A MLP-Hedge-Algebras Admittance Controller for Physical Human–Robot Interaction

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Featured Application: Potential applications of this research include: (a) the operator teaches the manipulator to implement complicated tasks, such as welding, whose purpose is to eliminate the path planning, or (b) the manipulator supports the operator to lift heavy objects up and down.

Abstract: Recently, the identification of inertia and damping matrices (IIDM) and safety issues, as well as natural cooperation, are interestingly considered to enhance the quality of the physical human–robot interaction (pHRI). To cover all of these issues, advanced admittance controllers, such as those based on fuzzy logic or hedge algebras, have been formulated and successfully applied in several industrial problems. However, the inference mechanism of those kinds of controllers causes the discreteness of the super surface describing the input–output relationship in the Cartesian coordinates. As a consequence, the quality of the safe-natural cooperation between humans and robots is negatively affected. This paper presents an alternative admittance controller for pHRI by using a combination of hedge algebras and multilayer perceptron neural network (MLP), whose purpose is to create a more accurate inference mechanism for the admittance controller. To our best knowledge, this is the first time that such a neural network is considered for the inference mechanism of hedge algebras and also the first time that such an admittance controller is used for pHRI. The proposed admittance controller is verified on a teaching task using a 6-DOF manipulator. Experimental results have shown that the proposed method provides better cooperation compared with previous methods.

Keywords: hedge algebras; natural linguistic semantics; physical human–robot interaction; fuzzy control; MLP neural network

1. Introduction

The safe, natural pHRI can be considered an efficient solution for enhancing flexibility and reducing human labor in industrial processes. For example: (a) the operator teaches the manipulator to implement complicated tasks, such as welding, whose purpose is to eliminate the path planning, or (b) the manipulator supports the operator to lift heavy objects up and down. The quality of pHRI depends on three issues: identifying inertia and damping matrices (IIDM), safety, and natural cooperation. To date, almost all studies have concentrated on the safety issue, while the IIDM is still an open problem since this work cannot be obtained analytically and is usually time-consuming. Moreover, the natural human–robot interaction is rarely of concern, yet it is crucial to obtain effective cooperation. These shortcomings can be found in previous studies on pHRI, such as [1–7], and are presented clearly in [8–10]. By contrast, the natural human–robot cooperation is considered elaborately for non-physical interactions, as presented in [11,12].

By the human-like inference mechanism, fuzzy logic has been researched and applied successfully to many engineering problems [13–22]. To construct fuzzy-based controllers,
the following scheme, including five main tasks, should be conducted: (1) determining inputs and outputs of control systems based on requirements of engineering tasks, (2) defining the membership function to fuzzify inputs and outputs, in which the physical domains of linguistic variables, the number of linguistic values, and the sub-physical-domain of each linguistic value should be defined suitably, (3) identifying the fuzzy rule base, demonstrating the relationship among inputs and outputs, (4) choosing the composition of fuzzy relations to infer the outputs’ fuzziness, (5) finally, the defuzzification must be conducted to map the fuzziness values of outputs to their physical values. This observation encouraged authors in [8,9] to use the fuzzy logic to eliminate the IIDM during the controller-making process, in which the end-effector’s velocity is adaptively adjusted by applied force/torque and power transmitted by the robot. Moreover, the safety issue is guaranteed by using ISO10218 safety standard, and the natural human–robot interaction was also presented in [9]. Unfortunately, the inference mechanism of the fuzzy logic cannot adequately simulate human language in nature since there is no formalized linkage of fuzzy sets with the natural linguistic term semantics. Moreover, the fuzzy base is formulated incoherently, based on membership functions, the composition of fuzzy relations, and defuzzification, which may also lead to errors during the data process.

In contrast, hedge algebras (HA) were proposed as an algebraic approach to the natural structure of semantic domains of linguistic variables in which linguistic values construct the semantic constraints to help linguistic terms avoid transfiguration during data handling. Furthermore, the fuzzy rule base is identified as a mathematical model using an HA-term transformation and semantically quantifying mappings (SQMs). Herein, SQMs of hedge algebras are functions used to calculate the semantic values of HA-terms based on the fuzziness measure. As a result, the fuzzy rule base can be defined as a real grid surface in Cartesian coordinates in which one fuzzy clause can be defined as a point in the Cartesian product of suitable hedge algebras. These properties enable HA to solve engineering problems effectively and are analyzed clearly in [23–33]. This analysis motivated authors in [10] to propose an admittance controller by using hedge algebras to discover the inherent order-based structures of the terms and term domains of linguistic variables. This approach also gives favorable conditions to reduce the complexity during the controller-making process by eliminating the membership functions, the composition of fuzzy relations and de-normalization. Normally, the product operator and average operator are used to transforming the real grid super surface in 3D space to a curve in 2D space, whose purpose is to simplify the semantic relationship between inputs and outputs before using the interpolation method. The horizontal axis of the 2D coordinates is the integration of semantics of inputs, and the vertical axis is semantic of outputs. However, these methods distort the input–output relationship and cause a loss in the data processing. To this end, four-point bilinear interpolation was used for the semantic relationship [10]. This method divides the super surface into small linear surfaces, which are bounded by four points in the 3D space. A small linear surface will be chosen to interpolate the semantics of the output if inputs are inside the corresponding surface’s boundary. Four-point bilinear interpolation helps to improve the accuracy of HA inference by using the product operator and average operator. Unfortunately, this method still cannot adequately reflect the real super surface since the input–output semantic relationship is nonlinear. By using four-point bilinear interpolation, the super surface will be discrete. This affects the accuracy of the admittance controller and the smoothness of the interaction between humans and robots. Moreover, this interpolation method is difficult to be applied if the number of the input of the control system is more than two ones.

Currently, artificial intelligence is an attractive research topic. Classes of networks such as multilayer perceptron networks (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) provide much flexibility and have proven themselves over decades to be useful and reliable in various areas [34–42]. RNNs were designed to work with sequence prediction problems, which are traditionally difficult to train and not appropriate for tabular datasets. CNNs were designed to map image data to an output
variable, developing an internal representation of a two-dimensional image. More generally, CNNs work well with data that has a spatial relationship. On the contrary, MLPs are suitable for classification prediction problems where inputs are assigned a class or label or regression prediction problems where a real-valued quantity is predicted given a set of inputs. Data is often provided in a tabular, such as in a comma-separated value file or a spreadsheet. MLP network class is very flexible and can be used generally to learn mapping from inputs to outputs. Interestingly, the semantic input–output relationship in the HA is a tabular type, which demonstrates the predefined policy of engineering systems. Moreover, the studies based on the theorems of Kolmogorov, for example, [43–45], have pointed out that all of the continuous mappings from \([0, 1]^p\) to \([0, 1]^n\) can be approximated by a multilayer perceptron network of which input layer includes \(p\) neurons, output layer includes \(n\) neurons and hidden layers include \((2p + 1)\) neurons. Coincidently, semantic values of all linguistic variables in the HA always belong to \([0, 1]\). In other words, the interpolation method for the input–output semantic relationship in the HA can be considered as a mapping from \([0, 1]^p\) to \([0, 1]^n\). Therefore, the MLP network is believed to become an efficient method for the input–output semantic relationship in the HA. In this paper, the MLP neural network is proposed for the semantic interpolation issue in hedge algebras to describe the relationship between inputs and output adequately. Semantic values of output will be interpolated in the global boundary of the real super surface, and therefore, the accuracy of the admittance controller is improved. To our best knowledge, a multilayer perceptron hedge algebras-based controller (MLP-HA-based controller) is first introduced, especially in robotics. Main contributions of this paper: (1) a new approach for the semantic relationship in hedge algebras is proposed by using a multilayer perceptron neural network (MLP). Existing methods for the input–output semantic relationship are product, average or four-point bilinear. However, product and average operators distort the input–output semantic relationship. The Four-Point-Bilinear makes the semantic relationship discretely. Moreover, those methods are difficult to be applied if the number of the input of the system is more than two ones. By contrast, the MLP network represents the super surface describing the input–output semantic relationship more accurately and smoothly. Semantic values of output will be interpolated in the global boundary of the real super surface. The MLP network also gives favorable conditions to deal with multi-input systems. (2) the combination of hedge algebras and multilayer perceptron neural network is considered for pHRI to eliminate the identification of inertia and damping matrices in the dynamic admittance model. Moreover, the safety issue and the natural cooperation are also covered.

The rest of this paper is organized as follows: In Section 2, a fuzzy-based admittance controller for safe, natural human–robot interaction is briefly presented, using constraints of ISO10218 safety standard. In Section 3, the HA-admittance controller with the four-point bilinear and the proposed MLP-HA-based admittance controller are formulated. Next, stability is considered in Section 4. After this, the proposed MLP-HA-based admittance controller is verified by a teaching task, which uses a 6-DOF manipulator. The last section presents the conclusion of the research work.

2. Fuzzy-Based Admittance Controller

This section presents an admittance controller based on the inference mechanism of fuzzy logic, in which the velocity of the end-effector will be adjusted directly via the external wrench and the transmitted power without the IIDM. To guarantee safety, constraints of ISO10218 standards are considered to formulate the controller:

\[
|\mathbf{F}| \leq F_M, \quad |\mathbf{V}| \leq V_M, \quad |\mathbf{M}| \leq F_M L, \quad |\mathbf{W}| \leq \frac{V_M L}{P} \quad (1)
\]

\[
P = \left< \mathbf{b}^T \mathbf{T} \mathbf{H} \mathbf{x} \right> \leq P_M \quad (2)
\]

\[
\mathbf{b}^T \mathbf{T} = \begin{bmatrix} \mathbf{b}^T R_T & 0_3 \\ 0_3 & \mathbf{b}^T R_T \end{bmatrix} \quad (3)
\]
Here, $F$ and $M$ are external force/torque, and $H = [F^T M^T]$. $V$ and $W$ are linear and angular velocities of the end-effector. $F_M$, $V_M$, and $P_M$ are the maximum external force, linear velocity, and transmitted power allowed, respectively. $x$ is the measured velocity. $\mathbf{B}_T$ is the rotation matrix between the TCP (tool center point) frame and the base frame, and $L$ is the length of the tool in the TCP frame. In the sequel, $|u|$ denotes the Euclidean norm of a vector $u$ and $\langle u, v \rangle$ represents the dot product of vectors $u$ and $v$.

To eliminate the IIDM, the fuzzy-based admittance controller is designed based on constraints Equations (1)–(3) of the safety standard, without the dynamic admittance model. $F_M$, $V_M$, and $P_M$ are used to determine physical domains demonstrating linguistic variables. The output is the velocity of the end-effector, including $V$ and $W$. The inputs are the external force $F$, external torque $M$, and the transmitted power $P$. Based on Equations (1)–(3), it is clear that $|F|$, $|M|$, $|V|$, $|W|$, and $P$ are used during data processing. Based on [46], the five triangular type membership function is used to describe $|F|$, $|M|$, $|V|$, $|W|$, and $P$ by linguistic values, and their physical domains are $[0, F_M]$, $[0, F_M L]$, $[0, V_M]$, $[0, V_M L]$, and $[0, P_M]$, respectively.

In the ISO10218 safety standard, $F_M$ and $V_M$ are two main constraints, which should be considered. Other allowed parameters $P_M$, $M_M$, and $W_M$ should be obtained based on Equations (1) and (2). Normally, these parameters must be chosen following the safety requirements of specific technological processes. In other words, these parameters are flexible, and the control rule-base should generate the output adaptively depending on different values of safety constraints. In this paper, the rule-based admittance controller adapts all values of desired user safety constraints since physical subdomains of linguistic values are adaptively adjusted based on their predefined proportion in the linguistic variables. This mechanism is available for all of the controllers in this paper, including fuzzy-based admittance controllers and hedge-algebra-based admittance controllers. However, it is noticed that the human effort will be proportional to $\delta$ (here, $\delta = \frac{V_M}{F_M}$).

The fuzzy rule base in Table 1 presents the relationship between $|V|$, $|F|$ and $P$, where $|V|$ is inferred based on $|F|$ and $P$. Then, $|W|$ is inferred via $|V|$ and $|M|$ using the fuzzy rule base in Table 2. Here, $Z$, $S$, $M$, $QB$ and $B$ stand for zero, small, medium, quite big, and big, respectively.

### Table 1. Fuzzy rule base for $|V|$.

| $|V|$ | $|F|$ | Z | S | M | QB | B |
|------|------|----|----|----|----|----|
| $Z$  | $Z$  | $Z$ | $S$ | $S$ | $M$ | $M$ |
| $S$  | $S$  | $S$ | $S$ | $M$ | $M$ | $QB$ |
| $M$  | $S$  | $M$ | $M$ | $QB$ | $QB$ | $QB$ |
| $QB$ | $M$  | $M$ | $QB$ | $QB$ | $QB$ | $B$ |
| $B$  | $M$  | $QB$ | $QB$ | $QB$ | $B$  | $B$  |

### Table 2. Fuzzy rule base for $|W|$.

| $|W|$ | $|M|$ | $|V|$ | Z | S | M | QB | B |
|------|------|------|----|----|----|----|----|
| $Z$  | $Z$  | $Z$  | $S$ | $S$ | $M$ | $M$ | |
| $S$  | $Z$  | $S$  | $S$ | $S$ | $M$ | $M$ | |
| $M$  | $S$  | $S$  | $S$ | $M$ | $M$ | $QB$ | |
| $QB$ | $M$  | $M$  | $M$ | $M$ | $QB$ | $QB$ | |
| $B$  | $M$  | $M$  | $QB$ | $QB$ | $QB$ | $B$  | |

The max–min composition is used to infer the fuzziness of outputs based on the fuzzy relations. This composition is defined by Equations (4) and (5) as follows:

$$
\mu(\mu_A, \mu_B) = \min(\mu_A, \mu_B)
$$
\[
\mu_{A \cup B}(x) = \max\{\mu_A(x), \mu_B(x)\}
\]

(5)

Based on [47], the centroid defuzzification is chosen to map the fuzziness values to the desired physical values. The physical values of outputs are identified by using Equation (6).

\[
x' = \frac{\int_S x\mu_B(x)dx}{\int_S \mu_B(x)dx}
\]

(6)

3. Hedge-Algebras-Based Admittance Controllers

3.1. HA-Based Admittance Controller with Four Point Bilinear Interpolation

In Section 2, a fuzzy-based admittance controller is formulated using constraints of the ISO10218 safety standard. As mentioned, to overcome shortcomings of fuzzy logic, an algebraic approach to linguistic hedges in fuzzy logic will be presented. First, each linguistic variable (|F|, |M|, |V| and |W|) is considered as an HA, \((X, G, C, H, \leq)\) [10], [23–27]. Here, \(X\) consists of all HA terms of a linguistic variable, \(\leq\) is an order relation on \(X\), \(G = \{c^-\), \(c^+\}\) is a set of generators, with \(c^- \leq c^+\), \(C = \{0, W, 1\}\) is the set of fixed points, where \(0\), \(1\) and \(W\) stand for the least, the greatest and the neutral term, respectively. \(H_I = H \cup \{I\}\), where \(H_I = \{H_I^-, H_I^+\}\) is a set of unary operations representing linguistic hedges of \(X\) in which \(H_I^- = \{h_j : -q \leq j \leq -1\}\) and \(H_I^+ = \{h_j : 1 \leq j \leq p\}\) stand for the set of negative and positive hedges, respectively; where \(q\) is the number of negative hedges, and \(p\) is the number of positive hedges.

In general, the HA of linguistic variables of inputs and output can be facultative. However, to perform the input–output relationship in a unified form, similar sets \(G\), \(C\), and \(H_I\) are used for all HA of inputs and output of this admittance controller and chosen as follows:

- \(G = \{I, C\}\), where \(c^- = I\), and \(c^+ = C\), stand for inconsiderable and considerable, respectively;
- \(C = \{0, W, 1\}\), where \(0\), \(W\), and \(1\) are fixed points, known, respectively, as the least, the medium and the greatest terms of the determined HA;
- \(H_I = \{Q, E\} \cup \{I\}\), where \(h^- = Q\); \(h^+ = E\), stand for quite and extremely, respectively.

Based on \(G\) and \(H_I\), the whole term-set \(X\) of every HA of linguistic variables in the linearly ordered relation is created \(X = \{0, EI, QI, W, QC, EC, 1\}\). Then, the fuzzy-terms of \(|F|, |M|, |V|\) and \(|W|\) are converted into HA-terms based on a term-transformation as presented in Table 3. Next, the fuzzy rule base for \(|V|\) and \(|W|\) in Tables 1 and 2 are transformed into the HA rule base as presented in Tables 4 and 5. As mentioned before, the semantics of HA-terms belong to the domain \([0, 1]\), and therefore, the points \(0\) and \(1\) are used in the HA rule base as semantic bounds for interpolation methods and to avoid the loss of the data during processing.

Table 3. Term transformation of the linguistic values.

| For FL | - | Z | S | M | QB | B | - |
|--------|---|---|---|---|----|----|---|
| For HA | 0 | EI | QI | W | QC | EC | 1 |

Table 4. Rule base for HA controller for \(|V|\).

| |F| | 0 | EI | QI | W | QC | EC | 1 |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | EI | EI | QI | QI | QI | W | W |
| EI | EI | EI | EI | QI | QI | W | W | QC |
| QI | QI | QI | QI | W | W | QC | QC | QC |
| W | QI | QI | QI | W | W | QC | QC | QC |
| QC | QI | W | W | QC | QC | EC | EC | EC |
| EC | W | W | QC | QC | EC | EC | 1 | 1 |
| 1 | W | QC | QC | EC | EC | 1 | 1 | 1 |
Table 5. Rule base for HA controller for $|W_1|$

| $|W_1|$ | $|M_1|$ | 0 | EI | QI | W | QC | EC | 1 |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | EI | EI | QI | QI | W | W |
| EI | EI | EI | EI | QI | QI | W | W | QC |
| QI | QI | QI | QI | W | W | QC | QC | EC |
| W | W | W | W | QC | QC | EC | EC | 1 |
| QC | QC | QC | QC | EC | EC | 1 | 1 | 1 |

The rule base of the HA controller is formulated as in Tables 4 and 5. Unlike fuzzy inference mechanisms, those rule bases are considered as super surfaces in the Cartesian coordinate by using an algebraic approach. Here, fuzziness measure and semantically quantifying mapping (SQMs) are used to convert Tables 4 and 5 into semantic relationships. From now on, $f_{m}(x)$ is used to denote the fuzziness measure of $x$ and $f_{m}(x)$ always belongs to $[0, 1]$. In addition, $v(x)$ is used to denote SQMs: $x \rightarrow [0, 1]$. Key features of $f_{m}(x)$ and $v(x)$ are briefly presented:

$$f_{m}(x) = 0 \quad x \in C$$

(7)

$$f_{m}(hx) = f_{m}(hy), \quad \forall x \in X, \forall y \in X, \forall h \in H$$

(8)

$$f_{m}(hx) < f_{m}(x), \quad \forall x \in X$$

(9)

$$f_{m}(hx) = \mu(h)f_{m}(x), \quad \forall x \in X$$

(10)

$$f_{m}(c^+) + f_{m}(c^-) = 1$$

(11)

$$\sum_{h \in H} f_{m}(hx) = f_{m}(x), \quad \forall x \in X$$

(12)

$$\sum_{h \in H} \mu(h) = 1$$

(13)

$$f_{m}(x) = \mu(h_{m})f_{m}(x_{m}) = \mu(h_{m}) \ldots \mu(h_{1})f_{m}(c)$$

(14)

where $x_{m} = h_{m-1}, \ldots, h_{1}c$ is the $m$th-suffix of $x$, and $\mu(h)$ is commonly called the fuzziness parameters of $X$.

$$v(W) = \theta = f_{m}(c^-)$$

(15)

$$v(c^-) = \theta - \alpha f_{m}(c^-) = \beta f_{m}(c^-)$$

(16)

$$v(c^+) = \theta + \alpha f_{m}(c^+)$$

(17)

$$v(h_{j}x) = v(x) + Sgn(h_{j}x)\left\{ \frac{1}{\sum_{i=Sgn(j)} f_{m}(h_{i}x) - \omega(h_{j}x)f_{m}(h_{j}x)} \right\}$$

(18)

where

$$\omega(h_{j}x) = \frac{1}{2} [1 + Sgn(h_{j}x)Sgn(h_{p}h_{j-1}x)(\beta - \alpha)]$$

(19)

$$j \in \{-q \leq j \leq p, j \neq 0\} = [-q \ldots p]$$

(20)

$$\sum_{i=-q}^{p} \mu(h_{i}) = \alpha \quad \text{and} \quad \sum_{i=1}^{p} \mu(h_{i}) = \beta \quad \text{with} \quad \alpha, \beta > 0 \quad \text{and} \quad \alpha + \beta = 1.$$
\( \alpha = \beta = 0.5 \) and \( f_m(C) = 1 - f_m(I) = 0.5 \). Moreover, \( H \) just includes two linguistic hedges, and therefore, we have \( q = 1 \) and \( p = 1 \).

Now, based on Equations (15)–(20), the HA rule base of \( |V| \) and of \( |W| \) in Tables 4 and 5 are transformed into the semantic relationships as presented in Tables 6 and 7. The semantic relationship between \( |F|, P, \) and \( |V| \) in Table 6 defines the super surface in Euclidean space, as shown in Figure 1. The semantic relationship between \( |M|, |V|, \) and \( |W| \) in Table 7 defines the super surface in the Euclidean space, as shown in Figure 2. Super surfaces in Figures 1 and 2 are obtained from the linearization of Tables 6 and 7 by using the four-point bilinear method.

**Table 6.** The semantic relationship-based rule base of \( |V| \).

| \( |V| \) | \( v(\emptyset) = 0 \) | \( v(EI) = 0.125 \) | \( v(QI) = 0.375 \) | \( v(W) = 0.5 \) | \( v(QC) = 0.625 \) | \( v(EC) = 0.875 \) | \( v(I) = 1 \) |
|---|---|---|---|---|---|---|---|
| \( v(\emptyset) = 0 \) | 0 | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 |
| \( v(EI) = 0.125 \) | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 |
| \( v(QI) = 0.375 \) | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 |
| \( P \) | \( v(W) = 0.5 \) | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 |
| \( v(QC) = 0.625 \) | 0.375 | 0.5 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 |
| \( v(EC) = 0.875 \) | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 | 1 |
| \( v(I) = 1 \) | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 | 1 |

**Table 7.** The semantic relationship-based rule base of \( |W| \).

| \( |W| \) | \( v(\emptyset) = 0 \) | \( v(EI) = 0.125 \) | \( v(QI) = 0.375 \) | \( v(W) = 0.5 \) | \( v(QC) = 0.625 \) | \( v(EC) = 0.875 \) | \( v(I) = 1 \) |
|---|---|---|---|---|---|---|---|
| \( v(\emptyset) = 0 \) | 0 | 0 | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 |
| \( v(EI) = 0.125 \) | 0 | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 |
| \( v(QI) = 0.375 \) | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 |
| \( |V| \) | \( v(W) = 0.5 \) | 0.125 | 0.125 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 |
| \( v(QC) = 0.625 \) | 0.375 | 0.375 | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 |
| \( v(EC) = 0.875 \) | 0.375 | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 | 1 |
| \( v(I) = 1 \) | 0.5 | 0.5 | 0.625 | 0.625 | 0.875 | 0.875 | 1 |

**Figure 1.** The real grid surface describes the semantic relationship between \( |V|, |F| \) and \( P \) based on the four-point bilinear interpolation method.
Finally, the four-point-bilinear interpolation [48] is used to approximate the semantic values of \( |\mathbf{V}| \) and of \( |\mathbf{W}| \) through the semantic relationships among inputs and outputs in Tables 6 and 7. The inference mechanism of four-point bilinear interpolation is briefly presented by Figure 3 and Equations (21)–(23). As presented above, the HA-based admittance controller consists of two inputs and one output. Now, semantic values of inputs are denoted by \( a \) and \( b \), the semantic value of output is denoted by \( z \). The small linear surface bounded by \( Q_{11}, Q_{12}, Q_{21}, Q_{22} \) will be chosen to approximate the semantic value of output if \( a \) belongs to \([a_1, a_2]\) and \( b \) belongs to \([b_1, b_2]\). Here, \( Q_{11} = (a_1, b_1, z_{11}), Q_{12} = (a_1, b_2, z_{12}), Q_{21} = (a_2, b_1, z_{21}), \) and \( Q_{22} = (a_2, b_2, z_{22}) \):

\[
\begin{align*}
z(a, b_1) & \approx \frac{a_2 - a}{a_2 - a_1} \cdot z_{11} + \frac{b - b_1}{b_2 - b_1} \cdot z_{21} \\
\frac{a_2 - a}{a_2 - a_1} \cdot z_{12} + \frac{a - a_1}{a_2 - a_1} \cdot z_{22} \\
z_q = z(a, b) & \approx \frac{b_2 - b}{b_2 - b_1} \cdot z(a, b_1) + \frac{b_1 - b}{b_2 - b_1} \cdot z(a, b_2)
\end{align*}
\]

Until now, only semantic values of outputs \(|\mathbf{V}|\) and \(|\mathbf{W}|\) are known. To receive their real physical values, their term semantics are mapped from \([0, 1]\) to their individual physical domains.
3.2. MLP-HA-Based Admittance Controller

As presented in the fourth paragraph of the Introduction section, the MLP network is chosen for the semantic input–output relationship in the HA based on its properties. The proposed MLP-HA-based admittance solution is presented in Figure 4, including two main blocks: the MLP semantic inference mechanism in HA and the MLP-HA-based admittance system. In the MLP semantic inference mechanism in HA, HA-terms and HA rule-base are defined based on requirements of engineering problems. In addition, in this paper, they are presented in Tables 3–5 to solve several issues of pHRI. The semantic relationship is presented in Tables 6 and 7. These relationships are then described by the MLP network, which is trained using backpropagation. This MLP network will be used as an interpolation method for the input–output semantic relationship in the HA-MLP-based admittance system.

![Figure 4. The diagram of the HA-MLP system, including two main processes: (1) the MLP network is used to represent the input–output semantic relationship, (2) the pre-trained MLP model is used for the admittance system.](image)

In the HA-MLP-based admittance system, human–robot interactive forces/torques are measured by using a real-time external force/torque sensor mounted on the end-effector of the manipulator (haptic). Transmitted power is calculated by using Equation (2). Those values are then mapped into HA-terms and HA-semantic values. Semantic values of these linguistic variables play as inputs of the pretrained MLP model to interpolate the semantic value of the output. Finally, the physical value of output is obtained by a simple map from [0, 1] to its physical domain.

The MLP neural network is used to predict output semantic values, which will add significant benefits to HA-based admittance controllers than existing approaches, namely:
- The semantic relationship between inputs and output is described adequately;
- The semantic real-super-surface in 3D space becomes smoother;
- Semantic values of output will be approximated in the global boundary;
- The interpolation accuracy is improved.
The configuration of the MLP network is characterized by the number of hidden layers and the number of neurons in hidden layers, the number of samples propagated through the network for each gradient update, the number of trained epochs, and the learning rate. The studies based on the theorems of Kolmogorov, for example, Refs. [43–45], have pointed out that all of the continuous mappings from $[0, 1]^p$ to $[0, 1]^n$ can be approximated by a multilayer perceptron network of which input layer includes $p$ neurons, output layer includes $n$ neurons, and hidden layers include $(2p + 1)$ neurons. However, the number of samples in the training data set is also an important factor in choosing the MLP configuration with well-fitting and capacity. To choose the configuration of the MLP network, the recommendation in [49,50] is used:

$$N_h = \frac{N_s}{\beta(N_i + N_o)}$$  \hspace{1cm} (24)

Here, $N_h$, $N_i$, $N_o$, $N_s$ and $\beta$ are the number of hidden neurons, the number of input neurons, the number of output neurons, the number of samples in the training data set, and the arbitrary scaling factor, respectively. Note, $\beta$ usually belongs to $[2,10]$.

In this paper, the input of the MLP-HA-based admittance controller are semantic values in the range $[0, 1]$, so the sigmoid is used as a transformation function since it well-handles the data in the range $[-1, 1]$.

$$g(\lambda) = \frac{1}{1 + e^{-\lambda}}$$ \hspace{1cm} (25)

The MLP-backpropagation in this paper is briefly described as below:

Step 1: Choosing the initial configuration of MLP network, learning rate $\eta > 0$, momentum parameter set $\alpha$, desired error $E_{max}$, initial weights $W$. Setting the current error $E = 0$, and the current sample $k = 1$.

Step 2: At the $k^{th}$ sample, the output of $i^{th}$ neuron at the input layer ($q = 1$) is measured as ($q$ is the order of layers in the network):

$$y^q_i = y^1_i = x^k_i$$ \hspace{1cm} (26)

The signal is propagated sequentially following the order input layer–hidden layers–output layer:

$$y^q_i = g(q^{net}_i) = g(\sum_j w^q_{ij} y^{q-1}_j)$$ \hspace{1cm} (27)

Here, $q^{net}_i$ is the effect of $(q - 1)^{th}$ layer on $i^{th}$ neuron in $q^{th}$ layer at the $k^{th}$ sample, and $j$ is the index of neuron in $(q - 1)^{th}$ layer.

Step 3: Measuring the error at the output layer:

$$E_t = \frac{1}{2} \sum_{i=1}^n (d^k_i - y^q_i)^2 + E_{t-1}$$ \hspace{1cm} (28)

$$\delta^q_i = (d^k_i - y^q_i) g'(q^{net}_i)$$ \hspace{1cm} (29)

Here, $d^k_i$ is the sample output.

Step 4: Back-propagating error and calculating the weights:

$$t^i \Delta w^q_{ij} = \eta \delta^q_i y^{q-1}_{ij} + a_q t^{-1} \Delta w^q_{ij}$$ \hspace{1cm} (30)

$$t^i w^q_{ij} = t^{-1} w^q_{ij} + t^i \Delta w^q_{ij}$$ \hspace{1cm} (31)

$$\delta^{q-1}_i = g'(q^{net}_i) \sum_j w^q_{ij} \delta^q_j$$ \hspace{1cm} (32)

where $q > 1$, $t$ is current weight update.

Step 5: Checking the training iteration:
If \( k < p \): \( k = k + 1 \) and return step 2;
Else: go to step 6;
Here, \( p \) is the size of the training data
Step 6: Checking the loop condition
If \( E < E_{\text{max}} \): finishing and returning the set of weights;
Else: setting \( E = 0 \), \( k = 1 \) and return to 2.

The initial weights \( w_{ij} \) are randomly chosen in the range \([-3 / \sqrt{m_i}, 3 / \sqrt{m_i}]\). Here: \( m_i \) is the whole number of links from neuron \( j \) to neuron \( i \) \([51]\). The initial value of the learning rate is randomly chosen in the range \([0.1, 0.6]\), as presented in \([52,53]\). In this paper, the MLP is used as an interpolation for the semantic relationship in the HA, which is predefined based on the policy of the engineering system. For the admittance controller, the semantic relationship among inputs (semantic values of the external wrench and transmitted power) and output (semantic value of the velocity of the end-effector) are presented in Tables 6 and 7. Therefore, the sample data for the MLP network is tabular, including Tables 6 and 7. Moreover, to speed up the convergence of the backpropagation, the adaptive learning rate and momentum parameters are necessary since the backpropagation converges slowly, even for the mediumsized network. A five-layer network is chosen, and, initial values of momentum parameters of connection groups are 0.01, 0.03, 0.1, and 0.09, respectively, and the initial value of the learning rate is 0.4. These values will be increased or decreased depending on the gradient of the error after a number of iterations (in this paper, this parameter is 99 iterations). The desired error is \( E_{\text{max}} = 0.0002 \). After the training process and removing redundant neurons (neurons have values of weights approximated zero), the configuration of MLP is chosen in this paper as presented in Figure 5. This MLP consists of 5 layers, including the input layer, three hidden layers and the output layer. The input layer has two neurons, hidden layer 1 has five neurons, hidden layer 2 has three neurons, hidden layer 3 has three neurons, and the output layer has one neuron. The input 1 and input 2 of the MLP network are semantic values of the controller’s inputs (semantic values of the external wrench and transmitted power), and the output of the MLP network is the semantic value of the controller’s output (semantic value of the end-effector’s velocity).

![Figure 5. The MLP network configuration.](image-url)

Semantic relationships in Tables 6 and 7 are represented by super surfaces in Cartesian coordinates by using the MLP network, as presented in Figures 6 and 7. It is clearly seen that these surfaces are smoother than Figures 1 and 2 using previous methods. Semantic relationships in Tables 6 and 7 are not linear. Moreover, semantic values of the output tend to change dramatically when semantic values of inputs are close to either 1 or 0. In Figures 1 and 2, the four-point bilinear method is used to describe those relationships, which divided the super surface into smaller linear surfaces, bounded by four linear points. As a result, surfaces in Figures 1 and 2 are created by a combination of small linear surfaces, which have continuous line intersections with each other. In contrast, semantic relationships in Figures 6 and 7 are considered in the global boundary
by using the MLP interpolation. Hence, wiggled values included in Figures 6 and 7 when semantic values of inputs are close to either 1 or 0.

**Figure 6.** The realgrid surface describes the semantic relationship between $|V|$, $|F|$ and $P$ based on the MLP network.

**Figure 7.** The realgrid surface describes the semantic relationship between $|W|$, $|M|$ and $|V|$ based on the MLP network.

Similarly, only the semantic values of outputs $|V|$ and $|W|$ are known. To receive their real physical values, their term semantics is mapped from $[0, 1]$ to their individual physical domains. After obtaining the physical values of $|V|$ and $|W|$, six components of the velocity’s elements of the end-effector can be calculated by Equations (33) and (34). These formulas are also used for all admittance controllers presented above:

$$V_j = \begin{cases} \frac{f_j|V|}{|F|} & \text{if } |F| \neq 0 \\ 0 & \text{if } |F| = 0 \end{cases}$$  \hspace{1cm} (33)
$W_j = \begin{cases} \frac{M_j||W||}{|M|} & \text{if } |M| \neq 0 \\ 0 & \text{if } |M| = 0 \end{cases}$

(34)

where $j$ indicates the direction of $x$, $y$ or $z$-axis.

4. Stability Considerations

In physical human–robot interaction, the human factor is a part of the controller, which is extremely difficult to model and prove the stability of the system. Normally, the derivative equation of the admittance controller is the relationship between the external force and the end-effector’s velocity. In other words, the linear/angular velocity of the end-effector only depends on the translation/rotation elements of the external wrench. Consequently, a large jerk during cooperation will appear if the external force changes dramatically. Experimental studies showed that the robot could present unstable behavior with very low virtual damping and high virtual inertia of stiff environment [54]. It is suggested that the human arm has a maximum impedance that occurs when the human increases the stiffness of their arm [55]. As analyzed in [9,10], the stability of the conventional admittance controller is guaranteed by setting the virtual inertia as constant and equal to half the effective inertia of the manipulator in the directions of the motions during the experiments. The effective mass $B_t$ is expressed as:

$$B_t^{-1}(q) = J(q)M^{-1}(q)J^T(q)$$

(35)

where $M \in \mathbb{R}^{6 \times 6}$ is the mass matrix of the manipulator’s configuration space, $B_t \in \mathbb{R}^{6 \times 6}$ is the effective mass in the frame, and $J$ is the Jacobian matrix.

By contrast, the stability and accuracy of fuzzy-based and HA-based controllers mainly depend on the expert knowledge-based rule base. As analyzed in [56], the fuzzy controller can be stable and ensure accuracy by choosing a good fuzzy rule and physical value domains of appropriate input and output variables. Furthermore, the mathematical foundation given by HA seems to form a new approach to solve fuzzy control problems, which is quite different from that based on the fuzzy sets. It has been shown that the HA-based controller causes smaller errors. Moreover, it can bring the controlled object to a stable state, while the controller based on other methods cannot. This point is clearly analyzed in [57,58]. Another point should be mentioned for the stability of the proposed method, which is the stability of the MLP-based input–output semantic interpolation. As presented in [59], the weight dynamics of the neural network are described by a gradient system in most cases. Therefore, the stability of the weight dynamics is not a worry since it is well-known that the gradient system possesses a Lyapunov function.

In addition, the proposed admittance controller uses the transmitted power as an additional input, which is the dot product of the external wrench vector and the actual velocity vector, whose purpose is to avoid the direct map from external forces/torques to linear/angular velocities. As presented, the natural human–robot interaction is also considered in this paper. Therefore, the velocity of end-effector and external forces include both linear and angular elements. Normally, the rotation elements have bigger effects on the stability and accuracy than translation elements since a small change of the rotation can lead to a big error. This observation raises the need to create a relationship between linear velocity and angular velocity to guarantee smooth cooperation. Based on this point, the linear velocity is calculated first based on translation elements of the external wrench and transmitted power, then the angular velocity is calculated based on the linear velocity and rotation elements of the external wrench. As shown in Equation (2), the value of transmitted power depends on $V_{k-1}$, $W_{k-1}$, $F$, and $M$. As a result, the value of the actual velocity will not change suddenly even when the external wrench changes sharply. By doing this, the jerk during cooperation is reduced.
5. Experiments

5.1. Experimental Setup

The proposed method is verified by a teaching task setup using a 6-DOF manipulator in which a real-time force/torque sensor is mounted at the end-effector, as presented in Figure 8. The operator pushes and pulls the end-effector to some desired positions to conduct the teaching task: first, the end-effector is moved to the position of an object (I), then the end-effector is moved to the desired target position (II); and finally, the end-effector is moved back to the initial position (III). In this experiment, the manipulator is moved passively based on human effort. Target positions in stages (I), (II), and (III) are memorized for later work. In this experimental implementation, the cooperation between humans and robots during conducting (I), (II), and (III) is mainly considered. This experiment is conducted sequentially using the proposed MLP-HA-based admittance controller, HA-based admittance controller with the four-point bilinear interpolation, and fuzzy-admittance controller, whose purpose is to give more circumstances to compare with the proposed method.

![Figure 8. The experimental setup for teaching tasks.](image)

In this paper, a group of ten persons, including eight men and two women, and their age ranges from 23 to 55 years, is chosen to implement this teaching task. The experiment should be conducted by a group of different persons since the manipulator reacts differently depending on the person's effort, which is different from person to person. Each person cooperates with the manipulator to serve a similar teaching task in three different scenarios using three different admittance controllers, as mentioned before.
5.2. System Framework

The workflow of the experimental setup is shown in Figure 9. At each iteration, the admittance controller calculates the velocity of the end-effector based on the external wrench and power transmitted by the robot. Depending on the scenario, the admittance controller can be the proposed MLP-HA-based admittance controller, four-point bilinear-HA-based admittance controller (Bi-HA-based admittance controller), or fuzzy-based admittance controller. Desired joint velocities of the manipulator are calculated using inverse kinematics with the Jacobian method. Finally, joints of the manipulator are controlled by the PID method to follow desired values. The CAN protocol is used for the communication between the master controller and the real-time force/torque sensor, and the sample time to send and receive data is 1 ms ($T_{CAN} = 1$ ms). The communication between the master controller and slave controllers is implemented by using the EtherCAT protocol, with the sample time 1 ms ($T_{com} = 1$ ms). These slave controllers are used to control motors at the joints of the robot. To cover constraints of the ISO10218 standard, the maximum allowed values of $|F|$, $|V|$, and $P$ should be given. In this paper, these values are set to $F_M = 120$ N, $V_M = 0.12$ m/s, $P_M = 15$ W, and $L = 0.058$ m.

![Figure 9. System framework, admittance controller block represents MLP-HA-based admittance controller, Bi-HA-based admittance controller, or fuzzy-based admittance controller depending on the scenario.](image)

5.3. Results

The percentage error in Equation (36) and the root mean square (RMS) in Equation (37) is used to estimate the error of controllers:

$$\Delta = \frac{|\text{measured velocity} - \text{calculated velocity}|}{\text{calculated velocity}} \times 100\% \quad (36)$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{N} Y^2}{N}} \quad (37)$$

Here, $Y$ is $\Delta |V|$, $\Delta |W|$, $|V_{k+1} - V_k|$, $|W_{k+1} - W_k|$, $|F|$, or $|M|$ depending on the value, which is estimated, as shown in Table 8. In addition, $N = 10$ n is the total number of samples obtained from one controller (there are three different admittance controllers). As mentioned before, ten is the number of persons, who participate in the experiment, and $n$ is the number of the repetition of the cooperation between one person and the manipulator using one different controller. In this paper, $n = 5$ means that there are 50 samples obtained from one admittance controller (the total sample number in this experiment is 150, obtained from three different admittance controllers). Those obtained results are processed by using Equations (36) and (37) and presented in Table 8.
Table 8. Estimated errors.

|                | Method          | MLP_HA | Bi_HA | FA   |
|----------------|-----------------|--------|-------|------|
| $|\Delta V|(|$ (%) | RMS   | 3.19  | 3.52 | 4.56 |
| $|\Delta W|(|$ (%) | RMS   | 6.6   | 8.1  | 9.24 |
| $|V_{k+1}-V_k|(|mm/s| | RMS   | 0.3757| 0.4647| 0.6498|
| $|W_{k+1}-W_k|(|rad/s| | RMS   | 0.0042| 0.0054| 0.0062|
| $|F|(|N| | max   | 92.99 | 95.38| 84.73|
| $|M|(|Nm| | max   | 1.0096| 1.91 | 1.79 |
| | RMS   | 0.473 | 0.86  | 0.72 |

The results are presented in Table 8 and Figures 10–13. In Table 8, MLP_HA represents the MLP-HA-based admittance controller, Bi-HA represents the Bi-HA-based admittance controller, FA the fuzzy-admittance controller. The horizontal red lines in Figures 10–12 are the maximum allowed values of the norm of linear velocity.

Figure 10. Experimental results using MLP-HA-based admittance controller, (a) presents the inputs $|F| (N)$, $|M| (Nm)$ and $P (W)$; (b) and (c) present outputs $|V| (mm/s)$ and $|W| (rad/s)$, respectively.

Figure 11. Experimental results using Bi-HA-based admittance controller, (a) presents the inputs $|F| (N)$, $|M| (Nm)$ and $P (W)$; (b) and (c) present outputs $|V| (mm/s)$ and $|W| (rad/s)$, respectively.
Figure 12. Experimental results using fuzzy-based admittance controller, (a) presents the inputs $|F|$ (N), $|M|$ (Nm) and $P$ (W); (b) and (c) present outputs $|V|$ (mm/s) and $|W|$ (rad/s), respectively.

Figure 13. The variation of end-effector during teaching task, (a) the variation of linear velocity (mm/s), (b) the variation of angular velocity (rad/s). Here, MLP-HA is the proposed MLP-HA-based admittance controller, Bi-HA is Bi-HA-based admittance controller, and FA is a fuzzy-based admittance controller. MLP-HA-based admittance controller is found to provide better cooperation compared to other controllers.

5.4. Discussion

The mean of velocity step for each admittance controller is presented in Table 8; for the proposed MLP-HA-based admittance controller, the linear velocity step is 0.3757 mm/s, and the angular velocity step is 0.0042 rad/s, whereas the linear velocity steps are 0.4647, 0.6498 mm/s and angular velocity steps are 0.0054, 0.0062 rad/s for the Bi-HA-based and fuzzy-based admittance controllers, respectively. In addition, for the proposed MLP-HA-admittance controller, the percentage errors of linear velocity and angular velocity are 3.19% and 6.6%, respectively. These percentage errors increase to 3.52% and 8.1% for the Bi-HA-based admittance controller, 4.56% and 9.24% for the fuzzy-based admittance controller. In Figure 13, maximum steps of linear and angular velocities are about 4 mm/s and 0.05 rad/s for the proposed MLP-HA-based admittance controller, whereas those values are around 6 mm/s and 0.1 rad/s for Bi-HA-based admittance controller, and approximate 10 mm/s and $-0.1$ rad/s for fuzzy-based admittance controller, respectively. This analysis has shown that the proposed MLP-HA-based, Bi-HA-based and fuzzy-based admittance controllers give favorable conditions to avoid instability during the cooperation even when the external wrench is suddenly changed. Moreover, the MLP-HA-based admittance controller provides better cooperation compared to other admittance controllers. In addition, even if the external wrench is larger than the allowed value, the velocity of the end-effector always belongs in a safe domain as the applied values of the external wrench in every DOF in the interactive space are always constrained based on the ISO10218 standard to guarantee safe and natural pHRI.
In an accurate manner, the proposed MLP-HA-based approach is found to provide better cooperation in comparison with previous methods. However, an aspect should be discussed, which is the computational complexities in different approaches, including conventional methods, fuzzy-based methods, and hedge-algebras-based methods (using average/product operators, four-point bilinear, and MLP interpolation). First of all, the order of the number of necessary rules of fuzzy or HA system is $O(N)$ [60], here $N = T^n$, $T$ is the number of fuzzy or HA terms, $n$ is the number of variables. Based on the rule base of the controller in this paper, $T = 7$, $n = 2$. The difference in the computational complexity of fuzzy and HA mainly depend on operators and interpolation methods, which are used for their inference mechanism. In this paper, max–min composition and centroid defuzzification is used for fuzzy logic. The complexity of max–min composition is $O(N^2)$ [61], the complexity of centroid defuzzification is $O(TS_1)$ [62], here $S_1 = 100$, is the total number of samples of physical sub-domains of the output in this paper. In the HA, the computational complexity of the product/average operator is equivalent to the computational complexity of the spline interpolation $O(m^2N)$ [63], where $m$ is the order of the spline function. By contrast, the computational complexity of the bilinear interpolation is nominally $O(N)$. In fact, the bilinear interpolation considers only $2 \times 2$ neighboring points and requires the least running time [64]. Finally, the computational complexity of MLP-backpropagation in this paper is $O(Co*N*ep)$ [65], here $Co = 37$ is the total number of connections in the MLP model, as presented in Figure 5, $ep$ is the number of epochs. It is noted that the computational complexity of the MLP-backpropagation is not included in the HA-MLP-Based Admittance System. However, it should be added to the complexity of the method in total. To our best knowledge, the complicated level of mentioned methods can be sorted from level 1 to level 5 (here level 1 stands for “most simple” and level 5 stands for “most complicated”), as (level 5) MLP-HA-based admittance controller, (level 4) fuzzy-based admittance controller, (level 3) HA-based admittance controller with Average/Product operator, (level 2) HA-based admittance controller with four-point bilinear, and (level 1) conventional methods. In detail, traditional methods are the most time-consuming since inertia and damping matrices must be experimentally pre-tuned (these methods require the dynamic admittance equation). The fuzzy-based method does not require a dynamic model. However, there is no formalized linkage of fuzzy sets with the natural linguistic term semantics. In other words, there are no order-relations between linguistic terms in fuzzy logic. Moreover, fuzzification, fuzzy composition and defuzzification are quite complicated. They cannot describe the nature of linguistics adequately. HA-based methods are proposed to overcome the shortcomings of the fuzzy-based method. Therefore, the linguistic values are represented in an order-relation based on semantic values. However, the input–output semantic relationship in HA should be considered. Average/product operators are most simple, but the semantic relationship is distorted. Four-point bilinear is more complicated than average/product operators, but the accuracy is better. In addition, it can represent the super surface of the semantic relationship by linearization. Unfortunately, it is difficult to deal with multi-input systems by using the above methods for the HA semantic interpolation. In contrast, MLP interpolation gives favorable conditions to represent the semantic relationship by a super-smooth surface in Cartesian coordinates and to deal with multi-input systems, although it is more complicated. In conclusion, it is a tradeoff between the accuracy and the computational complexity to choose a suitable method for desired applications.

6. Conclusions

This paper presented a new approach for the input–output semantic inference mechanism in Hedge Algebras by using an MLP neural network, whose purpose is to improve the accuracy of the semantic interpolation. Moreover, the proposed MLP-HA-based inference mechanism is also considered for the physical human–robot interaction to eliminate the IIDM in the dynamic admittance model during the process of the controller-making since the end-effector’s velocity is adjusted directly through the external wrench and the robot’s transmitted power. In addition, the natural human–robot cooperation and the safety issue
based on a specific ISO10218 standard are also covered. Potential applications of this research include: (a) the operator teaches the manipulator to implement complicated tasks, such as welding, whose purpose is to eliminate the path planning, or (b) the manipulator supports the operator to lift heavy objects up and down. The proposed MLP-HA-based admittance controller is found to provide better cooperation compared to other controllers. However, the dependency of the MLP model on the number of HA terms is still uncovered. This should be manifested in our coming research.

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