Fuzzy Logic-Based Inverse Dynamic Modelling of Robot Manipulators

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Abstract

This paper presents design and implementation of a systematic fuzzy modelling methodology for the inverse dynamic modelling of robot manipulators. The fuzzy logic modelling methodology is motivated in part by the difficulties encountered in the modelling of complex nonlinear uncertain systems, and by the objective of developing an efficient dynamic model for the real-time model-based control. The methodology is applied to build the fuzzy logic-based inverse dynamic model of a wire-actuated parallel manipulator with uncertain dynamics. The developed inverse dynamics has been used in a fuzzy model-based adaptive robust controller for the tracking control of the parallel manipulator.

Keywords: manipulator dynamics, fuzzy logic-based modelling, inverse dynamic modelling

1. Introduction

Robot manipulators are inherently complex and nonlinear uncertain systems. That is, it is not that possible to obtain their accurate model due to large dynamic coupling between different links, hard nonlinearity (e.g., Coulomb friction) and time-varying characteristics of the manipulators. To accommodate system uncertainties, variation of the parameters with time and disturbances; learning, reasoning, decision making and advance modelling techniques should be incorporated in the controller. Very often the approximation capabilities of the fuzzy systems are used for compensating the unknown dynamics or particular component of the dynamics of manipulators. For instance, in [1] a fuzzy system was utilized to compensate for the friction and payload variation, and in [2] a fuzzy system was used as an adaptive approximator for modelling a manipulator dynamics. Systematic fuzzy modelling of manipulator inverse dynamic model from input-output data was presented in [3]. In [4] fuzzy logic was applied for controlling a flexible link robot arm.

The inverse dynamic model of a robot manipulator is required to generate the control input (i.e., joint torques/forces). In addition, the size of the uncertainties can be reduced, to a large extent, by having a good dynamic model of the system, which in turn reduces the chattering and helps to stabilize the closed-loop system. In the following subsections, the general inverse dynamic model and fuzzy inverse dynamic model of manipulators are discussed.

1.1 General Inverse Dynamic Model

The inverse dynamic model of manipulators can be described as

$$\boldsymbol{\tau} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) \tag{1}$$

where $\boldsymbol{\tau} = [\tau_1, \tau_2, ..., \tau_n]^{\mathrm{T}}$ is the vector of input generalized forces, and n denotes the number of generalized coordinates of the manipulator. Inertia matrix $\mathbf{M}(\mathbf{q})$ is an $n \times n$ symmetric positive definite matrix; $\mathbf{q} = [q_1, q_2, ..., q_n]^{\mathrm{T}}$, $\dot{\mathbf{q}} = [\dot{q}_1, \dot{q}_2, ..., \dot{q}_n]^{\mathrm{T}}$ and $\ddot{\mathbf{q}} = [\ddot{q}_1, \ddot{q}_2, ..., \ddot{q}_n]^{\mathrm{T}}$ are the displacement, velocity and acceleration vectors of joints respectively; and

$$\mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) = \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\,\dot{\mathbf{q}} + \mathbf{f}_f(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{g}(\mathbf{q}) + \mathbf{f}_{\mathrm{ext}} \tag{2}$$

where $\mathbf{C}(\mathbf{q},\dot{\mathbf{q}})$ is an $n \times n$ matrix of centripetal and Coriolis terms, $\mathbf{f}_f$ is an $n \times 1$ vector denoting viscous and Coulomb friction forces, $\mathbf{g}(\mathbf{q})$ is an $n \times 1$ vector of gravitational terms, and $\mathbf{f}_{\mathrm{ext}}$ is an $n \times 1$ vector denoting the actuator reaction forces/torques corresponding to the external forces/torques on the end effector. For parallel manipulators, equation (2) may contain another term due to the holonomic constraints because of the closed-loops and existence of passive joints, e.g., $\mathbf{h}(\mathbf{q},\dot{\mathbf{q}}) = \mathbf{C}(\mathbf{q},\dot{\mathbf{q}})\,\dot{\mathbf{q}} + \mathbf{f}_f(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{g}(\mathbf{q}) + \mathbf{f}_{\mathrm{ext}} + \mathbf{F}_c^T\boldsymbol{\lambda}$ where $\boldsymbol{\lambda}$ is the vector of Lagrange multipliers and $\mathbf{F}_C$ accounts for constraint forces induced by closed-loop kinematic chains [5].

Because of the system uncertainty and external disturbances, equation (1), which describes the dynamic model of a manipulator, is not exactly known. Therefore, the dynamic model of manipulators is as

$$\boldsymbol{\tau} = \left(\hat{\mathbf{M}}(\mathbf{q},t) + \Delta\mathbf{M}(\mathbf{q},t)\right)\ddot{\mathbf{q}} + \left(\hat{\mathbf{h}}(\mathbf{q},\dot{\mathbf{q}},t) + \Delta\mathbf{h}(\mathbf{q},\dot{\mathbf{q}},t)\right) + \mathbf{d}(t) \tag{3}$$

where $\hat{\mathbf{M}}(\mathbf{q},t)$ and $\hat{\mathbf{h}}(\mathbf{q},\dot{\mathbf{q}},t)$ are the known (estimated) parts and $\Delta\mathbf{M}(\mathbf{q},t)$ and $\Delta\mathbf{h}(\mathbf{q},\dot{\mathbf{q}},t)$ are the unknown parts of $\mathbf{M}(\mathbf{q},t)$ and $\mathbf{h}(\mathbf{q},\dot{\mathbf{q}},t)$ respectively, and $\mathbf{d}(t)$ is an $n \times 1$ bounded vector arising from the external disturbances. Based on equations (1) and (3), the following expression holds

$$\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t) = \hat{\mathbf{F}}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t) + \tilde{\mathbf{F}}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t) \tag{4}$$

where $\mathbf{F}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t)=\mathbf{M}(\mathbf{q})\ddot{\mathbf{q}}+\mathbf{h}(\mathbf{q},\dot{\mathbf{q}})$, $\hat{\mathbf{F}}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t)=\hat{\mathbf{M}}(\mathbf{q})\ddot{\mathbf{q}}+\hat{\mathbf{h}}(\mathbf{q},\dot{\mathbf{q}})$ is the known (approximated) part of the manipulator inverse dynamic model and can be approximated using the fuzzy modelling method of [6, 7], and $\tilde{\mathbf{F}}(\mathbf{q},\dot{\mathbf{q}},\ddot{\mathbf{q}},t)=\Delta\mathbf{M}(\mathbf{q},t)\ddot{\mathbf{q}}+\Delta\mathbf{h}(\mathbf{q},\dot{\mathbf{q}},t)+\mathbf{d}(t)$ is the uncertainty vector of the inverse dynamic model.

1.2 Fuzzy Inverse Dynamic Model

The fuzzy dynamic model considered here is a qualitative explanation of the behaviour of manipulator in the framework of fuzzy logic (in the form of IF-THEN rules) instead of a mathematical equation. Conceptually, a multi-input-multi-output (MIMO) system with multiple independent outputs can be considered as a set of multi-input-single-output (MISO) systems [8]. In the inverse dynamic problem of a manipulator, the torque of each joint is a function of position, velocity and acceleration of that joint and the other joints. Therefore, for an n DOF manipulator, a MISO fuzzy model for joint k (k = 1, …, n) expresses variation of the torque/force of that joint, as a result of the motion of all joints, in the following form of the rules

$$R_i : \text{IF } q_1 \text{ is } A_{i1} \text{ AND } q_2 \text{ is } A_{i2} \text{ AND } \ldots \text{ AND } q_r \text{ is } A_{ir} \text{ THEN } \tau_k \text{ is } B_i \qquad (5)$$

where R_i is the i-th rule (i = 1, …, c), and q_1, …, q_r are the main input variables for joint k, k=1,…, n, that are identified among the elements of the joint displacement, velocity and acceleration. Fuzzy sets A_{ij} (j = 1, …, r) in the antecedent (IF part) are associated with r input variables, τ_k is the output torque of joint k and fuzzy set B_i in the consequent (THEN part) represents the output membership function of rule i.

The four principal components of a fuzzy system with crisp (non-fuzzy) inputs and outputs are fuzzification, fuzzy rule base, reasoning mechanism (also called fuzzy inference), and defuzzification [9]. The fuzzification refers to replacing the crisp input with a set whose boundaries are fuzzy, i.e., fuzzy set. As the central part of a fuzzy system, fuzzy rule base (a set of rules in the form of IF-THEN statements, also referred to as fuzzy model) describes the system behaviour. The reasoning mechanism is a decision making logic which employs fuzzy rules from the fuzzy rule base to determine the fuzzy outputs corresponding to the fuzzified inputs of the fuzzy system. The process of transforming the fuzzy output of a fuzzy system to non-fuzzy output (crisp output) is called defuzzification.

The methodology of fuzzy model construction from available input-output data is based on the improved systematic fuzzy modelling method through the following steps.

1. Generating/finding the optimum number of rules that can describe the behavior of a dynamic system accurately and robustly in whole domain of interest.
2. Finding/selecting the minimum number of input variables (referred to as the “main inputs”).
3. Designing the antecedent and consequent parts of each rule, which means how to partition the input space and output space respectively and how to assign the membership function to each partition.
4. Designing/selecting the appropriate reasoning mechanism.
5. Parameter identification (parameters of the clustering algorithm and parameters of the reasoning mechanism) and parameter tuning procedures.

2 Fuzzy Logic-Based Modelling of a Wire-Actuated Parallel Manipulator

In this paper, the improved systematic fuzzy logic modelling methodology from available information (e.g., a simplified analytical model) and experimental data (input-output data of a real system), proposed in [6, 7], is applied for developing an adaptive fuzzy-logic based inverse dynamic model of a 4 degrees of freedom (DOF) wire-actuated parallel manipulator depicted in Figure 1.

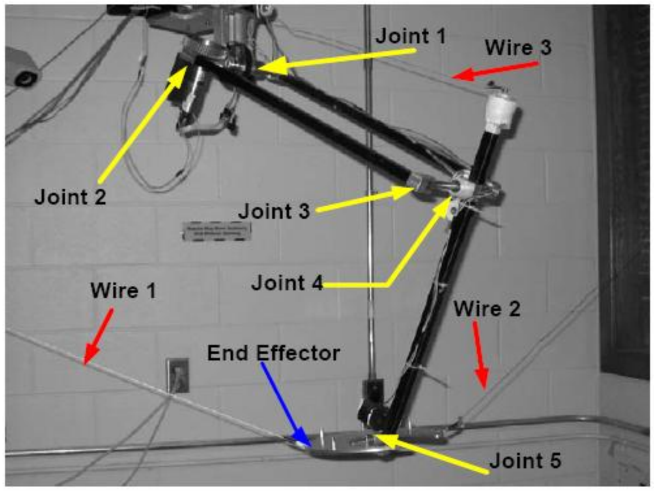

Figure 1. Wire-actuated parallel robot manipulator.

The manipulator has been designed for digging and soil sampling at the planetary explorations [10, 11]. The manipulator consists of a constraining linkage with seven joints and six links (excluding the base link) and three wires. The four degrees of freedom of the manipulator are controlled by five actuators (motors). All motors are 24 V DC servo motors equipped with gear reducers and encoders. The actuated joints one and two each is coupled with internal and external planetary gearboxes with a gear reduction of 134 to 1 and 4 to 1 respectively. The motion of joints four and five (each equipped with an encoder but no motor) are controlled by three actuated wires; since wires can only pull thus redundant actuation is needed. The motors of wires one and two are coupled with a gearbox with a gear reduction of 12.5 to 1 and the gearbox of wire three motor has a gear reduction of 45.5 to 1.

To construct the fuzzy inverse dynamic model of the actuated joint/wire *i* of the manipulator, the input-output data set for that actuated joint/wire need to be formed. The joint/wire torque τ_i (output) is proportional to the motor torque τ_{mi} of the actuated joint/wire *i* by its gear ratio N_{Gi} and efficiency of gear transmission η_i as $\tau_i = N_{Gi}\,\eta_i \tau_{mi} = N_{Gi}\,\eta_i K_{Ti}\, i_m$, where K_{Ti} and i_m are respectively the torque constant and current of the motor. The pertinent specifications for the actuators are reported in [12].

2.1 Data Acquisition and Preparation for Fuzzy Modelling

To construct a fuzzy inverse dynamic model of the parallel manipulator from input-output data, because the manipulator has five actuators, it can be considered as a composition of five MISO subsystems. Each MISO subsystem has one output, i.e., torque of joint/wire actuator, and 12 input candidates, i.e., position, velocity and acceleration of the four independent joints of the constraining linkage (actuated joints one and two and passive joints four and five). Because the configuration of the manipulator can be fully described in terms of the motion of independent joints of the constraining linkage [11], instead of the motion of actuated joints/wires, the motion of these four joints are used as inputs.

The first step in data driven modelling (i.e., modelling from input-output data) is to obtain an adequate amount of input-output data by moving the manipulator along different trajectories, and measuring the displacements (and velocities and accelerations) and torques. Since the test-bed is not equipped with velocity and acceleration sensors, the on-line calculation of velocity and acceleration is performed by a backward difference method as $\dot{\mathbf{q}}(k) = \left(\mathbf{q}(k+1) - \mathbf{q}(k-1)\right)/2T$ and $\ddot{\mathbf{q}}(k) = \left(\mathbf{q}(k+1) - 2\mathbf{q}(k) + \mathbf{q}(k-1)\right)/T^2$, where $\mathbf{q}(k)$ indicates the joint positions at the k-th sample and T is the sampling period. To have a rich yet small number of identification data (training data) and excite significant number of modes of the manipulator, random trajectories and harmonic trajectories with different frequencies and maximum desired amplitudes within the manipulator workspace are generated in the Simulink environment. To excite the wires, as wires can only pull, several harmonic and periodic trajectories are generated using the inverse kinematic model of the manipulator. It should be noted that when the exciting frequencies contain low-frequency motion friction effects become dominant, and when they contain high-frequency motion inertial effects are dominant.

Because the first derivative (velocity) and especially the second derivative (acceleration) of positions amplify the high frequency noise, the displacement reading is filtered using the digital low-pass Butterworth filter (recommended by many researchers) prior to computing the velocity and acceleration signals. To find a proper cut-off frequency of the filter (to keep the useful information while rejecting the high frequency components), initially the acceleration of a known trajectory (e.g., sinusoidal) was compared with the measured and filtered acceleration of corresponding known trajectory. Then, since the measured torque of each joint/wire actuator contains the effects of accelerations of all joints/wires, based on the power spectral analysis of the actuator torques, the cut-off frequency of 35 Hz and 30 Hz were obtained respectively for joints and wires. Because arbitrary random excitation cannot be applied to wires (wires can only pull) the 30 Hz cut-off frequency for wires was obtained mostly by trail and error.

The collected data are categorized for three purposes. The main part (about 80%) of the data (training data) is used for structure identification (generating fuzzy IF-THEN rules) that includes the output data clustering, main input selection, and input-output membership assignment. Part of the remaining collected data (tuning data) is used for parameter identification that includes the weights of fuzzy rules. The remaining data are used for fuzzy model validation by comparison of the output of fuzzy model with the measured torque of joint/wire actuators.

2.2 Fuzzy Model

The fuzzy logic-based inverse dynamic model of the manipulator is developed according to the fuzzy modelling algorithm in Figure 2, which is based on the proposed fuzzy modelling procedure of [6, 7]. The fuzzy modelling procedure consists of structure identification and parameter identification.

For structure identification, to build the fuzzy model, the output data, i.e., torque of joint/wire actuators, are clustered using the fuzzy c-means algorithm given in [7]. To determine the correct number of clusters/rules c (number of groups that exist in the data), i.e., for well-separated and compact clusters, the cluster validity index S_c of [13] is used

$$S_c = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \left(\|x_k - v_i\|^2 - \|v_i - \bar{v}\|^2 \right) \tag{6}$$

where N is the number of data vectors and u_{ik} is the membership degree of each data point to each cluster calculated as

$$u_{ik} = \left[\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|} \right)^{(2/m-1)} \right]^{-1} \tag{7}$$

The fuzziness parameter is denoted as m, $\|.\|$ is the Euclidean norm, x_k is the k-th data point, $v_i = \sum_{k=1}^{N} (u_{ik})^m x_k \Big/ \sum_{k=1}^{N} (u_{ik})^m$ is the cluster centre, and $\bar{v} = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m x_k \Big/ \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m$ is the fuzzy total mean vector which represents a weighted mean of data considering their membership to each of the clusters in fuzzy partition.

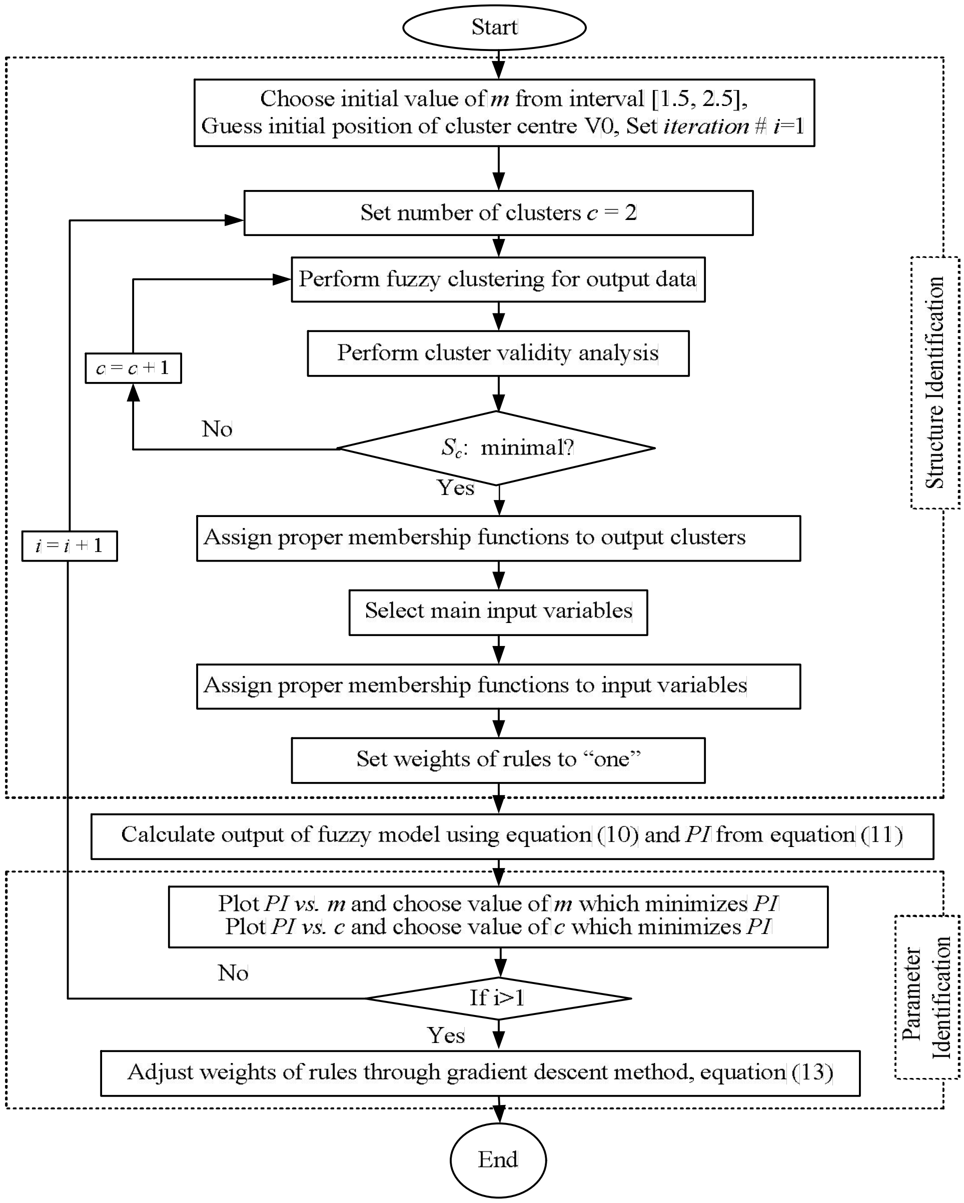

Figure 2. Proposed fuzzy modelling flowchart.

Using the cluster validity analysis, the optimum number of clusters is investigated for each joint/wire as depicted in Figure 3. Then, the main input variables for each joint/wire are identified based on the quantitative π index [7] that is computed for each joint and wire for the selected number of rules (clusters) c and different values of the fuzziness parameter m as

$$\pi_j = \prod_{i=1}^{c} \frac{\sum \Gamma_{ij}}{\max(x_j)} \tag{8}$$

where Γ_{ij} is the set of inputs x_j with $u_{ik} = 1$, j =1, 2, …, r_0, i = 1, 2, …, c and k = 1, 2, …, N, in the i-th cluster (rule), and r_0 is the number of input candidates. Equation (8) is concluded from the fact that, in the calculation of the firing strength (antecedent aggregation) ω_i of the i-th rule, either with the algebraic product operator or with the min operator, the membership degree "one" is the neutral element. Therefore, the input variables with many "one" elements in their membership function correspond to a large value of π (ineffective inputs), and can be discarded from the input candidates. That is, a small value of π represents a more dominant input. The main input selection results are listed in Table 1; for each column, the highlighted π indices represent the corresponding main inputs of each actuated joint/wire.

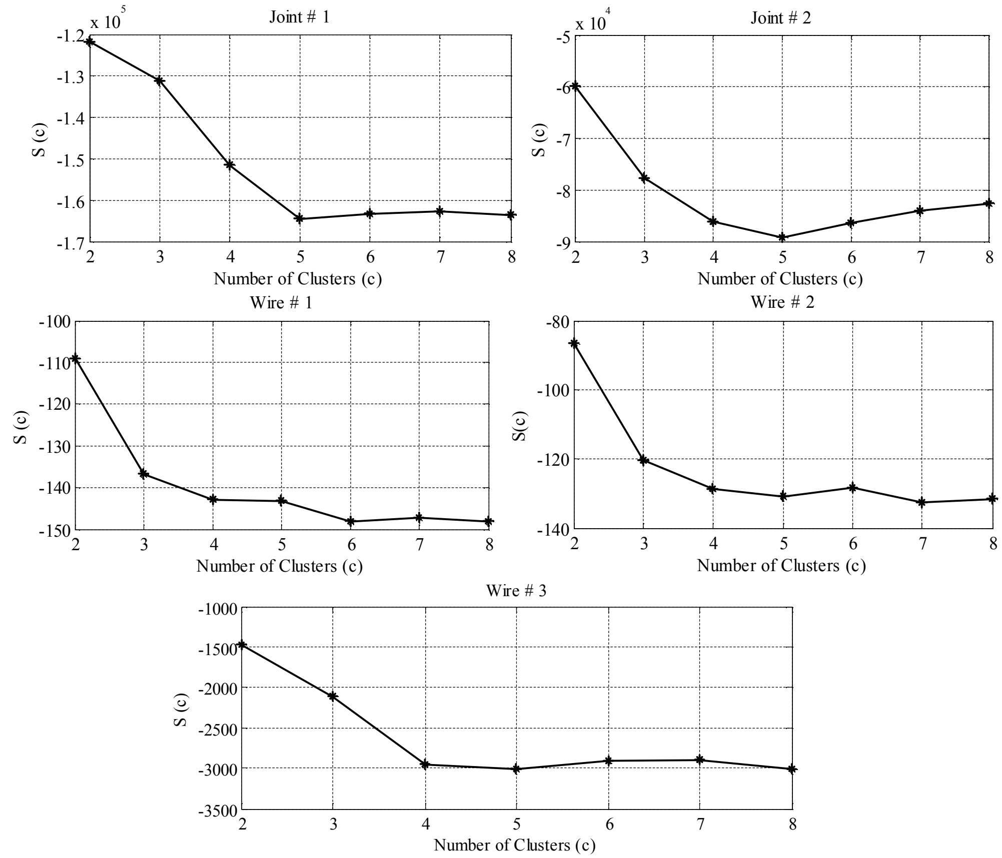

Figure 3: Cluster validity indices for the five actuators of manipulator.

To produce the antecedent fuzzy set of each rule, the selected main inputs are partitioned into the appropriate fuzzy sets, using the technique suggested in [13], to form the trapezoidal membership functions for each input. In this method, the membership degree of the peak points (data points with membership degree of "one" or close to "one") are the same for the input and output clusters and the membership degree of the remaining data points, e.g., j-th input variable, are calculated as

$$u_{ik}^{(j)} = \begin{cases} \mathrm{Max}\left[\left[\sum_{l=1}^{c}\left(\frac{\left|x_{jk}-v_{ij}^{1}\right|}{\left|x_{jk}-v_{lj}^{1}\right|}\right)^{(1/m-1)}\right]^{-1}, \left[\sum_{j=1}^{c}\left(\frac{\left|x_{jk}-v_{ij}^{2}\right|}{\left|x_{jk}-v_{lj}^{2}\right|}\right)^{(1/m-1)}\right]^{-1}\right] & : x_{jk} < v_{ij}^{1} \text{ or } x_{jk} > v_{ij}^{2} \\ 1 & : v_{ij}^{1} < x_{jk} < v_{ij}^{2} \end{cases} \quad (9)$$

for $i = 1, 2, \ldots, c$; $j = 1, 2, \ldots, r$; and $k = 1, 2, \ldots, N$; where r is the number of main input variables, x_{jk} is the k-th data of j-th input variable and v_{ij}^{1} and v_{ij}^{2} are points on the i-th cluster of j-th axes of input variables x_j $(j = 1, 2, \ldots, r)$, which have output membership degrees equal or close to one. At this point, the structure of the five MISO fuzzy models of the five actuated joints/wires has been identified.

Table 1. Main input indices of actuated joints and wires.

Joint 1 $c = 5$, $m = 2$	**Joint 2** $c = 5$, $m = 2$	**Wire 1** $c = 6$, $m = 1.5$	**Wire 2** $c = 5$, $m = 1.7$	**Wire 3** $c = 5$, $m = 1.8$
π_{q_1} =7.2673e+3	π_{q_1} =370.7045	π_{q_1} = 7.4174e+5	π_{q_1} =5.2432e+4	π_{q_1} =1.0864e+4
π_{q_2} =7.9446e+5	π_{q_2} =2.7136e+4	π_{q_2} = 4.2255e+7	π_{q_2} = 4.3882e+5	π_{q_2} =7.8353e+4
π_{q_4} =1.9536e+6	π_{q_4} =9.0021e+3	π_{q_4} =2.1979e+7	π_{q_4} =8.5291e+3	π_{q_4} =2.4266e+3
π_{q_5} =1.3341e+7	π_{q_5} = 1.0814e+5	π_{q_5} =1.1003e+9	π_{q_5} =6.3028e+8	π_{q_5} =1.5647e+8
$\pi_{\dot{q}_1}$ =2.4817e+4	$\pi_{\dot{q}_1}$ =273.7883	$\pi_{\dot{q}_1}$ =2.2641e+5	$\pi_{\dot{q}_1}$ =3.4352e+3	$\pi_{\dot{q}_1}$ = .1642e+3
$\pi_{\dot{q}_2}$ =8.1471e+4	$\pi_{\dot{q}_2}$ = 499.4337	$\pi_{\dot{q}_2}$ =8.4342e+6	$\pi_{\dot{q}_2}$ =5.8215e+3	$\pi_{\dot{q}_2}$ =1.5393e+3
$\pi_{\dot{q}_4}$ =3.2206e+3	$\pi_{\dot{q}_4}$ **=10.4070**	$\pi_{\dot{q}_4}$ =9.1016e+3	$\pi_{\dot{q}_4}$ =3.4641e+3	$\pi_{\dot{q}_4}$ =1.0945e+3
$\pi_{\dot{q}_5}$ **=0.0123**	$\pi_{\dot{q}_5}$ **= 8.2020e-4**	$\pi_{\dot{q}_5}$ **= 0.1308**	$\pi_{\dot{q}_5}$ **=2.8776e-6**	$\pi_{\dot{q}_5}$ **=1.9289e-5**
$\pi_{\ddot{q}_1}$ **= 28.3639**	$\pi_{\ddot{q}_1}$ **= 0.8618**	$\pi_{\ddot{q}_1}$ **= 666.5307**	$\pi_{\ddot{q}_1}$ **=72.2085**	$\pi_{\ddot{q}_1}$ **=6.0446**
$\pi_{\ddot{q}_2}$ **= 287.8772**	$\pi_{\ddot{q}_2}$ = 16.6549	$\pi_{\ddot{q}_2}$ **=5.3404e+3**	$\pi_{\ddot{q}_2}$ **= 33.5940**	$\pi_{\ddot{q}_2}$ **=6.2398**
$\pi_{\ddot{q}_4}$ **=1.0916**	$\pi_{\ddot{q}_4}$ **=0.0053**	$\pi_{\ddot{q}_4}$ **= 2.2590**	$\pi_{\ddot{q}_4}$ **= 36.2224**	$\pi_{\ddot{q}_4}$ **=6.2522**
$\pi_{\ddot{q}_5}$ **= 1.3706e-4**	$\pi_{\ddot{q}_5}$ **= 8.7143e-6**	$\pi_{\ddot{q}_5}$ **=0.0012**	$\pi_{\ddot{q}_5}$ **=1.4868e-6**	$\pi_{\ddot{q}_5}$ **=4.9392e-6**

The defuzzified output value for c fuzzy rules is as:

$$\hat{y} = \sum_{i=1}^{c} W_i y_i^* \tag{10}$$

where the design parameter $W_i \geq 0$ (i = 1, 2, …, c) is the weight of the i-th rule that should be identified such that to minimize the performance index (PI), which is the mean squared error between the fuzzy model output and the desired/actual output, $y_i^* = \omega_i y_i^o \Big/ \sum_{i=1}^{c} \omega_i$ which can be considered as a normalized defuzzified output value of the i-th rule, and y_i^o is a non-fuzzy representative of the output fuzzy set B_i of i-th rule and is selected according to the criteria defined in [14]. To account for the influence of the unmodelled effects (inaccuracies and uncertainties that may exist in the antecedent and consequent fuzzy sets of the rules), in equation (10) the parameterized form (weighted sum) of y_i^* is used.

Following the structure identification, the parameters of the fuzzy model (fuzziness parameter and weights of rules) are calculated for all five joints/wires. The weights of rules are identified in an on-line procedure using a gradient descent technique based on the instantaneous difference of the fuzzy model output and actual output, $e_k = y_k - \hat{y}_k$, by minimizing the performance index PI:

$$PI(\mathbf{W}) = \frac{\sum_{k=1}^{N}\left(y_k - (\sum_{i=1}^{c} W_i y_i^*)_k \right)^2}{N} \tag{11}$$

Using the gradient descent technique, the weight modification term for the i-th weight is:

$$\Delta W_i(z) = -\alpha_{Lr} \frac{\partial PI(\mathbf{W})}{\partial W_i} = \frac{2\alpha_{Lr} \sum_{k=1}^{N} e_k^{(z)} (y_k^*)^{(z)}}{N} \tag{12}$$

where α_{Lr}, $0 \leq \alpha_{Lr} \leq 1$, is the learning rate, also called the step size. Therefore, at step z+1 of learning process, the updating law for the weight of the i-th rule is obtained as:

$$W_i(z+1) = W_i(z) + \frac{2\alpha_{Lr}}{N} \sum_{k=1}^{N} \left(e_k^{(z)} \left(\frac{\omega_i y_i^o}{\sum_{i=1}^{c} (\omega_i)} \right)_k^{(z)} \right) \tag{13}$$

This parameterized direct fuzzy reasoning adds adaptive capability to a fuzzy model. In a real-time application, the rule weights can be updated at the same sampling rate that the control loop runs or at the sampling rate slower than the sampling rate of control loop (to reduce the computation burden). The rule weights are factors by which the contribution of each rule in the rule set are multiplied with as a fuzzy system adapts to its environment.

The fuzziness parameter *m* is identified by plotting the performance index *PI* versus *m* (Figure 4). It should be noted that by proper identification of *m*, there is no need to adjust the membership functions of input and output data. The results for the two joints and three wires are summarized in Table 2. The fuzzy logic inverse dynamic models of the five actuated joints/wires of manipulator are depicted in Figure 5.

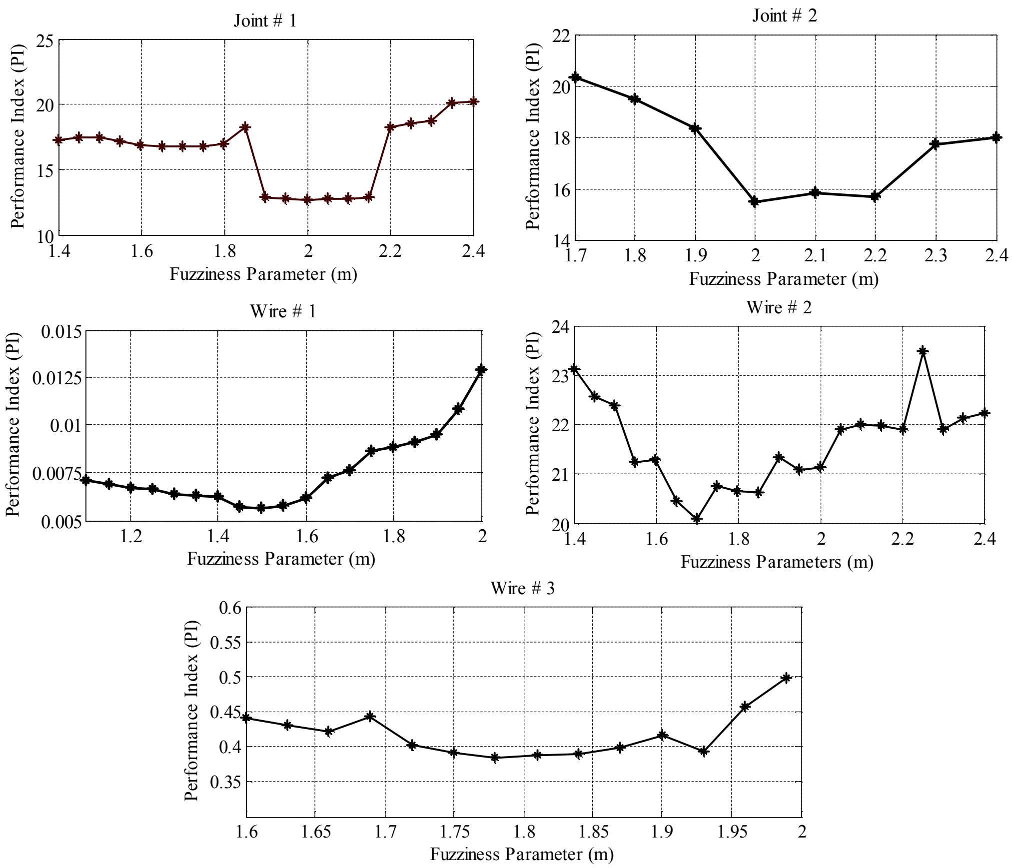

Figure 4. Performance index variation with the fuzziness parameter *m* for actuated joints/wires.

The identified fuzzy-logic-based inverse dynamic model was validated by applying a different set of trajectories. The evaluation experiment consisted of first a comparison study of the fuzzy model output and the calculated actuator torques using the measured current and torque constant of each joint/wire actuator, which indicated that the fuzzy model output follows the measured joint/wire torque with good accuracy (Figure 6). In the second step, effectiveness of the identified fuzzy model was assessed through the use of the fuzzy model as a model-based component of the proposed control methodology of [15] for trajectory tracking task. The experimental results verified that, in the controller, the main part of the control input was produced by the fuzzy inverse dynamic model of the system, i.e., the controller mainly relied on the model-based component rather than the error-based component.

Table 2. Specification of the fuzzy model of actuated joints/wires.

Joints/Wires	**# of Clusters** *c* (Figure 3)	**Fuzziness Parameter** *m* (Figure 4)	**Main Input Variables** (Table 2)
Joint 1	5	2	$\dot{q}_5, \ddot{q}_1, \ddot{q}_2, \ddot{q}_4, \ddot{q}_5$
Joint 2	5	2	$\dot{q}_4, \dot{q}_5, \ddot{q}_1, \ddot{q}_4, \ddot{q}_5$
Wire 1	6	1.5	$\dot{q}_5, \ddot{q}_1, \ddot{q}_2, \ddot{q}_4, \ddot{q}_5$
Wire 2	5	1.7	$\dot{q}_5, \ddot{q}_1, \ddot{q}_2, \ddot{q}_4, \ddot{q}_5$
Wire 3	5	1.8	$\dot{q}_5, \ddot{q}_1, \ddot{q}_2, \ddot{q}_4, \ddot{q}_5$

3 Discussion and Conclusions

In this paper a methodology for the development of fuzzy-logic based inverse dynamic model of robot manipulators, presented in [6, 7], was implemented to build an adaptive fuzzy model of a 4 DOF wire-actuated parallel manipulator. The optimum value of the fuzziness parameter m was identified using the variation of the performance index with m. This is justified by using the concept of the interval of confidence, which relates parameter m to the level of uncertainty contained in the input-output data. The optimum number of clusters (rules) was chosen based on an additional criterion using the variation of the fuzzy model output with respect to the number of clusters. A generalized and parameterized reasoning mechanism, constructed based on the weighted sum of the normalized defuzzified output value of each individual rule, was applied. To relax the persistent excitation condition (condition on the input signal that guarantees uniform asymptotic convergence of the identification algorithms) in the off-line identification procedure and to account for the effects of the time-varying parameters, a gradient-descent based parameter adjustment was implemented to tune the parameters of reasoning mechanism instead of the existing heuristic parameter identification. The identified fuzzy model (calculated actuated torques) of manipulator was verified by the corresponding measured quantities.

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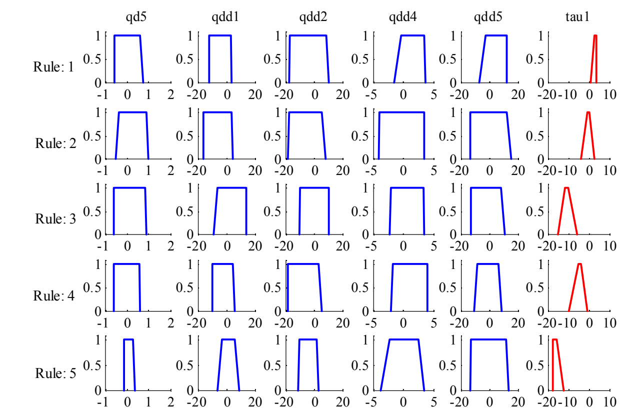
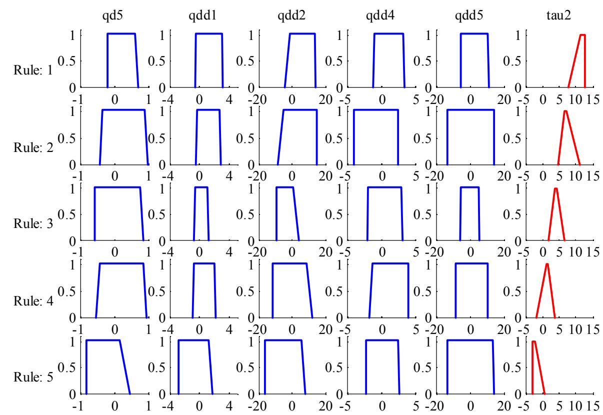
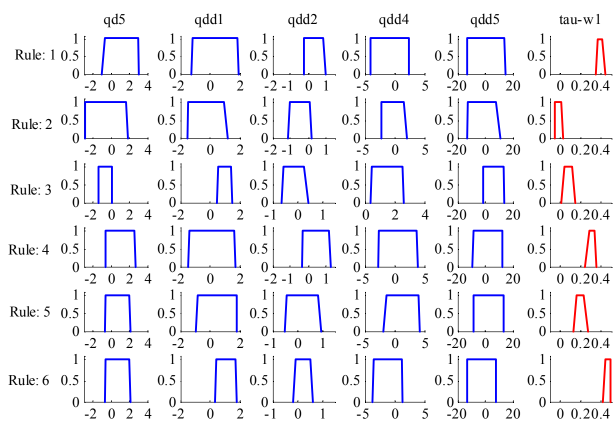


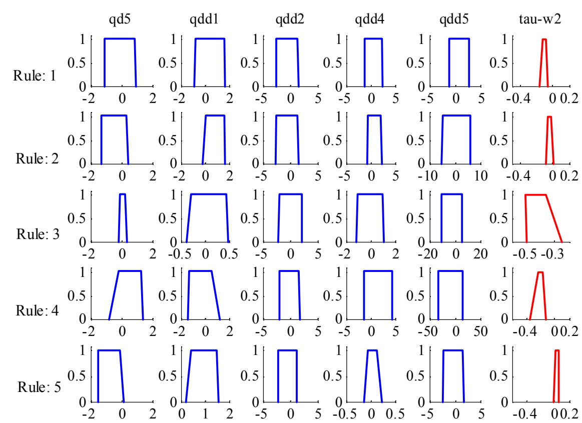
(a) Joint 1



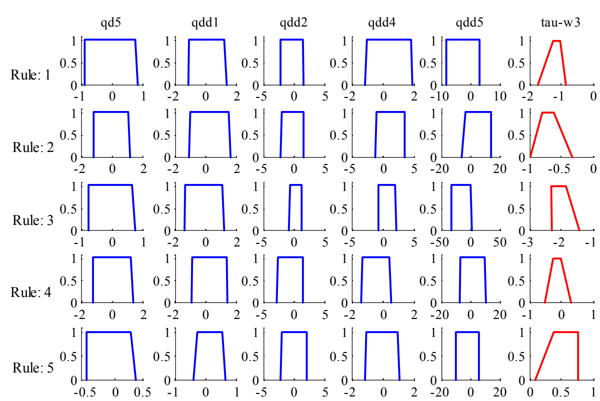
(b) Joint 2



(c) Wire 1



(d) Wire 2



(e) Wire 3

Figure 5. Fuzzy logic inverse dynamic model of the wire-actuated parallel manipulator.

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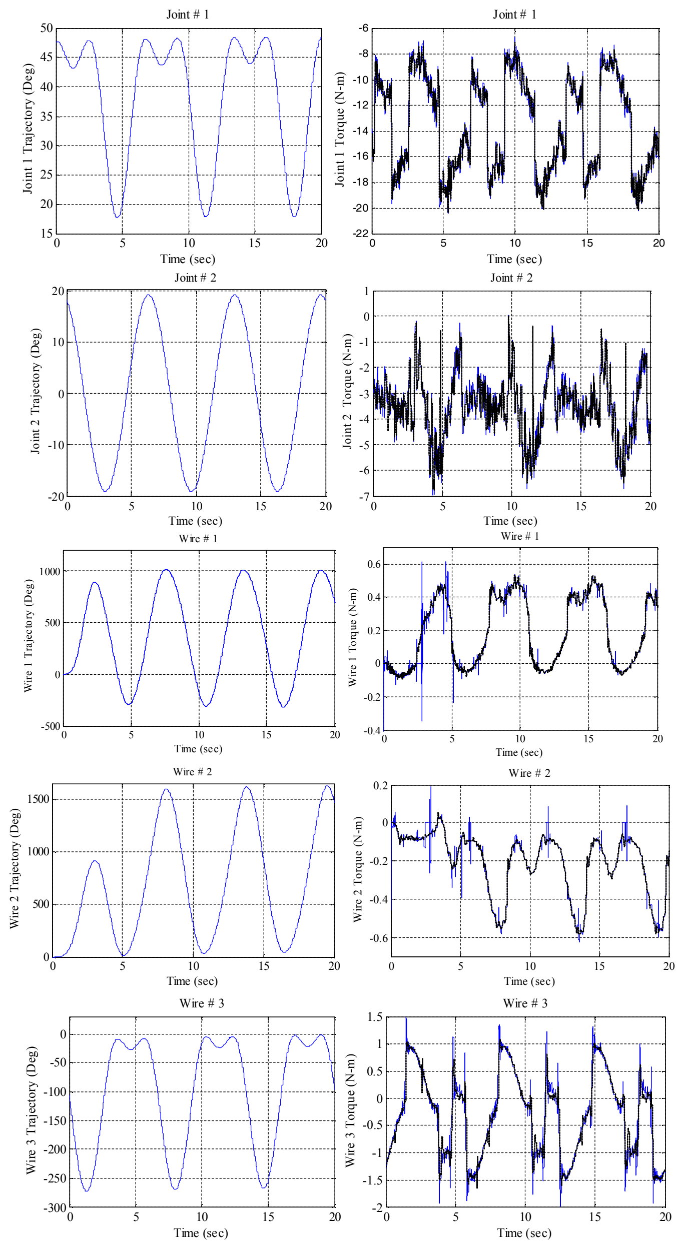

Figure 6: Comparison of the actuated joint/wire torque computed by fuzzy model (doted line) with the measured joint/wire torque (solid line) for the sinusoidal and periodic trajectories.