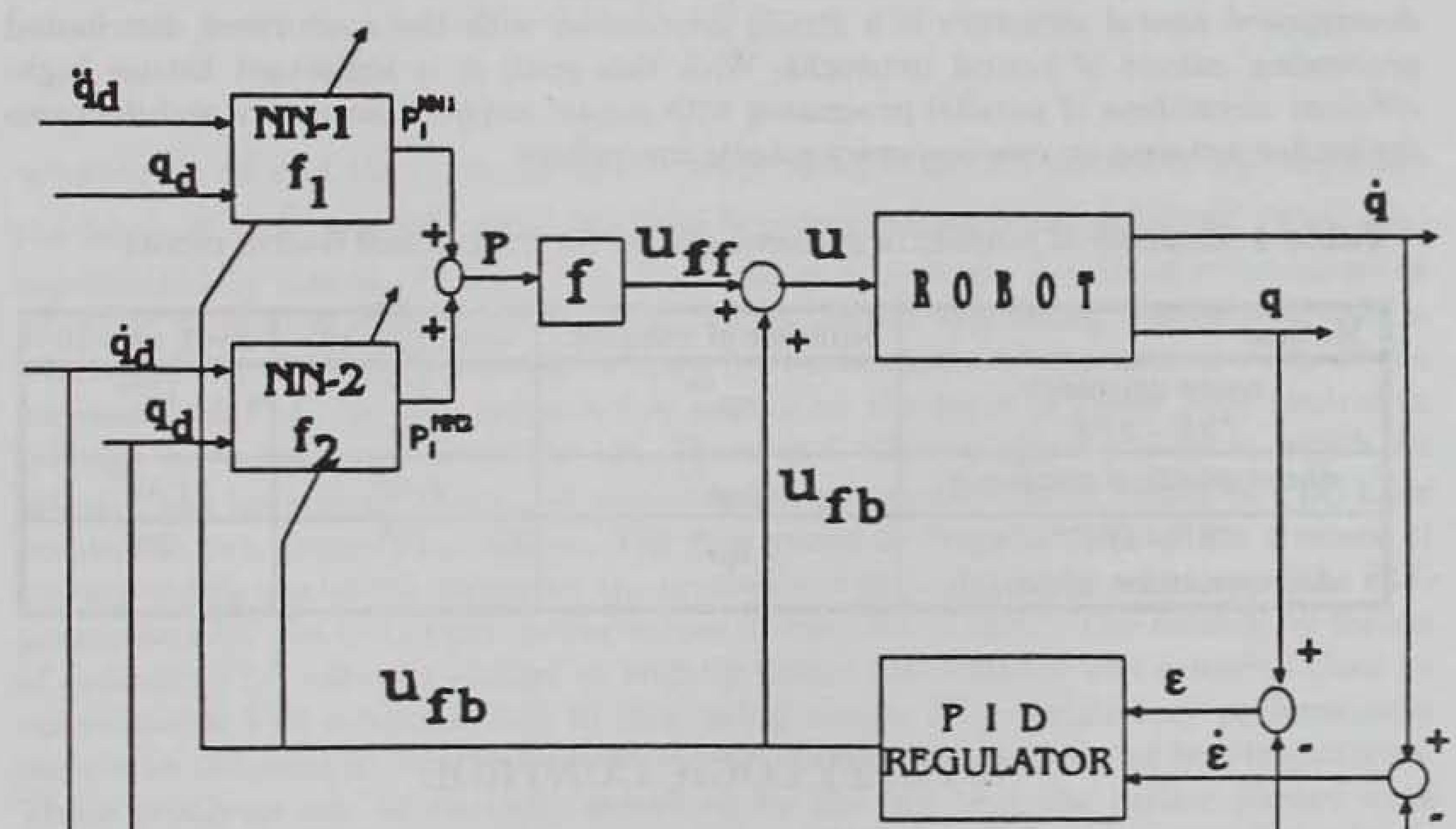

Figure 2: "$3F$–$2PF$" decomposition connectionist structure with feedback error learning

where F_i $(i=1,...,n+2)$ is the nonlinear mapping for perceptron NNi; P_{im}^{NNl} (l=1 or l=3,...,n+2, $i=1,...,n$; $m=1,...,n$) are the outputs of the perceptrons $NN1$; and P_i^{NN2} (i=1,...,n) are the outputs for perceptron $NN2$; w_{jk}^{NNlab} are the weighting factors for perceptron $NNlab(l=1,...,n+2)$.

It is important to emphasize that in both cases of decomposition, the outputs of connectionist structures P_i represent part of the decentralized control algorithm.

The main result of these decompositions is a significant reduction in the size of the trajectory input patterns. For example, an analysis can be carried out of the learning for standard robot configurations with 3 and 6 DOFs, knowing the number of different patterns necessary to train the proposed network structure. The number of patterns is determined by the number of samples per variable. Table 1 gives one example of the learning analysis with the number of samples for robots with 3 and 6 DOFs, using np=10 samples per dimension.

From Table 1 it is evident that the reduction of the number of patterns required for learning is $1 \cdot 10^6$ for $n=3$ and $1 \cdot 10^{12}$ for $n=6$. In this way, by dividing the large space into smaller subspaces more practical learning of the robotic system complex dynamics is allowed. On the other hand, instead of learning on a single perceptron, there is learning with several perceptions. Hence the real advantage of the decomposed neural structure is a strong connection with the concurrent distributed processing nature of neural networks. With this goal, it is important to use high-efficient algorithms of parallel processing with neural network hardware architectures for implementation on contemporary robotic controllers.

Table 1: Example of number of patterns needed for 3=d, of and 6=d of robots

Method	Number of samples	n=3, np=10	n=6, np=10
naive approach "$3F-2PF$"	np^{3n}	10^9	10^{18}
decomposition approach	$2np^{2n}$	$2 \cdot 10^6$	$2 \cdot 10^{12}$
"$3F-1PF$" decomposition approach	np^n	10^3	10^6

3. FUZZY LOGIC CONTROL

In case of fast trajectories, simple control based on traditional decentra-lized control does not behave well because of the effects of dynamic coupling between the robot joints. Hence different control schemes have been proposed aimed at the compensating the dynamic effects [1]. Common to all these control schemes is the introduction of additional feedback loops, intended to compensate nonlinear changes in the dynamic coupling forces. To determine the values of these dynamic forces, two basic methods are at our disposal: the forces can be calculated using the internal dynamics model of the robot, or be measured by means of sensors. However, both strategies have serious drawbacks. The dynamic model can become a very complex system of nonlinear differential equations [7]: it is always more or less an approximation of the real robot.

On the other hand, using force sensors in the robot joints usually requires special design of robot joints and at the same time lowers the structual stiffiness of the robot arm: the force sensors behave like an elastic member of the system which can lead to instability of control.

A potentially powerful alternative for solving the complexity problem and model unreliability lies in the techniques of reasonable approximation and knowledge-based control. In this field of investigation fuzzy logic controllers acquired enormous popularity during the last few years [8]. Most FLC (fuzzy logic controller) schemes follow the basic structure established by Mamdani [9]. The core of this structure is formed by a rule base, the elements of which are the control rules, which in the case of simple FLC with two inputs, error c and velocity of error change Δ_c, as well as with one input - the velocity of the input signal Δ_u change, obtain the form:

Rule: r if it holds

$$\widetilde{E} \text{ is } \widetilde{E}_r \quad \text{and} \quad \Delta\widetilde{E} \text{ is } \Delta\widetilde{E}_r$$

then form the output in such a way that it holds:

$$\Delta\widetilde{U} \text{ is } \Delta\widetilde{U}_r$$

whereby $\widetilde{E}$, $\Delta\widetilde{E}$ and $\Delta\widetilde{U}$ are fuzzy sets corresponding to the I/O controller signals, while the labels $\widetilde{E}_r$, $\Delta\widetilde{E}_r$ and $\Delta\widetilde{U}_r$ designate fixed linguistic values (such as "small", "big", etc.) represented by means of fuzzy sets. The rules can be static (i.e. fixed in advance) or dynamic: a classical example of dynamic FLC is the self-organizing controller (SOC) in which the set of fuzzy meta-rules is used for modification of the control rules of the conventional FLC. To date quite a few papers on the topic of fuzzy logic control in robotics have been published [10-12]. These and other original papers in which an attempt has been made to control manipulation robots directly by means of FLC have pointed to two groups of problems. The first group is characterized by the absence of corresponding analytical means for the synthesis of control, i.e. the selection of the FLC parameters (or the initial parameter values in the case of SOC). The second, by means of ordinary FLC schemes similar or slightly better performance was achieved than by conventional PID schemes. Due to this, using simple FLC satisfactory performances cannot be obtained in complex robotic tasks, such as the tracking of fast trajectories. These problems can be partially explained by the fact that the earlier papers were primarily concetrated on demonstrating the possibility of methods based on fuzzy logic, in order to master the problems of nonlinear control without the need of exact mathematical modelling of the controlled mathematical system. Hence the role of a priori available mathematical knowledge in situations when the system dynamics was deterministic, as well as the control technique developed using the model, were put aside.

A two-level hierarchy in which the expert system is being used to tune the control at a lower level can bring closer approaches based on fuzzy logic to those based on classical techniques of control synthesis, but it basically does not solve the problem of weak performance. This indicates that knowledge about the mathematical model at our disposal should not be ignored. It is very important that this knowledge can be used to lower the nonlinear dynamic coupling between the robot joint subsystems. Thus, what is desirable is a hybrid approach in which fuzzy logic control is combined with model-based control. Thus, we do not want substitution of model-based approach by the fuzzy logic approach, but their integration.

The basic idea of the hybrid approach consists of using a satisfactory approximation of the robot dynamic model aimed at weakening the dynamic coupling between the robot joints, and further in using heuristics, based on fuzzy logic, as efficient means to process the effects not covered by the approximative model adopted [13, 14].

The hybrid scheme presents an extension of the decentralized control structure and consists of a set of subsystems closed about the individual robot joints. Each of these subsystems is formed by two components: a traditional model-based controller and an optional fuzy logic based tuner (Fig. 3).

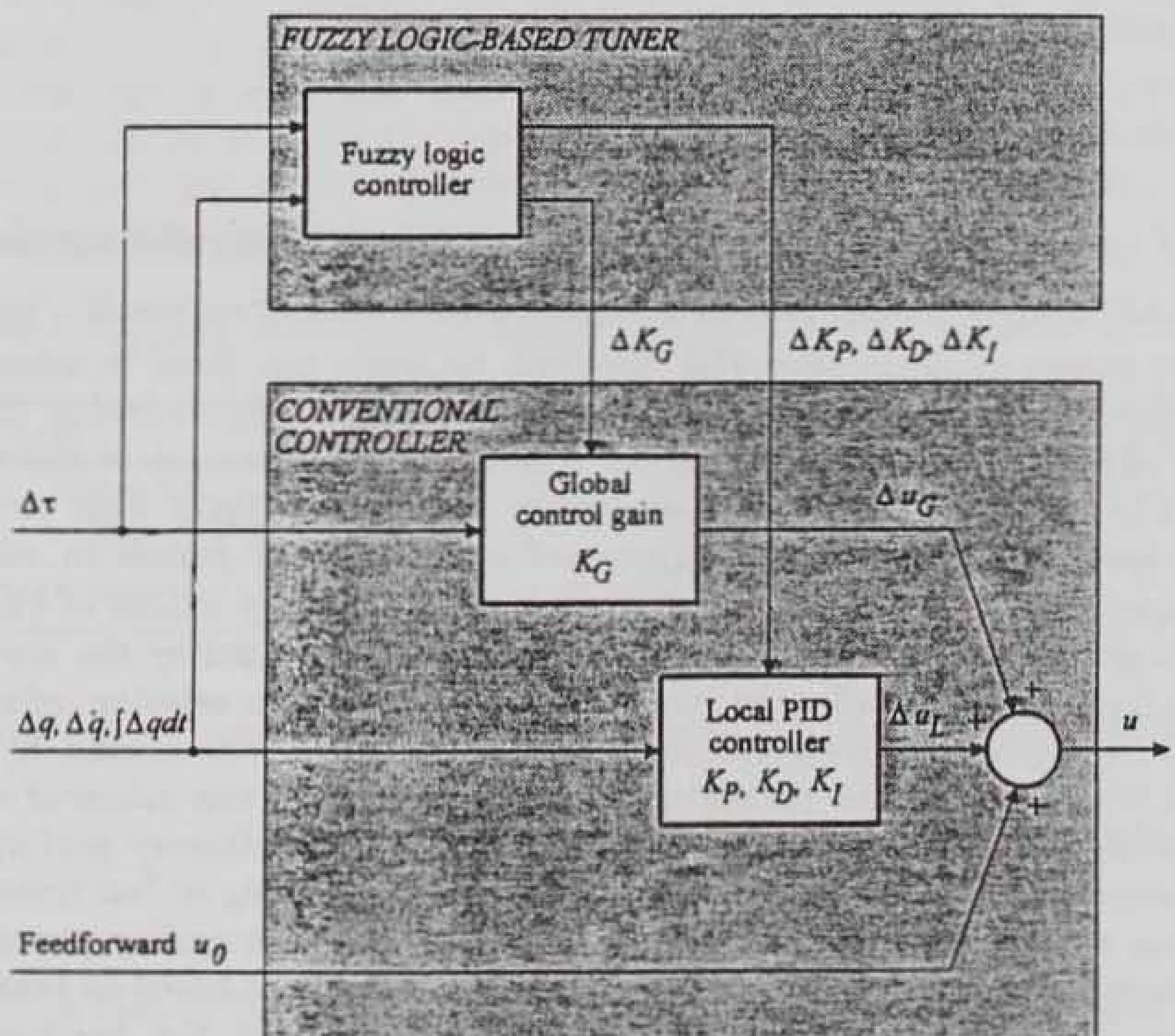

Figure 3: Hybrid control scheme

Inputs for the i^{th} subsystem $i = 1.....n$ where n is the number of active joints, are: the nominal control signal u_{i0}, the positional error in the joint Δq_i and the velocity error in the joint $\Delta\dot{q}_i$. The nominal u_{i0} is calculated for the prescribed trajectory on the basis of the robot internal dynamics model, and the gains of the local PID servos are synthesized in such a way that the free (decoupled) subsystem is stabilized. In cases where high precision of trajectory tracking is demanded, it is possible to add the global feedback (full dynamic compensation), whereby the global feedback signal is formed based on the calculated and measured deviation of the dynamic torque ΔP_j acting at the joint. Further refining introduces a tuner at the higher control level, dedicated to fine tuning of traditional controller gains. The tuner is designed as a controller with fuzzy logic, observing the response characteristic in the joint and modifying the gains in such a way as to ensure better responses for large deviations of the tracked quantities.

The general structure of the fuzzy controller permits the construction of sophisticated control rules for tuning the gains of joint servo systems. The tuner may have a centralized, hierarchical, or decentralized structure and its inputs may be the performance characteristics that are derived after extensive analysis of system response. For the sake of the hybrid approach verification, a simulation study with the industrial robot Manutec-R3 was carried out [15].

Table 2: Average and maximal errors óf trajectory tracking (mm)

Effect included in dynamics model	PID		PID+FLC	
	$\bar{\Delta}_p$	$\Delta_{p\,max}$	$\bar{\Delta}_p$	$\Delta_{p\,max}$
actuator model+gravitation	2.12	8.34	0.52	2.04
dtto+diagonal elements of inertia	2.00	4.03	0.63	1.26
dtto+full matrix of inertia	1.26	2.62	0.51	1.41
dtto+velocity terms	0.34	1.75	0.20	0.64
dtto+global control	0.29	1.51		

A systematic survey of the results obtained using various control schemes is given in Table 2, containing the values of the maximal position errors. This table indicates that PID control with fuzzy logic leads in all cases to reduction of errors. For a predetermined trajectory, a PID controller with fuzzy logic and a nominal calculated on the basis of the approximative model including the actuator models and gravitational effects only, enables achieving similar performances as with a PID controller with constant gains and a nominal calculated on the basis of a complete model.

In the last row of Table 2 results are presented for the case of added global control with a global gain set at value $K_G i = 0.5$ for $i = 1,2,...,6$ (all DOF). It can be noted that even such control is inferior as compared with the PID controller with fuzzy logic and a nominal determined on the basis of the complete model.

Numerical complexity is one òf the most important criteria linked to the digital implementation of the considered control scheme. Although implementation of a tuner based on fuzzy logic introduces additional calculations, the tuners can reduce the total calculating complexity by significantly lowering the necessary level of robot dynamics modelling. Time histories of tracking accuracy depending on numerical complexity are presented in Fig. 4. From these diagrams the benefits of the PID controllers with variable gains become even more clear. It can be seen for the trajectory taken as an example that using a PID tuner with fuzzy logic and a simple model including only gravitational effects leads to a slightly smaller tracking accuracy as compared with a PID controller with fixed gains. Hereby, this slight degradation of quality is compensated for by a reduction in numerical complexity of about 40%. Although problems connected with the sensitivity of parameter variations have not been analyzed explicitly, the results obtained using approximative robot models imply an improved robustness of the presented controller with variable gains. The procedure used for the modification of parameters is based on simple static search tables which approximate the decision taken for the tuning of control in the error space on the joints. A possible direction of further improvement could consist of the synthesis of more complex tuning rules, which would also include decision based on the derived performance characteristics, both in the joint coordinate space and the task coordinate space. An other possibility lies in using specific adaptive tuning rules, depending on the tasks, along with an adaptive algorithm led by the realized performance characteristics (e.g. adaptation algorithms used in self-organizing controllers). Significant improvements can be expected from hybrid control using this concept on the adaptive control of manipulation robots in which the uncertainties concerning the characteristics of the manipulated objects or the dynamic environment (contact tasks) are taken into account. Only in the field of adaptive control algorithms of robots in noncontact and contact tasks, the integration of control techniques based on using mathematical models and techniques based on expert knowledge should demonstrate important advantages over traditional control.

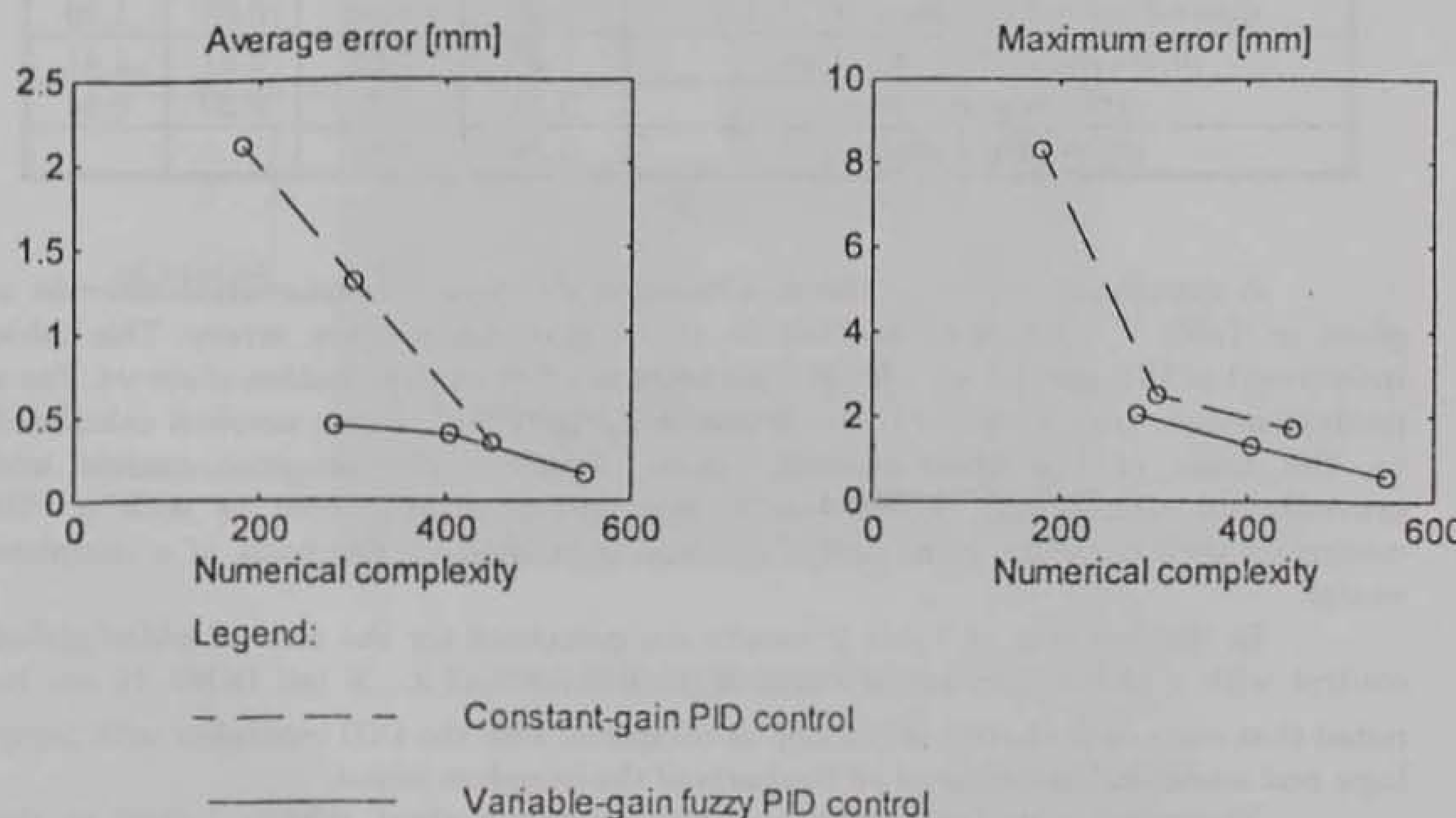

Figure 4: Tracking accuracy as a function of numerical complexity

4. CONTROL OF CONTACT TASKS IN ROBOTICS

In recent years, the control of compliant motion has appeared as one of the most attractive and fruitful research areas in robotics. Increased needs for contemporary robots have brought an enormous growth in interest in the development of various concepts and schemes of compliant motion control.

It is well known that the traditional procedure of control with respect to position and force, called hybrid control [16], consists of two parallel branches of feedback: position feedback and force feedback. Beside this theoretically incorrect control decoupling, another drawback of hybrid control is related to contradictory demands concerning the subtasks of position and force control. Namely, position control requires relatively large stiffness of the servo system in the robot joints. Force control however, favours relatively small robot stiffness, in order to ensure compliant behaviour of the robot gripper (tool) in contact with the environment (workpiece). In order to avoid this drawback of the basic version of hybrid control, the control concept with respect to implicit force was proposed [17, 18]. This control concept is based on the identification of stiffness (or damping) using information from the force sensors and calculation of the equivalent position (velocity) based on the desired contact force. The basic advantage of this scheme lies in its reliability and robustness. However, this scheme shows some deficiences, too. The basic problem of this scheme lies in the identification of contact force and its characteristics. This contact scheme has a relativaly slow response to the perturbation forces. As a logical consequence, a control scheme with respect to explicit/implicit force was proposed [19, 20]. The basic idea of this scheme is to combine control with respect to explicit and implicit force, aimed at:

1. improving the realization of the desired force,
2. increasing the response speed of the system to the perturbation of force,
3. compensating for the identification error of contact force characteristics,
4. making the system robust to errors at estimating unknown system parameters.

In order to avoid the theoretical drawback mentioned earlier, a new approach was proposed, based on environment dynamics [21-26]. Let us briefly present the essence of this method.

The robot dynamics model in contact with second-order dynamics is described by a vector differential equation of the form:

$$H(q)\ddot{q} + h(q,\dot{q}) = \tau - J^T(q)F \tag{13}$$

where $q = q(t)$ is an n-dimensional vector of the robot generalized coordinates; $H(q)$ is $n{\times}n$ positive definite matrix of the moments of inertia of the robot mechanism; $h(q,\dot{q})$ is an n-dimensional nonlinear function of the centrifugal, Coriolis and gravitational moments; $\tau = \tau(t)$ is an n-dimensional vector of the control input; $J(q)$ is an $n{\times}m$ Jacobi matrix connecting the robot gripper velocities with the velocities of the generalized (internal) robot coordinates; $F = F(t)$ is an m-dimensional vector of generalized forces and moments of the environment acting on the robot gripper (tool).

In the case where the environment itself does not move independently from the robot motion, the mathematical model of the environment expressed in robot coordinates can be described by nonlinear differential equations [27]:

$$M(q)\ddot{q} = L(q,\dot{q}) = S^T(q)F \tag{14}$$

where $M(q)$ is a nonsingular $n\times n$ matrix; $L(q,\dot{q})$ is a nonlinear n-dimensional vector function; under the assumption that $m=n$ (components number of contact force equal to the number of degrees of freedom), $S^T(q)$ is an $n\times n$ matrix of rank n, $rank(s)=n$. Thus, system (13,14) describes the robot dynamics interacting with the dynamic environment.

In the case of contact with the environment, the contact task of the robot can be described as robot motion along a programmed trajectory $q_d(t)$ which represents a twice continuously differentiable function, when the desired interaction force $F_d(t)$ cannot be arbitrary. These two functions must satisfy the relation:

$$F_d(t) = f(q_d(t), \dot{q}_d(t), \ddot{q}_d(t)) \tag{15}$$

The control goal of robot interacting with the environment can be formulated in the following way.

Let control $\tau(t)$ be formulated for $t \ge t_0$ in such way as to satisfy the conditions:

$$\begin{aligned} q(t) &\to q_d(t) \quad \text{as} \quad t \to \infty \\ F(t) &\to F_d(t) \quad \text{as} \quad t \to \infty \end{aligned} \tag{16}$$

In relation to this, two alternative questions can be formulated:

Is it possible to choose a control law which would satisfy conditions (16) while satisfying the set robot motion quality ?

Is it possible to choose a control law in such a way as to ensure the desired robot interaction force quality and also satisfy conditions (16) ?

The answer to the first question is quite simple, as shown in [21, 22]: the inverse dynamics method ensures the desired motion quality and at the same time guarantees stable interaction force. Generally, the second question cannot be answered affirmatively. In order to do that, we need additional conditions which will be discussed in the following text.

The stabilization task of the programmed (demanded) interaction force $F_p(t)$ can be set via a family of certain transitional responses with respect to force, in the form [19, 20]:

$$\dot{\mu} = Q(\mu), \quad \mu = F(t) - F_d(t) \tag{17}$$

and by the choice of the continuous vector function $(Q(0) = 0)$ of dimension n, such that asymptotic stability in the whole is ensured for the trivial solution $\mu(t) \equiv 0$.

Let "complete" control with respect to force be now considered for $m=n$, i.e. when the number of reaction forces components is equal to the number of robotic mechanism DOFs.

For suitability, the quality of the transient response (17) can be represented by an equivalent relation of the form:

$$\mu(t) = \mu_0(t) + \int_{t_0}^{t} Q(\mu(w))dw \tag{18}$$

Without loss of generality $\mu_0 \equiv 0$ is adopted.

Let only one of the possible control laws with feedback loops with respect to $q, \dot{q}$ and F be considered in the form:

$$\tau = H(q)M^{-1}(q)[L(q,\dot{q}) + S^T(q)F_d + \int_{t_0}^{t} Q(\mu(w))dw] + h(q,\dot{q}) + J^T(q)F \tag{19}$$

Applying this control law to the robot dynamics model (13) the following law of a robot in contact with the environment is obtained:

$$\ddot{q} = M^{-1}(q)[\, L(q,\dot{q}) + S^T(q)(F_d + \int_{t_0}^{t} Q(\mu(w))dw)]$$

or $$M(q)\ddot{q} = L(q,\dot{q}) + S^T(q)F$$

Taking into account the environment dynamics model (14) we arrive at the following control system in the feedback loop:

$$S^T(q)\mu(t) - \int_{t_0}^{t} Q(\mu(w))dw = 0 \tag{20}$$

and because $rank(s) = n$, this equation is equivalent to the equation:

$$\mu(t) = \int_{t_0}^{t} Q(\mu(w))dw \tag{21}$$

wherefrom relation (17) follows directly.

In this way control law (19) ensures the stabilization of the contact force $F_d(t)$.

In order to investigate the problem of motion (displacement) stability for the last considered case of stabilized contact force, relation (14) will be used in the form of deviations:

$$M(\eta + q_d)\ddot{\eta} + [\, M(\eta + q_d) - M(q_d)\,]\ddot{q} - [\, S^T(\eta + q_d) - S^T(q_d)\,]\, F_d + \\ + L(\eta + q_d, \dot{\eta} + \dot{q}_d) - L(q_d, \dot{q}_d) = S^T(\eta + q_d)(F - F_d) \tag{22}$$

where $\eta = q - q_d$. q is the real displacement (motion) and q_d is the nominal (ideal) displacement (motion).

Relation (22) can be written in a more compact form:

$$\ddot{\eta} + K(\eta, \dot{\eta}, t) = M^{-1}(\eta + q_d) S^T(\eta + q_d)(F - F_d) \tag{23}$$

where

$$K(\eta, \dot{\eta}, t) = M^{-1}(\eta + q_d)\{\, L(\eta + q_d, \dot{\eta} + \dot{q}_d) - L(q_d, \dot{q}_d) + [M(\eta + q_d) - M(q_d)]\ddot{q}_d + \\ + [S^T(\eta + q_d) - S^T(q_d)\,]\, F_d \,\}$$

Let the homogeneous part of system (23) now be considered. In fact, it represents the environment dynamics equation (14), written in deviation form for $F(t) = F_d(t)$. It is clear that the environment dynamics should satisfy the property of asymptotic stability of the homogeneous part of trivial solution (23), so that the following is fulfilled:

$$\eta(t) \to 0 \quad \text{as} \quad t \to \infty \tag{24}$$

However, it is necessary to satisfy the sufficient stabilization conditions of $q_d(t)$, i.e. conditions for which the asymptotic stability of the homogeneous solution (23) induces the asymptotic stability of the perturbed motion $\eta(t)$ of system (23), fulfilling (24).

Aiming at this, supposing that function K is continuously differentiable, the application of this function in the vicinity of point $(\eta, \dot{\eta}) = (0,0)$ is considered:

$$K(\eta, \dot{\eta}, t) = \left.\frac{\partial K(t)}{\partial \dot{\eta}(t)}\right|_{(\eta, \dot{\eta}) \to (0,0)} \dot{\eta} + \left.\frac{\partial K(t)}{\partial \eta(t)}\right|_{(\eta, \dot{\eta}) \to (0,0)} \eta + \alpha_0(\eta, \dot{\eta}, t)$$

where $\alpha_0(\eta, \dot{\eta}, t) = o\left(\sqrt{\|\eta\|^2 + \|\dot{\eta}\|^2}\right)$.

By introducing notation: $x_1 = \eta$, $x_2 = \dot{\eta}$, $x = (x_1, x_2)^T$

$$A(t) = \begin{bmatrix} 0_n & I_n \\ -\left.\dfrac{\partial K(t)}{\partial \eta(t)}\right|_{(\eta, \dot{\eta}) \to (0,0)} & -\left.\dfrac{\partial K(t)}{\partial \dot{\eta}(t)}\right|_{(\eta, \dot{\eta}) \to (0,0)} \end{bmatrix}$$

$$\alpha(x,t) = \begin{bmatrix} 0 \\ -\alpha_0(x_1,x_2,t) \end{bmatrix}, \quad \beta(x,t) = \begin{bmatrix} 0 \\ M^{-1}[x_1 + q_d(t)]S^T[x_1 + q_d(t)] \end{bmatrix}$$

Then system (23) can be represented as:

$$\dot{x} = A(t)x + \alpha(x,t) + \beta(x,t)\mu(t) \tag{25}$$

Sufficient conditions of asymptotic stability of the differential equation (25) solution, together with the fulfilment of conditions $x(t) \to 0, \quad t \to \infty$ are given by the following theorem [21];

Theorem

Let the environment dynamics satisfy the following conditions:

1. first approximation of the system:

$$\dot{x} = A(t)x \tag{26}$$

is regular, and:

$$\lim_{t\to\infty} \frac{1}{t}\int_{t_0}^{t} SpA(w)dw = \sigma_0 \qquad \text{and} \qquad \sigma_0 = \sum_{k=1}^{2n}\alpha_k$$

where $\alpha_k (k = 1,2,...,2n)$ are characteristic indices of the solution of the system (26); SpA is the trace of matrix A;

2. all the characteristic indices $\alpha_k (k = 1,2,...,2N)$ are negative. Let the equation (17) defining the quality of transition responses be such that the following estimation for the arbitrary solution of $\mu(t)$ holds:

$$\| \mu(t) \| \le Ce^{-\lambda(t-t_0)} \| \mu(t_0) \| \tag{27}$$

with the constant C positive and index λ satisfying $-\lambda < \min_k \alpha_k$.

Let the number γ satisfy the inequality: $\max_k \alpha_k < -\gamma < 0$.

Then for sufficiently small initial perturbations $x(t_0)$ and $\mu(t_0) = F(t_0) - F_p(t_0)$, the transition response of the differential equations (25) will behave according to inequality:

$$\|x(t)\| \le \left[a\| x(t_0) \| + \frac{b\| \mu(t_0) \|}{\lambda - \gamma} \right] e^{-\gamma(t-t_0)}, \qquad \forall t \ge t_0 \tag{28}$$

with positive constants a and b, leading to the fulfilment of the conditions of the exponential stability of system (25):

$$x(t) \to 0 \quad \text{as} \quad t \to \infty \tag{29}$$

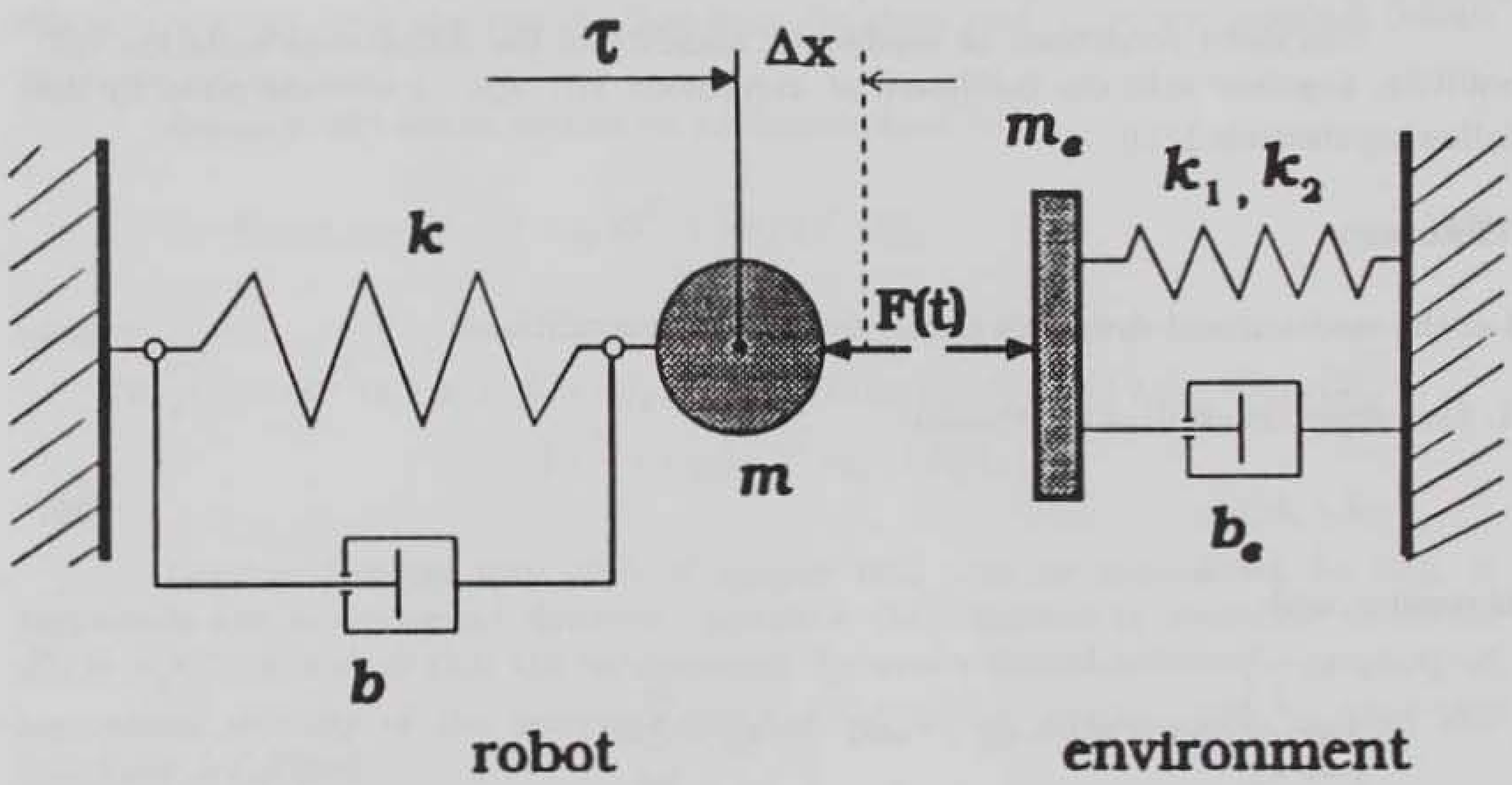

Figure 5: Single robotized link interacting with dynamic environment

In this way, along with the conditions of the Theorem, the control law (19) enables the desired quality of contact force $F_d(t)$ stabilization and also ensures the stabilization of $q_d(t)$, since it fulfils the following conditions implied by condition (29):

$$\eta \to 0, \dot{\eta} \to 0, \quad \text{as} \quad t \to \infty$$

Let it be noted that conditions 1) and 2) of the Theorem define the environment property which can be called the "internal stability" of the environment. The importance of the environment dynamics in the stabilization, when the asymptotic stability of the contact force is achieved, is illustrated by the example of one robotized link in contact with the dynamic environment (Fig. 5).

Let the environment be described by the dynamic model of the form:

$$F = m_e \ddot{x} + b_e \dot{x} + k_1 x + k_2 x^3 \tag{30}$$

where m_e is the environment mass, b_e is the corresponding environment damping, and k_1 and k_2 are the stiffness coefficients of the environment.

Using equations (23), i.e. their linear forms (25), we have:

$$\ddot{\eta} = -\frac{k_1 + 3k_2 x_d^2}{m_e}\eta - \frac{b_e}{m_e}\dot{\eta} + \frac{1}{m_e}\mu \tag{31}$$

In the state space the previous form (31) is given by:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & I \\ -\frac{k_1+3k_2x_d^2}{m_e} & -\frac{b_e}{m_e} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m_e} \end{bmatrix} \mu \tag{32}$$

where $x_1 = \eta,\ x_2 = \dot{\eta}$.

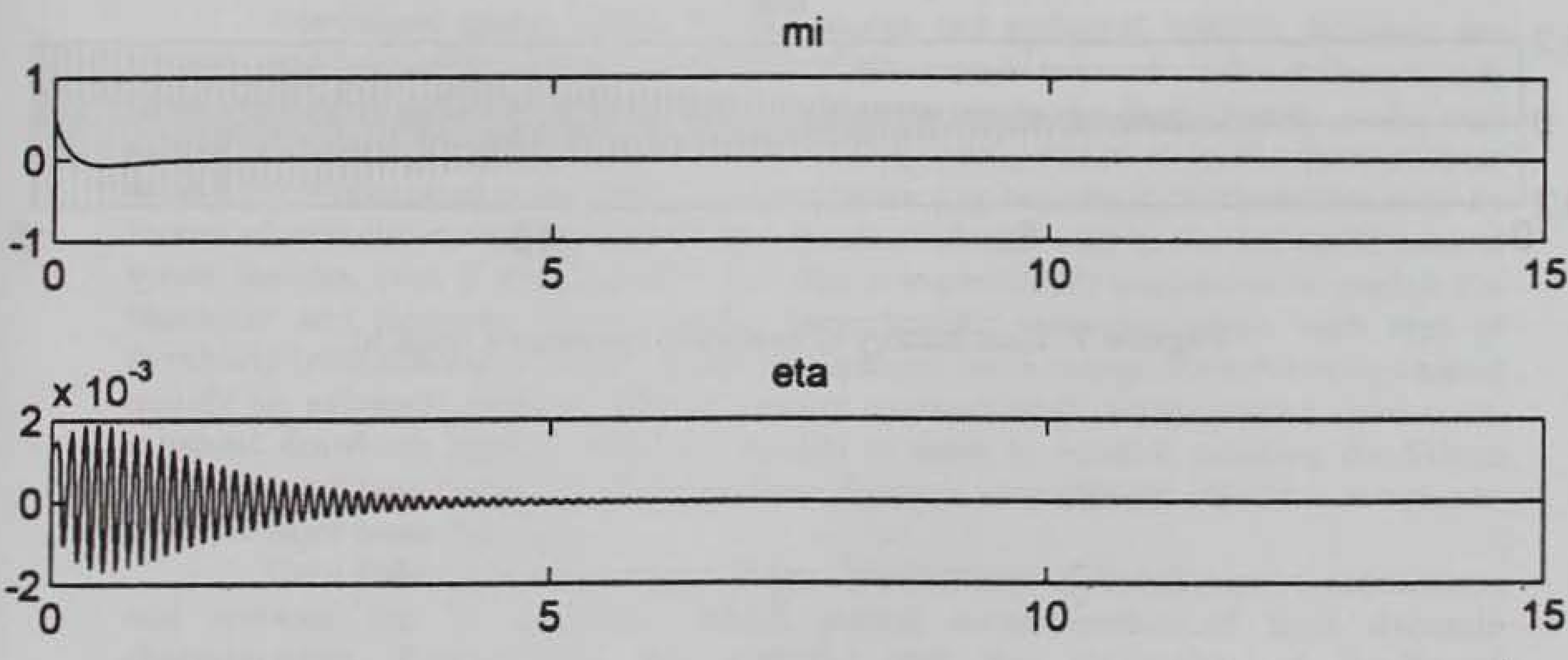

Figure 6: Time history of deviation response η (case a)

The characteristic equation of system (32) is:

$$\det(sI - A) = s^2 + \frac{b_e}{m_e}s + \frac{k_1+3k_2x_d^2}{m_e} = 0 \tag{33}$$

Conditions of the Theorem:

1. Regularity of the matrix is always fulfilled because:

$$\lim_{t\to\infty} \frac{1}{t}\int_{t_0}^{t} -\frac{b_e}{m_e}\,dw = -\frac{b_e}{m_e} \tag{34}$$

2. The character of the solution of equation (32) depends on the eigenvalues of matrix A, i.e. the terms:

$$\frac{k_1+3k_2x_d^2}{m_e} \quad \text{and} \quad \frac{b_e}{m_e}$$

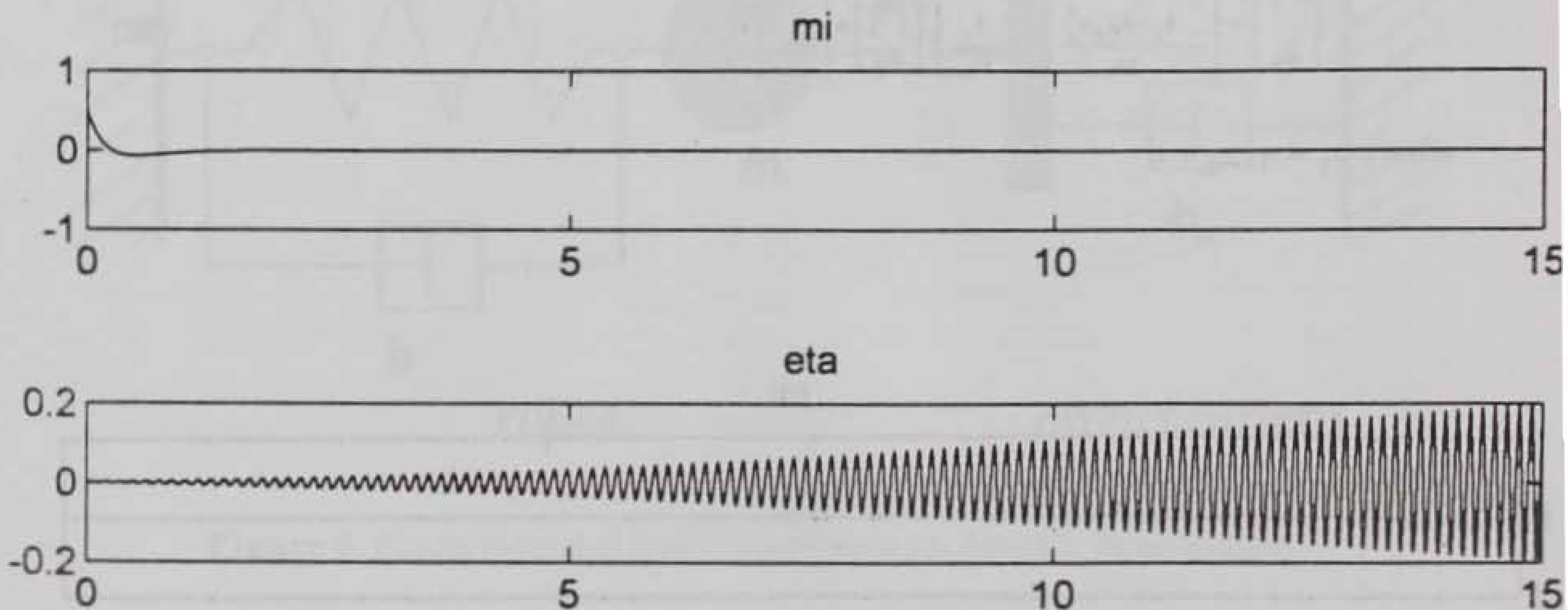

Figure 7: Time history of deviation response η (case b)

Example:

For a desired interaction force in the form:

$$F_p = F^0(1-\exp(-\alpha_p t)),$$

where $F^0 = 10N$ and $\alpha_d = 20$ the corresponding displacement is obtained from relation (30):

$$x_p \sim x_1^0 e^{-\alpha P t} + x_2^0$$

where x_2^0 is the stationary value of the programmed motion. Two cases were considered:

a) Environment parameters:

$$m_e = 2.81\text{kg},\quad b_e = 5.3\times10^2\text{Ns/m},\quad k_1 = 10^2\text{N/m},\quad k_2 = 1.5\times10^8\text{N/m}^3,$$

b) $b_e = 0$, (other environment parameters are the same as in case a).

In Fig. 6 and Fig. 7 the stabilization responses of displacement are given for the case of stabilized contact force using the control law (19).

In case b) the asymptotic stability of the contact force does not satisfy the conditions for the asymptotic stability of position (displacement). Moreover the numerical solution of the perturbation model for the parameters in this case shows rising amplitudes of displacement.

5. ACTIVE STRUCTURES

Conditions under which the structures and technical systems function are diverse, and frequently unpredictable. One of the ways to take into account the variable conditions of construction and systems functioning is in their design with high durability. The durability of constructions and systems, designed on the basis of their nonadaptive operation is, however, a conservative way because it is achieved mainly by means of overdimensioning, both in the structure design and in the energetic-control sense. Besides, even if we ignore the fact that it is practically impossible to predict the character and intensity of all possible perturbations (variable loads), such type of durability (robustness) of constructions and systems leads to unpurposeful design based mainly on extremal regimes. Hence, passive (conventional) constructions possess an inherent drawback because they are unable to react to variable working conditions (including extremal ones) by changing their dynamic properties in real time in order to preserve their basic functions.

Even today, clear directions of the development of "intelligent" constructions and systems can be perceived, which means active control of their dynamic characteristics. Expectations are realistic that the realization of intelligent constructions and their real applications will lead to essential improvements in system dynamic performances, particularly under conditions in which the capabilities of conventional constructions and systems are exhausted. Also, the techniques of computer design (CAD) with efficient and reliable user software have become broadly accessible today, so that their introduction for the automatic presentation of responses and the analysis of performances in real time contributes to the development and application of intelligent constructions and systems.

Important experience with active control, e.g., in the aviation industry can be utilized in other areas too, i.e. in other classes of systems. This primarily concerns practically all kinds of vehicles, ranging from ground transportation (road, railways), to floating, submarine and cosmic. When we speak about constructions this also include civil engineering structures, above all large-span suspension bridges, foundations of high buildings, the construction of high-speed aircraft, working performances of various exploatation platform environments type, etc.

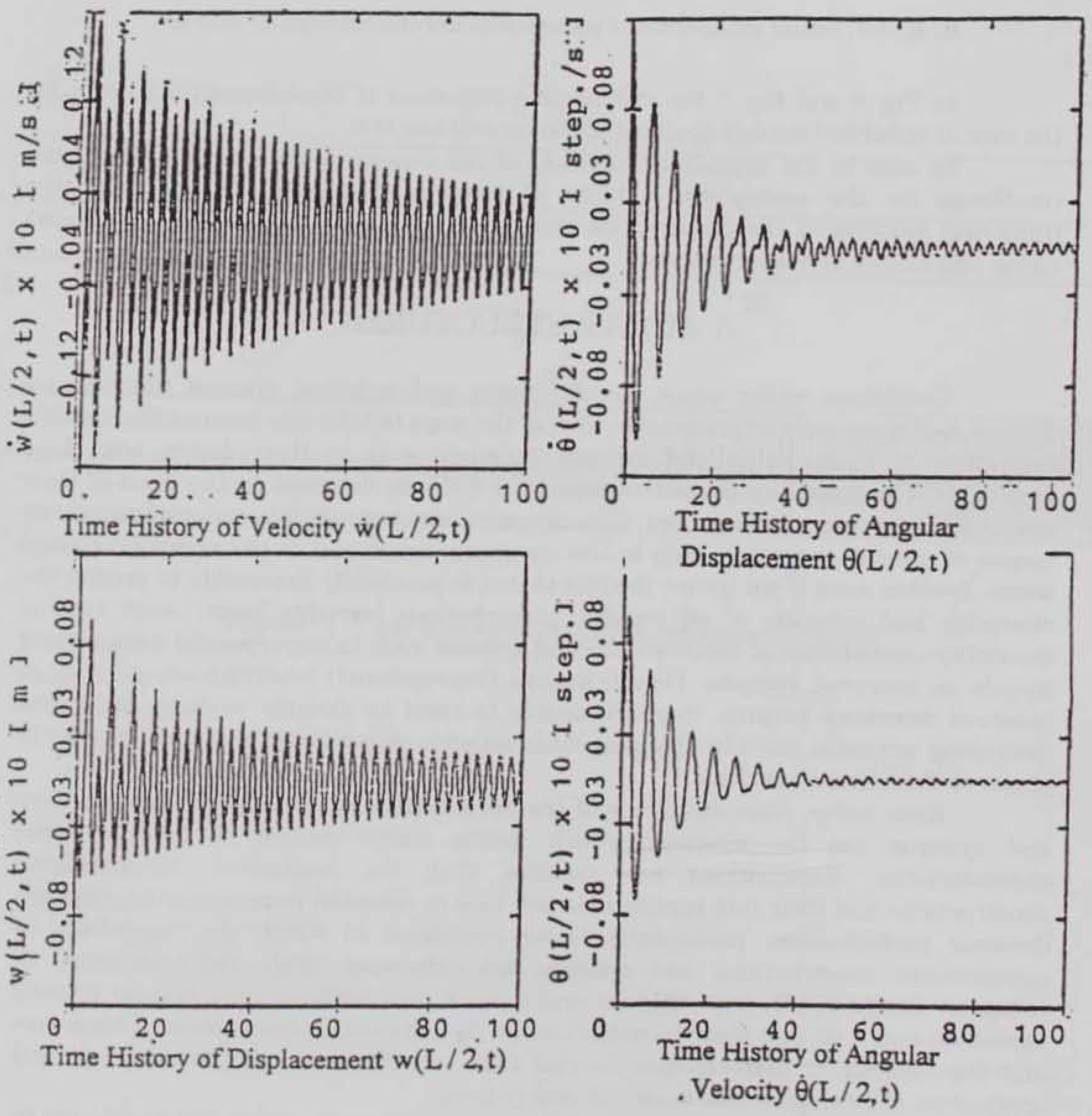

Figure 8: Responses of active bridge construction

These enumerated examples alone point to the need for active control of the dynamic performances of systems and constructions which are under conditions of both regular and extreme perturbations. Exploitation of the enumerated constructions led us in the past to the conclusion that it is their passive character that has frequently been the reason for their bad functioning, even for catastrophic outcomes in conditions of extreme perturbations. One possibility for constructions of various uses which can be put under extreme conditions is to attempt to control their dynamic characteristics and preserve the basic function of the system. Let us just recall the catastrophic outcome due to uncontrolled growth of vibration amplitudes on the Tacoma Bridge numerous breakdowns of airplane structures due to critical self-excited oscillations (airplane flutter), derailing of railway vehicles and their lateral instability, the collapse of high edifices due to destructive earthquakes, etc.

In the course of the last few years studies and realizations have appeared of semi-active controls of constructions and various types of systems, such as flutter control of large-span bridges [28], flutter control of the aerodynamic surfaces of aircraft [29], and particularly the results of semi-active and active control vehicles (road, rail, etc.) [30]-[32]. Due to limited space, only the results of the active control of a bridge construction will be presented, aimed at preventing critical oscillations (flutter) [28]. A mathematical model of the bridge dynamics was developed, consisting of the midsection of the bridge, supported by its two towers. The partial differential equations of the bridge dynamic model were transformed in the usual way to a system of ordinary second-order differential equations. Design of optimal control was performed using the procedure of control in modal space. The eigenvalues of the closed loop were chosen in such way that the flutter mode possesses a negative real part, while the frequency of the open loop stays unchanged. As it is known, motion stability is determined by the real part of the system eigenvalues, where the eigenvalues depend on velocity V. For small V, the eigenvalues possess negative real parts, so that the motion is asymptotically stable. As velocity V increases, some of the real parts may become positive, leading the system into an unstable working regime. Flow velocity corresponding to the zero value of the real part of the system eigenvalues is known as the critical velocity V_{cr}. If the critical velocity corresponds to the value for which the imaginary part of some eigenvalue is different from zero, it can be said that the structure (construction) is in flutter condition. It was proposed that the control of the dynamic bridge condition, aimed at avoiding the flutter, be for the time being realized by means of a certain number of motors (reaction, or sim.). A numerical example is given, in which bridge deck flutter possesses geometrical and aerodynamical characteristics as well as stiffness parameters similar to those of the Tacoma Bridge [28]. Calculation of the oscillatory bridge regime was carried out for a wind velocity of $V = 20m/s$. This velocity of the passive construction of the considered bridge was greater than the velocity at which the flutter with the disastrous outcome occured. By applying the synthesized control ensured by the negative real eigenvalues in the closed feedback loop damped oscillation of the bridge model corresponding approximately to the Tacoma Bridge was obtained. In Fig. 8 the time responses of vertical displacement and the torsion angle θ of the bridge at its midspan are presented.

Due to limited space some other examples of constructions subdued during their functioning to the influence of various dynamic environments could not be presented. Such constructions have experienced, like the Tacoma Bridge, collapse under the very specific regimes of their functioning.

6. CONCLUSION

Only four subjects within the scope of the set topic were presented in this survey paper. Two reasons exist for such a small number of subjects. The first is the limited space, and the second, more important, is that in the author's opinion, the presented topics are essential and characteristic of the development of robotics, which in the course of the last few years has attained more and more the character of special purpose. In connection with this, in the last segment of the paper the problem of active constructions was emphasized, which can be understood both as the partial or complete robotization of traditional constructions, structures and systems. At the same time, the author wanted to herald broad activity in the area of "controlled" responses of systems and constructions within the scope of very broad problems of contact tasks. After the third section of the paper dedicated to a new aspect of the role of the dynamic environment in which active systems function, the problem of the behaviour of constructions was presented, which in the future should be the subject of, at least partial, robotization. However, a dilemma remains about the purposefulness of taking such a direction, despite the need to make various constructions active, at least those which during their service life can, but need not come into extremal conditions, whereby the installation must be permanently maintained.

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