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CONCURRENT ENGINEERING: Research and Applications

Neural-network-driven Fuzzy Reasoning of Dependency Relationships among Product Development Processes

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Abstract: Product development process can be viewed as a set of sub-processes with stronger interrelated dependency relationships. In this article, the quantitative and qualitative dependency measures of serial and parallel product development processes are analyzed. The neural-network-driven fuzzy reasoning mechanism of dependency relationships is developed in the case that there is no sufficient quantitative information or the information is fuzzy and imprecise. In the reasoning mechanism, a three-layer feedforward neural network is used to replace fuzzy evaluation in the fuzzy system. A hybrid learning algorithm that combined unsupervised learning and supervised gradient-descent learning procedures is used to build the fuzzy rules and train membership functions. Results show that the proposed method can improve the reasoning efficiency, reduce the cost and complexity degree of process improvement, and make a fast response to the dynamic development environment.

Key Words: neural network, fuzzy logic, fuzzy reasoning, process programming, product development.

1. Introduction

Process is the basic unit of activity that is carried out during a product's life cycle. The whole development process can be viewed as a set of sub-processes where their physical meanings are varied continuously along with time [1]. There exist complicated relationships among processes, such as dependency relationship, constraint relationship, and logic relationship, in which the dependency relationship is one of the most important relationships. Moreover, product development itself is a complex, dynamic, and uncertain system. The change of one process will result in the change of other processes. The purposes of analyzing the dependency relationship are as follows:

1. Offering a method for design candidate identification under the dynamic and uncertain development environment.
2. Reducing the cost and complexity of process improvement.
3. Increasing the amount of information provided to the designers for making decisions in the case that design information is incomplete and imprecise.

However, it is very difficult to analyze the quantitative and qualitative dependency relationships because of the complexity, fuzziness, and dynamic uncertainty of product development process. The designer can not make a fast and right decision when the interrelated processes change at the same time. Moreover, due to the interrelated dependency relationships, the designers can not make a right evaluation on the design candidates. Either, they can not make a fast response to the process improvement or process reorganization. These disadvantages will prolong the development time and increase the cost. The most important is that it may become the loser of market competition because it can not make a fast and right response to the change of outer development environment. Fuzzy logic and neural network provide stronger tools for process modeling under the fuzzy and uncertain development environment.

Fuzzy logic coupled with rule-based system is enabling the modeling of approximate and imprecise reasoning processes common in human problem solving. Zakarian [2] presented an analysis approach for process models based on fuzzy logic and approximate rule-based reasoning. He used possibility distributions to represent uncertain and incomplete information of process variables, and developed an approximate rule-based reasoning approach for quantitative analysis of process models. Kusiak [3] developed a fuzzy-logic-based

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approach to model imprecise dependencies between variables in the case when no sufficient quantitative information is available. Xue and Dong [4] developed a fuzzy-based design function coding system to identify design candidates from design functions.

The reason for incorporating neural network into the fuzzy logic system is that neural network has the characteristics of self-learning capacity, fault tolerance, and model-free. Neural network and fuzzy logic have been put to use in the following ways [5]:

1. Using neural network to replace fuzzy rule evaluation in fuzzy logic system.
2. Neural network as correcting mechanisms for fuzzy system.
3. Using neural network to simulate membership functions in fuzzy logic system.
4. Combining neural network and fuzzy system.

Sun et al. [6] presented an approach for design candidate identification using neural-network-based fuzzy reasoning. Takagi [7] proposed a neural-network-driven fuzzy reasoning system that was able to partition and adjust fuzzy rules and their membership values automatically. Hayashi et al. [8] identified a new algorithm from the neural-network-driven fuzzy reasoning of Takagi, which can adjust the inference rule in response to a dynamic environment. Hsu et al. [9] proposed a product development model based on multiple attribute decision-making with emphasis on the treatment of the linguistic and vague aspects by fuzzy logic and up-dating or learning by neural network.

In this article, we present an approach to analyze the dependency relationships among product development processes using fuzzy logic and neural network. First, the quantitative and qualitative dependency measures of serial and parallel product development processes are analyzed in detail. Second, we develop a fuzzy-logic-based reasoning mechanism to analyze the dependency relationships among processes under the fuzzy and imprecise design environment. Then, a neural-network-driven fuzzy reasoning system is developed to improve the reasoning efficiency, where the neural network is used to replace fuzzy evaluation in the fuzzy reasoning system. Finally, a development case is used to illustrate the proposed neural-network-driven fuzzy reasoning.

2. Dependency Relationships and Reasoning Mechanism for Product Development Processes

There exist direct or indirect collaborative or conflict relationships between development processes. The strength degree of these relationships has important influence on the performance and improvement of product development processes. Therefore, to develop the reasoning mechanism of process dependency is not only to avail to improve the concurrency degree of processes, but also to avail to decrease the complexity and the cost of process improvement. The physical meanings of symbols are listed in Table 1.

2.1 The Reasoning Rules for Serial Processes

As shown in Figure 1(a), the qualitative and quantitative dependency measures for serial processes can be denoted as follows:

$$\psi_{i,j\to k} = \psi_{ij} \otimes \psi_{jk}, \quad \delta_{i,j\to k} = \delta_{ij} \times \delta_{jk} \tag{1}$$

where ψ represents the qualitative influence of one process on the other process. δ is the degree of influence.

The dependency reasoning rules for serial processes are developed and listed as follows:

1. If ψ_{ij} = ‘+’ and ψ_{jk} = ‘+’, then $\psi_{ij\to k}$ = ‘+’.
2. If ψ_{ij} = ‘+’ and ψ_{jk} = ‘−’, then $\psi_{ij\to k}$ = ‘−’.
3. If ψ_{ij} = ‘−’ and ψ_{jk} = ‘−’, then $\psi_{ij\to k}$ = ‘+’.
4. If ψ_{ij} = ‘−’ and ψ_{jk} = ‘+’, then $\psi_{ij\to k}$ = ‘−’.
5. If ψ_{ij} = ‘+’(‘−’) and ψ_{jk} = ‘0’, then $\psi_{ij\to k}$ = ‘0’.
6. If ψ_{ij} = ‘0’ and ψ_{jk} = ‘+’(‘−’), then $\psi_{ij\to k}$ = ‘+’(‘−’).

2.2 The Reasoning Rules for Parallel Processes

As shown in Figure 1(b), the qualitative and quantitative dependency measures for parallel processes can be denoted as follows:

$$\psi_{i,j\to k} = \psi_{ik} \oplus \psi_{jk}, \quad \delta_{i,j\to k} = \delta_{ik} + \delta_{jk} \tag{2}$$

The reasoning rules are developed and listed as follows:

1. If ψ_{ik} = ‘+’ and ψ_{jk} = ‘+’, then $\psi_{ij\to k}$ = ‘+’.
2. If ψ_{ik} = ‘−’ and ψ_{jk} = ‘−’, then $\psi_{ij\to k}$ = ‘−’.

Table 1. The physical meanings of symbols.

ψ_{ij}	Physical meanings
+	The change of process p_i has a good influence on the improvement of process p_j
−	The change of process p_i has a bad influence on the improvement of process p_j
0	The change of process p_i has no influence on the improvement of process p_j
?	Otherwise

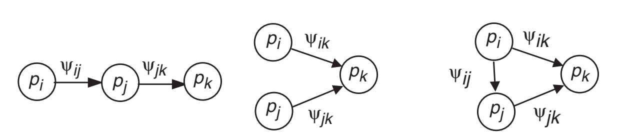

Figure 1. Structure of process.

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3. If $\psi_{ik}(\psi_{jk}) =$ '0' and $\psi_{jk}(\psi_{ik}) =$ '+'('−'), then $\psi_{ij\to k} =$ '+'('−').
4. If $\psi_{ik}(\psi_{jk}) =$ '+'('−') and $\psi_{jk}(\psi_{ik}) =$ '−'('−'), then $\psi_{ij\to k} = ?$.

There exists loop structure as shown in Figure 1(c). If $\psi_{ik} =$ '0' (i.e., there does not exist direct dependency relations between processes p_i and p_k), the loop structure transforms into serial structure. If $\psi_{ij} =$ '0' (i.e., there does not exist direct dependency relations between processes p_i and p_j), the loop structure transforms into parallel structure. If there exist direct dependency relations among the three processes, the qualitative and quantitative dependency measures for loop structure can be denoted as follows:

$$\psi_{i,j\to k} = \left(\psi_{ij} \otimes \psi_{jk}\right) \oplus \psi_{ik}, \quad \delta_{i,j\to k} = \left(\delta_{ij} \times \delta_{jk}\right) + \delta_{ik} \tag{3}$$

3. Neural-network Driven Fuzzy Reasoning Mechanism for Process Dependency

To serial structure, its quantitative dependency relationships are very obvious. To parallel structure, if the two processes change along the same direction, the common influence on the third process is to make it be strengthened. However, if the directions of the change of the two processes differ, the common influence on the third process is sometimes vague. Point to this, fuzzy logic and neural network are used to reason the dependency relationships among the development processes. The neural-network-driven fuzzy reasoning approach provides a more flexible and natural way to represent the quantitative dependency among parallel processes.

3.1 Fuzzy Set and Fuzzy Logic [2,10,11]

Fuzzy logic has emerged as a mathematical tool to deal with the uncertainties associated with human cognition processes. A fuzzy logic system translates crisp input into linguistic variables through membership functions, evaluates using fuzzy rules, and then outputs defuzzified values. A fuzzy logic consists of IF-THEN fuzzy rules, where IF portion of the fuzzy rule includes the premise part and THEN portion, the consequence part. The premise and consequence of fuzzy rules contain linguistic variables. An inference process of fuzzy logic takes the fuzzy sets representing the rules and the facts and produces a resultant fuzzy set, over the domain of discourse of the consequent.

In order to present an approximate reasoning method for the process modeling, the operations of fuzzy set include fuzzy intersection, fuzzy union, and fuzzy complement.

The intersection of fuzzy sets A and B can be obtained from

$$\mu_{A\cap B}(x) = \min\left\{\mu_A(x), \mu_B(x)\right\} = \cap\left\{\mu_A(x), \mu_B(x)\right\} \tag{4}$$

by taking minimum of the degrees of membership of the elements in fuzzy sets A and B.

The union of fuzzy sets A and B can be obtained from

$$\mu_{A\cup B}(x) = \max\left\{\mu_A(x), \mu_B(x)\right\} = \cup\left\{\mu_A(x), \mu_B(x)\right\} \tag{5}$$

by taking maximum of the degrees of membership of the elements in fuzzy sets A and B.

The complement of fuzzy sets A can be obtained from

$$\mu_{-A}(x) = 1 - \mu_A(x) \tag{6}$$

3.2 Fuzzy Reasoning Approach for Process Dependency

The dependency between processes can be described as a linguistic variable characterized by a quintuple (V, $T(V)$, U, G, M), where V is the linguistic variable 'dependency', $T(V)$ is the set of names of linguistic terms of V, U is the universe of discourse, G is the syntactic rule for generating terms in the term set $T(V)$, M is the semantic rule that assigns a meaning, i.e., fuzzy set, to the terms.

Let V is the rate of change of process p_k caused by the change of processes p_i and p_j.

$$\begin{aligned} T(V) &= \{\text{PL, PM, PS, NL, NM, NS}\} \\ &= \left\{ \begin{aligned} &\text{Positive large, Positive same, Positive small,} \\ &\text{Negative large, Negative same, Negative small} \end{aligned} \right\} \end{aligned}$$

Membership functions of the linguistic terms can be defined as follows.

$$\mu_{\mathrm{PS}}(\psi) = \frac{1}{1+100\psi^4}, \quad 0 \le \psi \le 1$$

$$\mu_{\mathrm{PM}}(\psi) = \frac{1}{1+100(\psi-1)^4}, \quad 0 \le \psi \le 2$$

$$\mu_{\mathrm{PL}}(\psi) = \begin{cases} \dfrac{1}{1+100(\psi-2)^4}, & 1 \le \psi \le 2 \\ 1, & \psi \ge 2 \end{cases}$$

$$\mu_{\mathrm{NS}}(\psi) = \frac{1}{1+100\psi^4}, \quad -1 \le \psi \le 0$$

$$\mu_{\mathrm{NM}}(\psi) = \frac{1}{1+100(\psi+1)^4}, \quad -2 \le \psi \le 0$$

$$\mu_{\mathrm{NL}}(\psi) = \begin{cases} \dfrac{1}{1+100(\psi+2)^4}, & -2 \le \psi \le -1 \\ 1, & \psi \le -2 \end{cases}$$

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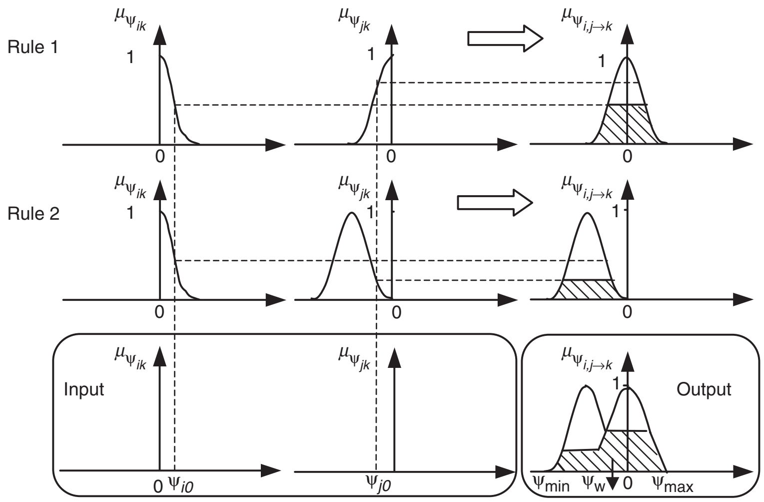

Figure 2. Fuzzy-logic-based fuzzy reasoning process.

The fuzzy rule is represented as follows:

$$\text{IF } \psi_{ik} = V_m \quad \text{and} \quad \psi_{jk} = V_n, \quad \text{THEN} \quad \psi_{ik} \oplus \psi_{jk} = V_k$$

where V_m, V_n, and V_k are fuzzy linguistic terms.

Thirty-six fuzzy rules can be developed to represent the dependencies among processes p_i, p_j, and p_k. In fuzzy reasoning, the minimum and maximum membership function values can be obtained using logical 'and' and 'or' operations. We can achieve the output value by calculating the center of gravity of the output membership function. As shown in Figure 2, for each rule we can obtain the membership function measures for the two input variables ψ_{i0} and ψ_{j0}, and the smaller value can be selected as the measure to evaluate matching of the rule. The resulting membership function of fuzzy reasoning considering only one rule is the minimum of the membership function at the THEN part of the rule and rule matching measure. The resulting membership function of fuzzy reasoning $\mu_{i,j\to k}(\psi)$ considering all the relevent rules can be achived by obtaining the maximum value of these result membership functions for these rules. Output value of variable is the gravity center of the output membership function $\mu_{i,j\to k}(\psi)$, calculated by [6]

$$\psi_w = \frac{\int_{\psi_{\min}}^{\psi_{\max}} \mu_{i,j\to k}(\psi)\psi d\psi}{\int_{\psi_{\min}}^{\psi_{\max}} \mu_{i,j\to k}(\psi) d\psi} \tag{7}$$

Assume the following two fuzzy rules and the values of input variables:

Rule 1: IF $\psi_{ik} =$ 'PS', and $\psi_{jk} =$ 'NS', then $\psi_{i,j\to k} =$ 'PS' or 'NS'.

Rule 2: IF $\psi_{ik} =$ 'PS', and $\psi_{jk} =$ 'NM', then $\psi_{i,j\to k} =$ 'NM'.

Input: $\psi_{ik} = \psi_{i0}$, $\psi_{ik} = \psi_{j0}$.

The fuzzy reasoning process can be illustrated by Figure 2.

3.3 Neural-network-driven Fuzzy Reasoning Approach for Process Dependency

However, with the increase of number of fuzzy rules and complexity of membership functions, the calculation of output variable values becomes difficult. In order to decrease the computational tasks and improve the reasoning efficiency, it is necessary to improve the fuzzy reasoning process. Because neural network have learning capacity and model-free characteristics, it can be used to replace the fuzzy reasoning process in fuzzy logic systems.

In our model to reason the dependency relationships among product development processes, a three-layer feedforward neural network with an input layer, a hidden layer, and an output layer was used to replace the fuzzy reasoning process, as shown in Figure 3.

The input nodes are used to describe the fuzzy membership functions for different fuzzy sets. The input nodes can be grouped based on the number of processes. In each group, there exist six nodes used to represent the fuzzy set membership function measures. x_0 and y_0 are the initial values of processes p_i and p_j. The output nodes are used to describe the output membership functions for output variables. There exist six output nodes used to represent membership functions of six output variables, i.e., $\mu_{\mathrm{PL}}(z_w)$, $\mu_{\mathrm{PM}}(z_w)$, $\mu_{\mathrm{PS}}(z_w)$, $\mu_{\mathrm{NL}}(z_w)$, $\mu_{\mathrm{NM}}(z_w)$, $\mu_{\mathrm{NS}}(z_w)$, where z_w is the gravity center of the output membership function. The hidden layer functions are operated as membership functions and fuzzy rules.

In the training process, a hybrid learning algorithm that combined unsupervised learning and supervised gradient-descent learning procedures is used to build the fuzzy rules and train membership functions. Through assigning values to the input variables, calculating the membership function measures of the input nodes, and achieving the output membership function using fuzzy reasoning, the correct data set can be achieved. All the fuzzy rules are involved and can be encoded in the

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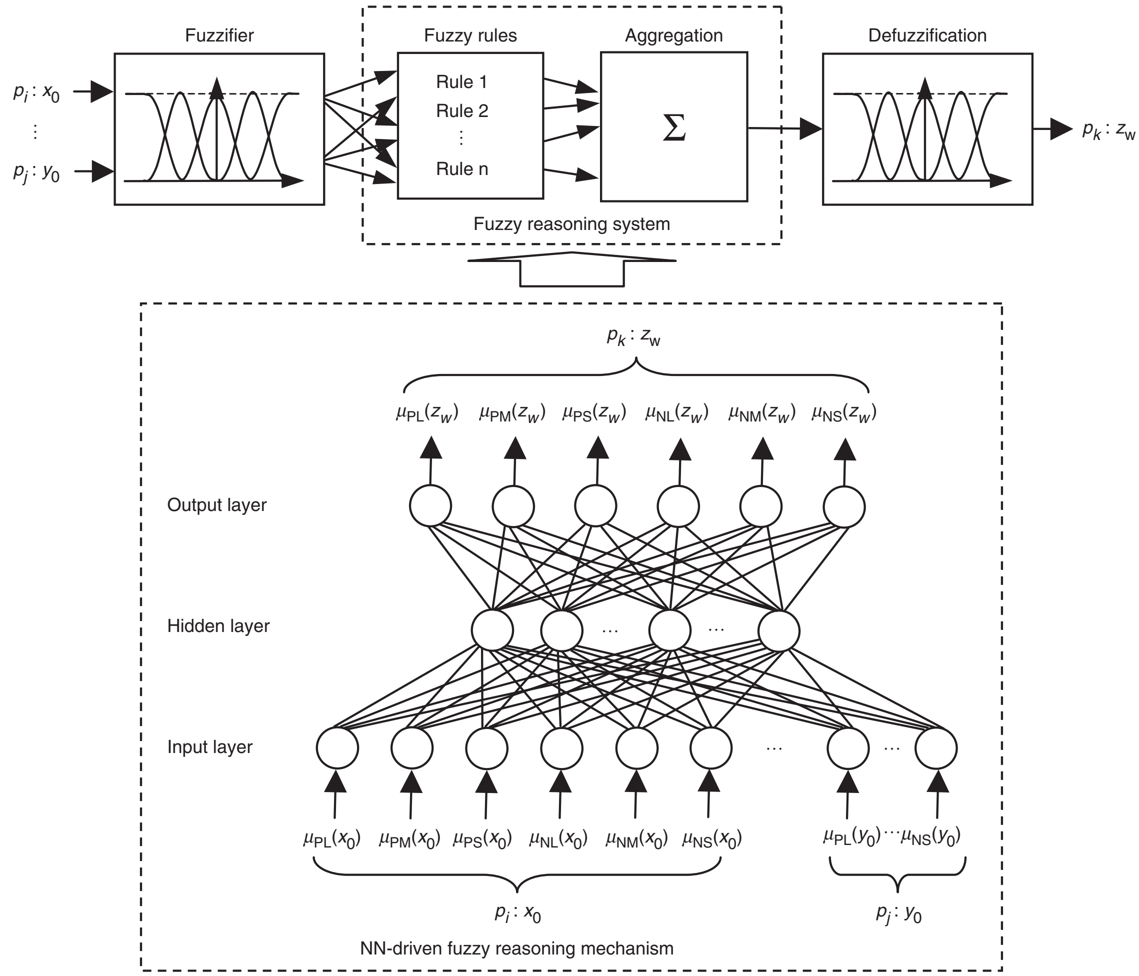

Figure 3. A three-layer feedforward neural network for fuzzy reasoning.

neural network. When a set of input data is provided to the neural network, these encoded rules are activated to different degree at the same time. The output membership function can be generated by the neurocomputing, and it is related to all the fuzzy rules.

4. Case Study

Let us take the design process of worm drive as an example to analyze the dependency relationships using the proposed neural-network-driven fuzzy reasoning mechanism. Requirement analysis (p_1), cost analysis (p_2), and concept design (p_3) are the three sub-processes of the whole development process.

The process structure of the three processes is parallel. First, we pick up the key process variables of each process respectively, v_1 = transmission efficiency, v_2 = cost, v_3 = satisfaction degree of scenario. The change of key process variables is the dominant factors to result in the change of the process and its relative processes. The key of improving the process is to improve its key variables.

Table 2. Fuzzy rules.

		IF ψ_1					
Then ψ_3		**PS**	**PM**	**PL**	**NS**	**NM**	**NL**
IF ψ_6	PS	PS	NS	NM	PS	PM	PL
	PM	PM	PS	NM	PM	PL	PL
	PL	PL	PS	NM	PL	PL	very PL
	NS	NS	NM	NL	PS	PM	PL
	NM	NM	NL	NL	NS	PS	PM
	NL	NL	NL	very NL	NL	NL	NM or NL

Thirty-six fuzzy rules can be developed as shown in Table 2.

Now, the process variable v_1 (transmission efficiency) will increase 20% because of the change of working conditions of worm, which will make v_2 (cost) increase 30% at the same time. The neural-network-driven fuzzy reasoning mechanism proposed in Section 3.3 can be used to analyze the change of v_3 (satisfaction degree of concept), which is resulted from the change of transmission efficiency and cost. A three-layer feedforward neural network is developed to reason the dependency relationships among the three processes, as shown in Figure 4.

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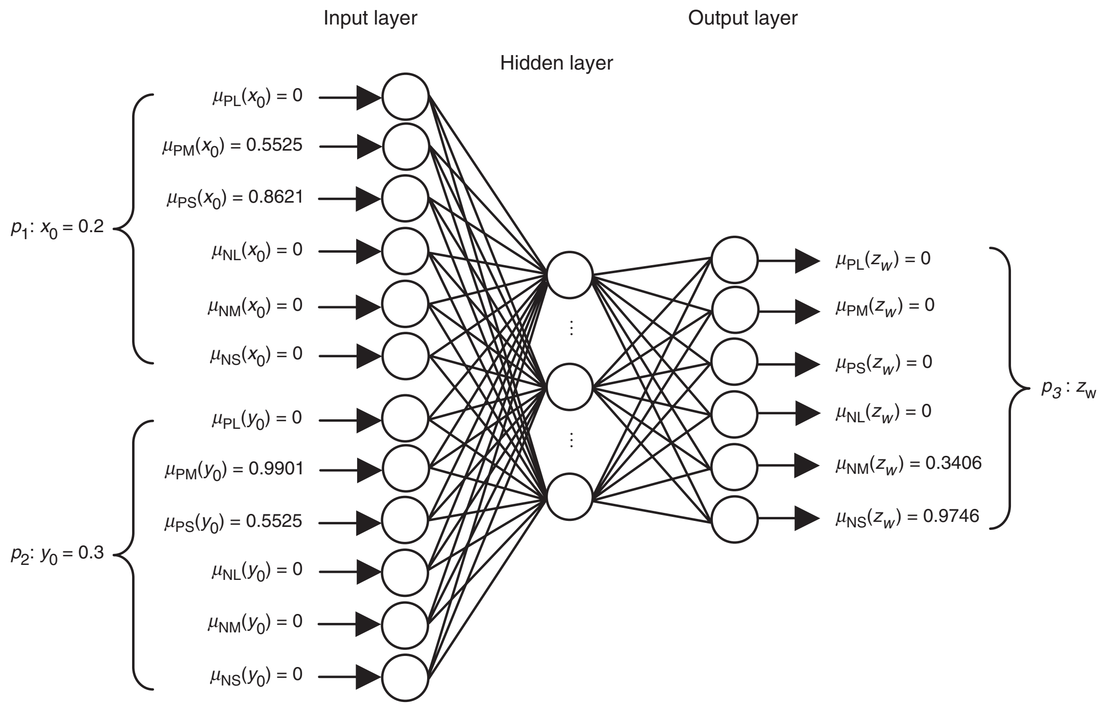

Figure 4. The NN-driven fuzzy reasoning for dependency relationships among process p_1, p_2, and p_3.

Table 3. Input variables and their corresponding nodes.

Variable names	Variable values	Input nodes	Fuzzy sets	Membership functions
The change of ψ_1	0.2	$\mu_{PL}(\psi_1)$	Positive large	0
		$\mu_{PM}(\psi_1)$	Positive same	0.5525
		$\mu_{PS}(\psi_1)$	Positive small	0.8621
		$\mu_{NL}(\psi_1)$	Negative large	0
		$\mu_{NM}(\psi_1)$	Negative same	0
		$\mu_{NS}(\psi_1)$	Negative small	0
The change of ψ_2	0.3	$\mu_{PL}(\psi_2)$	Positive large	0
		$\mu_{PM}(\psi_2)$	Positive same	0.9901
		$\mu_{PS}(\psi_2)$	Positive small	0.5525
		$\mu_{NL}(\psi_2)$	Negative large	0
		$\mu_{NM}(\psi_2)$	Negative same	0
		$\mu_{NS}(\psi_2)$	Negative small	0

The neural network includes 12 input nodes and 6 output nodes. The input nodes can be classed into two groups. The input variables and their corresponding values are listed in Table 3. The final output variable values can be obtained by training the neural network, and list in Table 4.

From the results we can see, the satisfaction degree of scenario decrease a little when the transmission efficiency increases 20%. That is to say, the process p_3 changes along the negative direction in some sort when p_1 and p_2 change according to the design requirements.

5. Conclusions

In the development process, the design information is fuzzy and sometimes incomplete. In order to offer a stronger decision-making tool for the designers, fuzzy logic, and neural network are used to develop an intelligent reasoning mechanism. The neural-net-driven fuzzy reasoning mechanism can be used to analyze the dependency relations of development processes. The proposed method is effective in process programming and improving when the information is incomplete or the design knowledge is limited. It provides a method and theory foundation for realizing automatization of product development.

Table 4. The final output variable values.

Variable names	Output nodes	Fuzzy sets	Membership functions
The change of ψ_3	$\mu_{PL}(\psi_3)$	Positive large	0
	$\mu_{PM}(\psi_3)$	Positive same	0
	$\mu_{PS}(\psi_3)$	Positive small	0
	$\mu_{NL}(\psi_3)$	Negative large	0
	$\mu_{NM}(\psi_3)$	Negative same	0.3406
	$\mu_{NS}(\psi_3)$	Negative small	0.9746

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