Research Paper | E-ISSN : 2455-295X | Volume : 2 | Issue : 3 | March 2016

FUZZY PETRINET FOR MODELING IN BIOLOGICAL EXPERIMENTATIONS

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ABSTRACT

The regulatory mechanism of gene expression can be modeled using deterministic techniques only when all the physical laws of the mechanism is well known. This requires time series data. Since the feasible experiment does not produce time series data, only a static predictive model can be developed. This model produces the effect of the input on the gene regulation mechanism and the products of the gene regulation. The measurement error and the uncertainties of the deducted model make the modeling of the phenomenon challenging. The uncertainties can be due to the effective variables which are uncontrollable during the experiments. Hence the model is essentially stochastic with deterministic and uncertainty components. Hence a statistical model can be used as a mathematical tool for the modeling and simulation of the observed phenomenon of GRN. It can be observed that the domain expert can heuristically predict the behavior of the GRN with reasonable accuracy.

KEYWORDS: Fuzzy Logic, Petrinet, Clustering, Defuzzification, Modeling, Inference Mechanism

Abbreviations

FIS-Fuzzy Inference System
GRN-Genetic Regulatory Network
FPN- Fuzzy Petrinet

Introduction

The fuzzy logic is one of the best tools listed under soft computing to model such type of systems. Also the computational complexity of the fuzzy logic systems are lesser when compared to other soft computation techniques like genetic algorithm, spider web algorithm, evolutionary computing, artificial neural networks, swarm intelligence and bacteria forage algorithm. The real life model of the systems can be implemented using the Petrinet framework. This is due to the fact that the Petri net model is the ideal model to simulate the concurrent and network models of processing elements. Hence the combination of the two called fuzzy Petri net (FPN) technique is been adopted.

Fuzzy Logic

The experimental data collected is clustered and made to represent the group of categories that can be easily represented by context based labels. These labels are called as the linguistic variables (Mamdani, 1977). The linguistic variables are the core of the heuristic thinking capacity possessed by the domain expert. The examples for the linguistic variables are representation of the fuel level in the car as Low, Medium and High. Here it can be easily seen that the level of the fuel is not measured or represented by the numerical values. The mapping of these linguistic variables to the measured quantity reveals the fact that the linguistic variables actually overlap on the measured quantity thereby creating a possibility of attachment to multiple linguistic variables which are closer. This possibility of the attachment to a particular linguistic variable is called as the membership. Normally the membership is represented as a mathematical function called membership function.

Fuzzyfication

Fuzzyfication is the process of conversion of crisp values of the physical variables into fuzzy variables with membership values. The type and bounds of the membership functions are selected for each linguistic variable. When the value of the crisp variable falls within the bounds of a linguistic variable it is said to be triggered and thus produce a non-zero membership value calculated using the membership function. (Zadeh, 1997)

Inference Mechanism

Inference is the process by which the rules are used to make decision based on the inputs presented to FIS. The heuristic knowledge is coded in the form of rules. The collection of these rules is called as rule base. (Pavelka, 2006). The rule base in fuzzy logic is the correlation of the input linguistic variables and its combination to the output linguistic variables. The important advantage of the rule base is that it can even capture the non-linearity in the modeled phenomenon.

DeFuzzyfication

DeFuzzyfication is the process of transformation of the output of fuzzy inference to physical real life values or crisp values. The inference mechanism produces the fuzzy membership values for all the output linguistic variables involved in the FIS. (Leekwijck and Kerre, 1999). The shape and bounds of the output member functions are selected based on the requirement of accuracy and tuned to achieve the final required values. The membership functions used for the output linguistic variables are similar to the membership functions used for input linguistic variables. The DeFuzzyfication is most complex and time consuming part of the fuzzy logic computations and can be performed using various methods. The centroid method is the simplest one.

Tuning Method

The process of tuning in Fuzzy systems is the adjustments made to the FIS engine to create the desired output. The process of tuning aims at reducing error, improving precision, reducing noise sensitivity, ensuring smooth transitions and ability to handle uncertainty.

Clustering

The experimental data are plotted into multiple charts to correlate the inputs and outputs to elucidate the relationship among them. The clusters are identified by their nature of representing a common feature or property. The clusters are used to make piecewise linear curve fits to approximate the actual phenomenon observed. The fundamental fact is that the clusters are centered on data representing the true phenomenon. The deviations are due to the error due to measurement and variations in other uncontrolled parameters. (Vesely et al, 2016)

Normalization

In most cases to create reusable components of FIS the input variable need to be standardized. The ratio is the best tool to implement this requirement. The input variables are normalized to transform the variation within the range of 0 to 1. Here the interpretation of the process is defined as the conversion of the absolutes into percentages. But in order to avoid the value represented falling outside the range, a tolerance quantity is added after careful study of the process to be modeled using FIS. Normally 20 % tolerance is added. This normalization procedure converts all parameters into uniform base thereby ensures ease of comparison.

Validation

The fuzzy model developed is validated by comparison of the result with the experimental data. This procedure is used to confirm the completeness, accuracy and precision of the Fuzzy GRN model developed.

The fuzzy model is tuned using multiple experimental data in case of deviation. The closeness of the estimate to the actual experiment data is related to the quality and accuracy of the experimental data used for validation and the sample size used for modeling and tuning the fuzzy model. The final target in any model is to eliminate the error. To make error zero is impossible; hence an allowable or minimal error may be specified as the criteria of the system.

Petrinet

The Petrinet is the mathematical modeling graphical tool used to represent a concurrent, real time and network based system with multiple interconnected components with many parallel paths of flow. The components of Petrinet are graphical. The fundamental components of the Petrinet are Place, Arc, Transition and Token (Liu et al, 2016).

Fuzzy Petrinet (FPN)

The concept of Petrinet is specialized into various operations involved in fuzzy logic. The fuzzy operations are normalization, Fuzzification, inference, rule base, defuzzification, denormalisation and dispatching. The places are used to hold the various data and states of the system modeled using FPN. (Yan et al, 2016)

Genetic Regulatory Network (GRN) Model

The Fuzzy GRN model can be used for modeling the GRN. The sensing part and the activation parts of the gene can be separated into two components and the interaction between each gene can be explained using the conceptual variables. These conceptual variables are to be tuned to achieve the final required accuracy. (Vela and Diaz, 2016)

Acknowledgement

We are thankful to Dr. Maria Zeena Johnson and Dr.Maria Johnson, Directors, Sathyabama University, Chennai for providing us with all the necessary facilities for the research. We also express our sincere thanks to Dr. S. Nandi, NIANP, Bangalore for his valuable encouragement.

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