Original Article

www.jmss.mui.ac.ir

Specification and Verification of Medical Monitoring System Using Petri-nets

Negar Majma[1,2], Seyed Morteza Babamir[1]

Departments of Computer, [1]University of Kashan, Kashan, [2]Naghshejahan Higher Education Institute, Isfahan, Iran

Submission: 13-04-2013 Accepted: 08-02-2014

ABSTRACT

To monitor the patient behavior, data are collected from patient's body by a medical monitoring device so as to calculate the output using embedded software. Incorrect calculations may endanger the patient's life if the software fails to meet the patient's requirements. Accordingly, the veracity of the software behavior is a matter of concern in the medicine; moreover, the data collected from the patient's body are fuzzy. Some methods have already dealt with monitoring the medical monitoring devices; however, model based monitoring fuzzy computations of such devices have been addressed less. The present paper aims to present synthesizing a fuzzy Petri-net (FPN) model to verify behavior of a sample medical monitoring device called continuous infusion insulin (INS) because Petri-net (PN) is one of the formal and visual methods to verify the software's behavior. The device is worn by the diabetic patients and then the software calculates the INS dose and makes a decision for injection. The input and output of the infusion INS software are not crisp in the real world; therefore, we present them in fuzzy variables. Afterwards, we use FPN instead of clear PN to model the fuzzy variables. The paper follows three steps to synthesize an FPN to deal with verification of the infusion INS device: (1) Definition of fuzzy variables, (2) definition of fuzzy rules and (3) design of the FPN model to verify the software behavior.

Key words: *Continuous infusion insulin device, fuzzy Petri-net, fuzzy rule, wireless body area network*

INTRODUCTION

A medical monitoring system is a wearable computing device, including a microcontroller and a transceiver to record human body activities and statuses.[1] Such systems are initially applied in the field of healthcare, especially for continuous monitoring and logging patients vital parameters. A typical of such devices is the mobile insulin (INS) infusion whose task is constant monitoring of diabetic statuses. Diabetes is a common condition caused when the human pancreas is unable to produce sufficient quantities of a hormone called INS. The World Health Organization[2] reported that there are nearly 180 million diabetic people, and this number is expected to reach 350 million by 2030; accordingly, the device plays an important role in diabetes treatment. A diabetic person experiences hyperglycemia and hypoglycemia when his/her level of blood glucose remains high or low; which may lead to complications such as eye, kidney and nerve damage. To avoid these complications: (1) Diabetic's blood sugar (BS) is sampled by an external meter, (2) the glucose level and INS dose are calculated by the software device and (3) the INS is injected if necessary.

There are two types of INS doses: (1) Basal (small) dose which must be injected to the body constantly and (2) bolus dose which must be injected before or after meals or when the blood glucose level is high. The infusion device injects the basal INS continuously; nevertheless, the bolus one is calculated by the software device. Sommervile[3] showed a typical of continuous infusion device structure.

The infusion device technology helps patients to have normal and healthy life, however; at the same time, it could endanger the patient's health as a safety-critical system, if: (1) The device fails to operate properly, (2) the dosage is calculated incorrectly or (3) the device fails to satisfy the normal BS. The manufacture and user Facility Device Experience database maintained by the U.S. Food and Drug Administration[4] announced that there were over 5000 adverse events reported for the infusion device in year 2008. Therefore, it is imperative to comprehensively identify risks and develop some solutions to prevent such events.

One way for reducing risks in such devices is verification of their behavior against the patient's requirements. The high-level requirements need to be satisfied by the device are as follows:

Address for correspondence:
Dr. Seyed Morteza Babamir, Department of Computer, University of Kashan, Kashan, Iran. E-mail: babamir@kashanu.ac.ir

- Available dose injection when required
- Delivering the correct dose
- Not delivering the unnecessary INS
- The device sensor should not be late/early for sampling
- The blood glucose should never move downward/upwards safe-min/safe-max.

This paper aims to deal with verification of the device behaviors which are against patient's safety requirements using fuzzy rules and fuzzy Petri-net (FPN). Using the FPN, we propose a visual and a mathematical model through which one can formally verify the device behaviors against user's requirements. This is carried out by determining hazards and unsafe statuses of the device. Five requirements mentioned above include variables that are not crisp in the real world because they have uncertain values; therefore, we represent them by fuzzy variables and use these variables to synthesize the fuzzy rules. These rules are used for knowledge representation of the device behavior. Afterwards, fuzzy rules, which are used to synthesize the FPNs, are applied to analyze the device behavior. The main advantage of this study is using a fuzzy rule-based system along with the FPNs. It provides a structured knowledge representation in which the relationships between the rules in knowledge base are easily understood; moreover, a systemic inference capability is also provided. FPNs have already been used in software when needed a level of expertise and intelligence.[5]

Figure 1 shows our proposed model where the safety verification of the dose calculated by the device is carried out using a FPN. There are two kinds of paths in this figure: (1) The red ones indicate the paths which are used just once to build the FPN model. The fuzzification interface block converts input parameters to the fuzzy values, which are used by the inference engine to select the fired rules form the knowledge base. These rules are used to generate outputs. Our proposed FPN model will be generated using these inputs and output, where fuzzy values will be inputs of the FPN model. (2) The blue lines indicate the paths followed whenever the software runs. Each input to the model leads to traverse a path in the model and the expected output will be the model output. Outputs are defuzzified by the defuzzification inference block and finally the infusion output is compared with the output of our model for making a decision on safety block. If two outputs are the same, the software behavior is safe; otherwise, the software suffers from some hazard. We used Mathworks MatLAB 2012 to generate the rules and Petri-nets (PNs) to test the rules and check system outputs against the safety requirements.

We continue our study as follows: In Section 2, fuzzy variables and fuzzy rules are defined to construct a rule-base system for the infusion device. In Section 3, FPNs are formally introduced and in Section 4, we map the fuzzy rules in to FPNs. In Section 5, we deal with the related work and finally in Section 6, the conclusion is drawn and directions for the future studies are proposed.

DEFINING FUZZY VARIABLE AND FUZZY RULES

Fuzzy logic is a relatively new concept introduced in 1965 by Zadeh. Fuzzy logic studies vague reasoning, with classical logic as special case. The central idea of fuzzy logic is to model the human way of reasoning in an environment of uncertainty and imprecise concepts. Fuzzy logic introduced appropriate fuzzy sets for representing certain types of linguistic terms that are employed in human reasoning. For example, a fuzzy set of truth-values is represented as true, false, very true, very false, truer and less false.

The difference between crisp and fuzzy sets is established by introducing a membership function. A membership

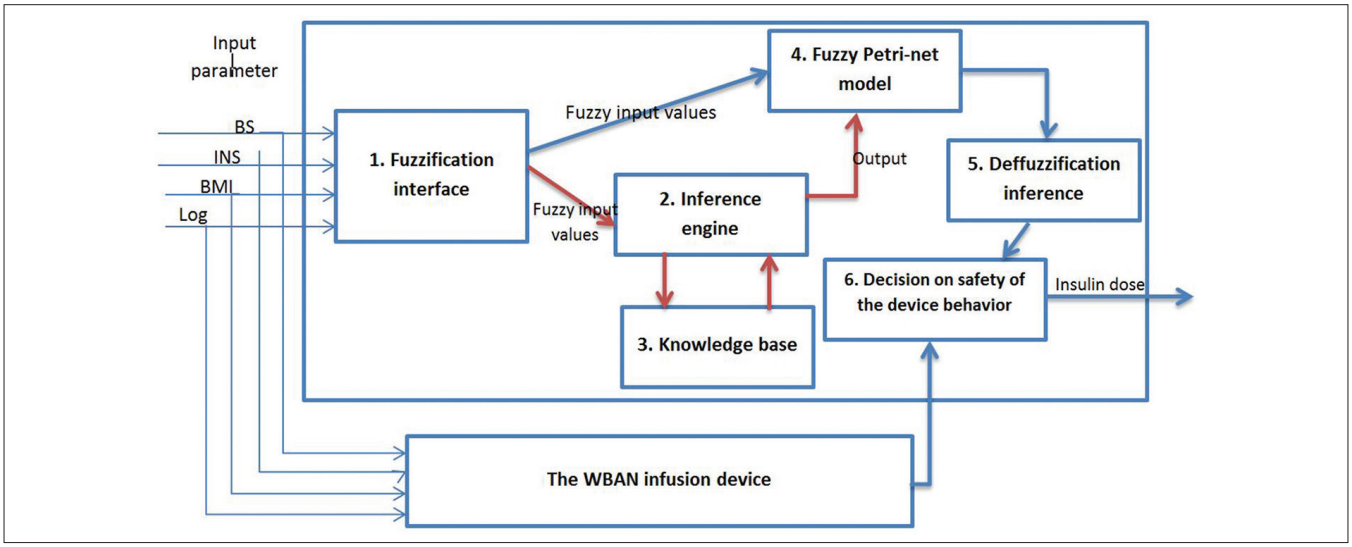

Figure 1: The proposed system diagram

function indicated by $\mu_A(x)$ describes the membership of element x of the base set x in the fuzzy set A. Each membership function has a set of important properties and characteristics of fuzzy sets: (1) The support zone of fuzzy set A is the crisp (definite) set containing all x elements having nonzero membership degrees in A, (2) The core zone of the normal fuzzy set A is the crisp set that contains all x elements having a membership degree in A, (3) The boundary zone is the crisp set that contains all x elements having the membership degree $0< \mu_A(x) <1$ in A.

Fuzzy systems [Figure 2] have usually four major components: (1) Fuzzification interface; this component is used to define the fuzzy sets used to represent linguistic values in the fuzzy rules and translate crisp (definite) values into linguistic values, (2) fuzzy knowledge base; this component consists fuzzy rules in form of IF-THEN, (3) fuzzy inference engine; this component is used for reasoning fuzzy rules and input values and (4) defuzzification interface, which translates fuzzy set output values into crisp values.

Our approach for designing the fuzzy rule-based system is as follows: A fuzzy rule-based system is synthesized using definition of fuzzy variables and fuzzy sets. A fuzzy set is characterized by a membership function associating each variable with a membership degree value. In real world, the variables of the infusion INS device are fuzzy. The membership functions of fuzzy variables are designed by MatLAB 2012.

We consider 4 variables as input parameters: (1) Blood glucose level (indicated by BS), (2) produced INS by patient's body (indicated by INS), (3) body mass index (indicated by BMI) and (4) the dose log consisting of doses injected in the last day. The amount of injected dose indicates the output parameter. The membership function of input and output variables is explained as mentioned.

BS

The BS ranges from zero to 320 mg/dl. According to the physician, BS is divided into 5 levels [Table 1]: (1) Hypoglycemic, (2) hypo-danger, (3) normal, (4) hyper-danger and (5) hyperglycemic and according to Section 2, each membership function consists of support, core and boundary zones. Table 1 shows range values of each zone and their overlaps; for instance, the support and hypo-danger values respectively are between 0 and 70 and 50 and 110, where the zone of 50-70 is shared between them. According to Figure 3, the membership degree for the value 65 in the hypoglycemic and hypo-danger zones is 0.4 and 0.6 and for the value 55 is 0.2 and 0.8 respectively.

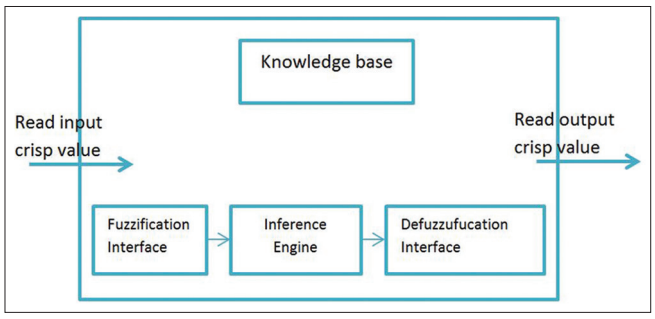

Figure 2: Fuzzy system components

Blood INS

The patient's body produces INS from 0 to 35 units. According to the physician, INS is divided into 3 levels: (1) Minimum, (2) normal and (3) maximum whose support, core, left and right boundary values are given in Table 2. The INS membership function for these levels is shown in Figure 4.

BMI

The third input fuzzy variable is BMI. According to the physician and Jayaraj *et al*.,[6] it varies from 0 to 35 falling into 4 levels: (1) Light-weight (blow), (2) normal-weight (normal), (3) over-weight and (4) obese whose support, core, left and right boundary values are given in Table 3. The BMI membership function for these levels is shown in Figure 5.

Log of Dose Injection

The last input variable is the dose injection log in the last day. The log membership function is the same as the output variable. It varies from 0 to 8 and is divided into 5 levels: (1) Less, (2) average, (3) medium, (4) high and (5) very high whose support, core, left and right boundary values are

Table 1: BS membership function values

Zone name	Support value	Core value	Left boundary value	Right boundary value
Hypoglycemic	0-70	0-50	-	50-70
Hypo-danger	50-110	60-100	5-60	100-110
Normal	100-190	110-180	100-110	180-190
Hyper-danger	180-260	190-250	180-190	250-260
Hyperglycemic	250-320	260-320	250-260	-

BS – Blood sugar. Support: The crisp set containing nonzero membership degrees for all elements. Core: The crisp set containing membership degree in A for all x elements. Boundary: The crisp containing membership degree $0<\mu A(x)<1$ in A for all x elements

Table 2: INS membership function values

Zone name	Support value	Core value	Left boundary value	Right boundary value
Minimum	0-7	0-5	-	5-7
Normal	5-30	7-28	5-7	28-30
Maximum	28-35	30-35	28-30	-

INS – Insulin. Support: The crisp set containing nonzero membership degrees for each all x elements. Core: The crisp set containing membership degree in A for all x elements. Boundary: The crisp containing membership degree $0<\mu A(x)<1$ in A for all x elements

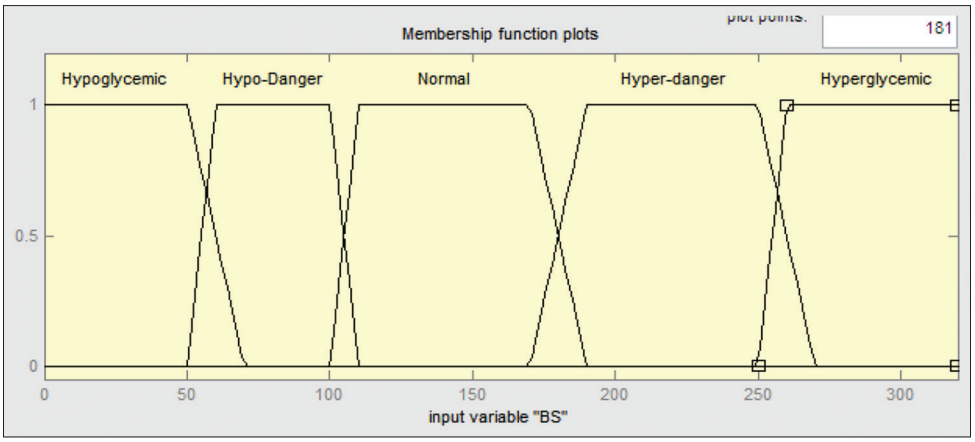

Figure 3: Blood sugar membership function

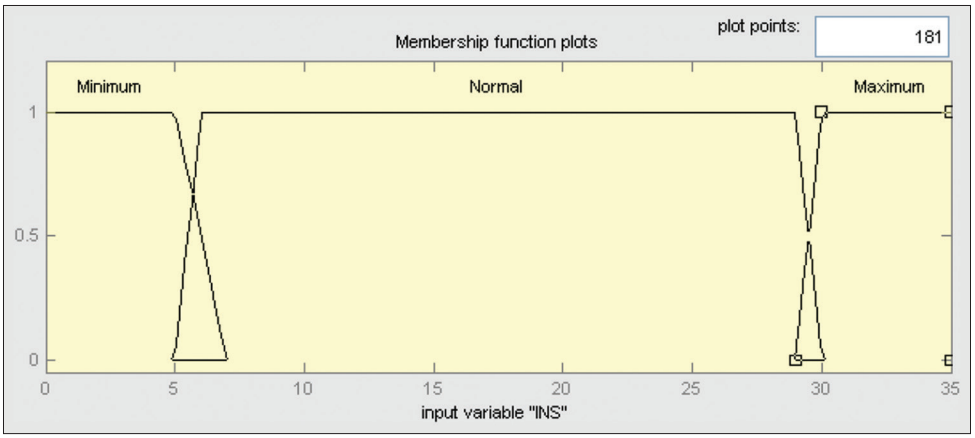

Figure 4: Insulin membership function

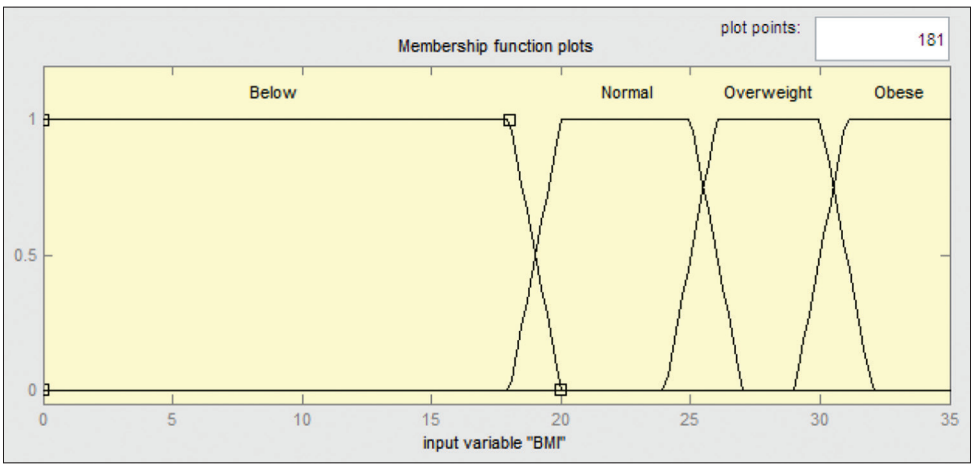

Figure 5: Body mass index membership function

shown in Table 4. The membership function for these levels is shown in Figure 6.

The Output Variable

The output value of the system is the dose that should be injected. It varies from 0 to 8 and falls into 5 levels: (1) Less, (2) average, (3) medium, (4) high and (5) very high whose support, core, left and right boundary values are given in Table 4. The output membership function for these levels is shown in Figure 7.

Determining Fuzzy Rules

Fuzzy knowledge base definition is the second step to design a fuzzy system. In this section, the relations between the

Table 3: BMI membership function values

Zone name	Support value	Core value	Left boundary value	Right boundary value
Light-weight (blow)	0-20	0-18	-	18-20
Normal-weight (normal)	18-27	20-25	18-20	25-27
Over-weight	25-32	27-30	25-27	30-32
Obese	30-35	32-35	30-32	-

BMI – Body mass index. Support: The crisp set containing non-zero membership degrees for each all x elements. Core: The crisp set containing membership degree in A for all x elements. Boundary: The crisp containing membership degree $0<\mu A(x)<1$ in A for all x elements

Table 4: The log membership function and output values

Zone name	Support value	Core value	Left boundary value	Right boundary value
Less	0-2	0-1.5	-	1.5-2
Average	1.5-3.5	2-3	1.5-2	3-3.5
Medium	3-5	3.5-4.5	3-3.5	4.5-5
High	4.5-6.5	5-6	4.5-5	6-6.5
Very high	6-8	6.5-8	6-6.5	-

Support: The crisp set containing non-zero membership degrees for each all x elements. Core: The crisp set containing membership degree in A for all x elements. Boundary: The crisp containing membership degree $0<\mu A(x)<1$ in A for all x elements

variables which introduced in Sections 2.1-2.5 are indicated. A fuzzy rule is defined as "IF antecedent THEN consequent." According to the physician and requirements in Section 1 fuzzy rules were synthesized to monitor device's behavior. Some of the rules were shown in Figure 8 and all of them are given in the appendix.

These rules are stored in the knowledge base of the system and are applied to the fuzzified input. The third step is applying the inference engine. It extracts the rules that are fired with inputs value. The output of each rule is fuzzy and should be converted into a crisp output. The process of converting the fuzzy output is called defuzzification, which is the fourth step in designing a fuzzy system. For defuzzification of output, all fuzzy outputs of the system are aggregated with a union operator. In fact, aggregation is unification of all rule outputs. An example of this process is shown in Figure 9. This figure indicates the aggregation of three types of fuzzy rules where output of rules C1, C2 and C3 are 0.1, 0.2 and 0.5, respectively and the aggregated rule has been specified by the $\sum$ notation.

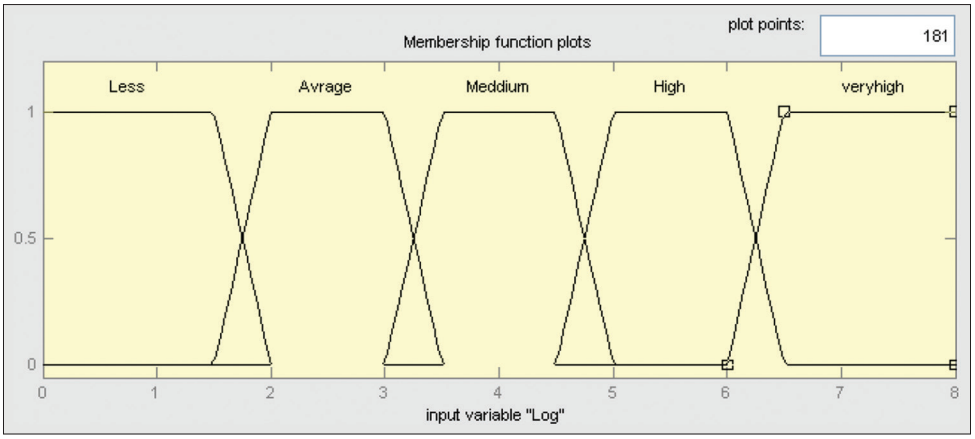

Figure 6: Dose injection log membership function

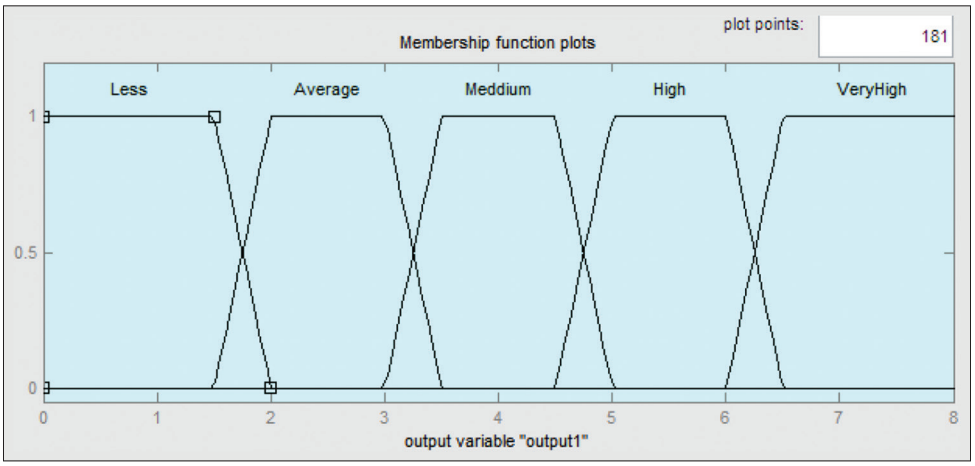

Figure 7: Output dose membership function

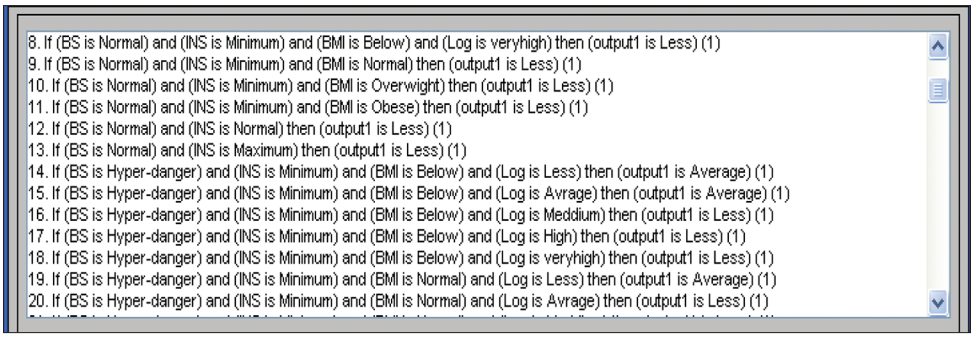

Figure 8: Fuzzy rules to verify behavior of the medical monitoring device

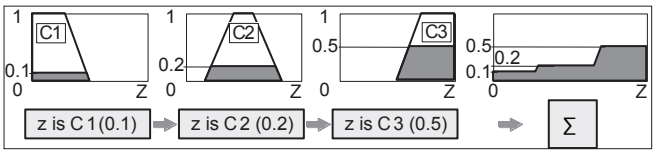

Figure 9: Aggregation of three rules

Among other defuzzification techniques, we use the centroid defuzzification known as center of gravity or center of area defuzzification. This is the most commonly used and accurate technique, which is expressed as follows:

$$X^{*} = \frac{\int \mu_i(x)\, x\, dx}{\int \mu_i(x)\, dx}$$

Where x^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable. It must be noted that the difficulty of computation for complex membership functions is the main problem of this method.

A sample output has been shown in Figure 10 consisting of 5 columns where the first four columns represents the input values indicated by BS, INS, BMI and log and the last column represents the INS dose. Each row forms a rule, and totally there are 110 rules; among them 30 rules are given in Figure 10. The yellow/white trapezoids indicate the membership function of fired/not fired rules. We defuzzified fired rules and obtained crisp values of outputs using the centroid defuzzification technique. The output membership functions were shown in the blue trapezoid. For instance, the BS, INS, BMI and log values, given in Figure 10, have values of 200, 2, 30 and 1, respectively; also, the obtained output dose has the value of 4.54.

Figure 11 illustrates a surface view of rules shown in Figure 10 where X, Y and Z axes indicate BS, INS and the output values, respectively. While the BS value is low (approximately lower than 250) the output value is close to zero. When the BS value is above 250 and the INS is <20, the output value rises sharply (indicated in yellow). By increasing the amount of INS, the output values are reduced (indicated in green).

After defining the rule-based system, we can model the rules as FPNs. We use FPNs, since normal PNs cannot deal with vague or fuzzy values such as "very high" or "minimum." FPNs are used for representation of fuzzy knowledge and reasoning knowledge-based systems. In fact, by implementing the FPN model, we are able to utilize major features of PN models, such as correctness, circular rules, consistency, and completeness checking. PNs have an inherent quality in expressing logic in an intuitive and visual way and also can be implemented to simulate systems practically. Therefore, a reasoning path in a complex fuzzy expert system can be reduced to a simple tree using a FPN based reasoning algorithm as an inference engine. In Section 5, we use FPNs to present the rules.

PNs

A PN provides a visual formal modeling method to study the dynamic behavior of systems, in terms of the system states and states changes. A PN is formally defined as 5-tuple, PN = (P, T, I, O, M_0).[7] $P = \{p_1, p_2, \ldots, p_m\}$ is a finite set of places, $T=\{t_1, t_2, \ldots, t_m\}$ is a finite set of transitions where $P \cap T \neq \emptyset$ and $P \cup T \neq \emptyset$, I: $(P \times T) \rightarrow N$ is an input function that defines directed arcs from places to transitions where N is a set of nonnegative integers, O: $(P \times T) \rightarrow N$ is an output function that defines directed arcs from transition to places, and M_0: $P \rightarrow N$ is the initial marking.

Assume that *n* and *w* are respectively the number of tokens in a place *P* and weight of the directed arc from *P* to transition *t*; we say transition *t* is enabled if $n \geq w$. An enabled transition is a candidate transition to fire. Firing the enabled transition *t* removes *w* token from input place *p*. Moreover; firing transition *t* inserts *w´* tokens in output place *P´* of *t* where w´ is weight of the arc from *t* to *p´*.

FPN

A FPN is a combination of a fuzzy set and a PN. A FPN is used to represent knowledge and to model the system behavior. Basic FPN, fuzzy colored PN[8] and Adaptive FPN[9] have been investigated as tools for representing rules of knowledge-based systems. According to Chun and Bien,[10] the main advantage of using PNs in a rule-based system is providing a structured knowledge representation; where

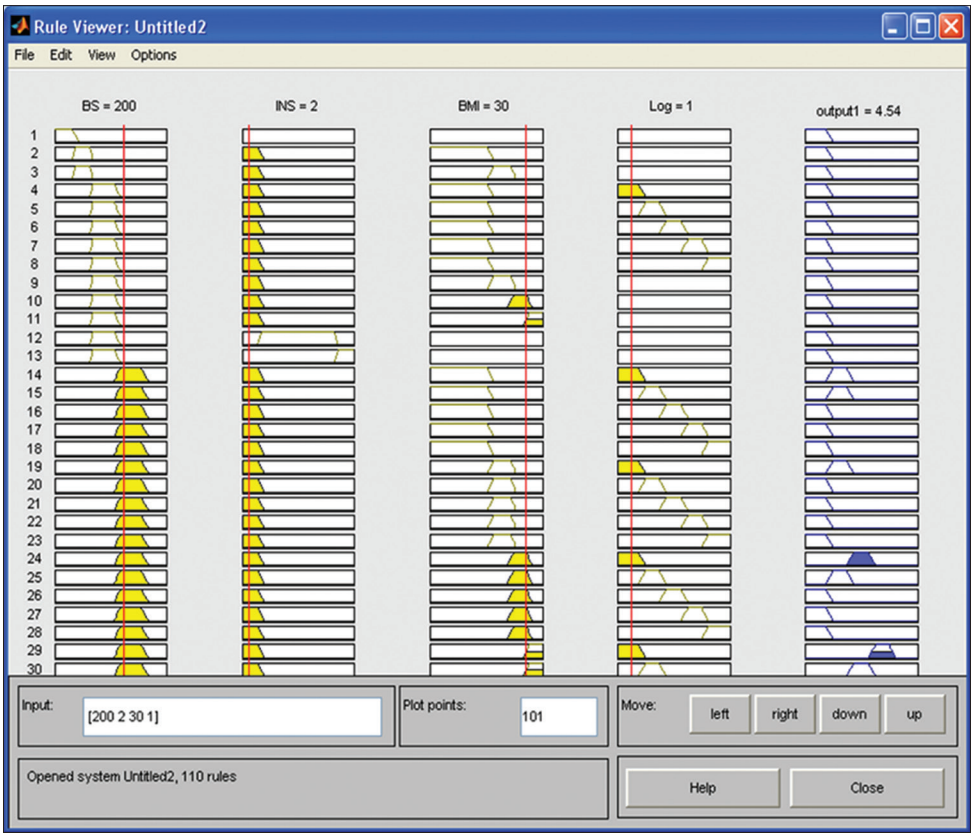

Figure 10: A sample output

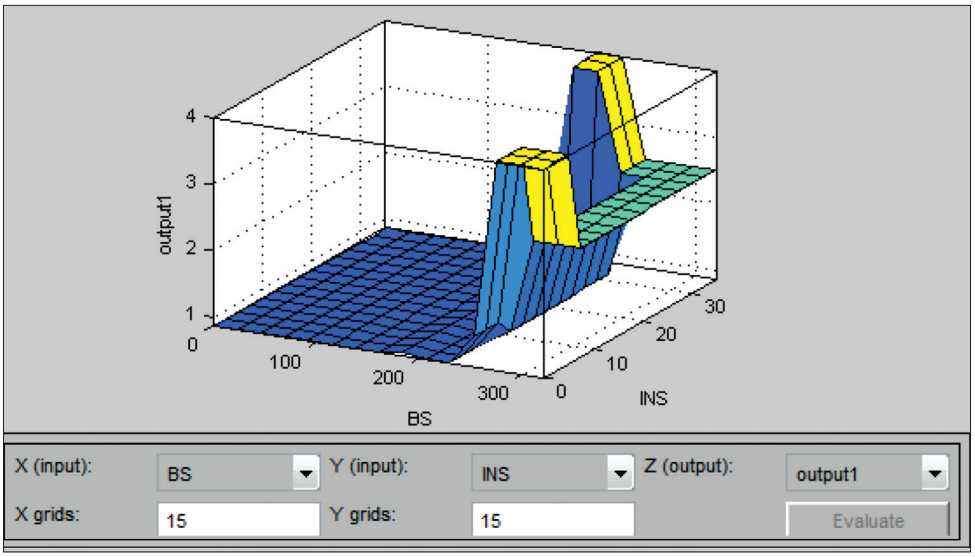

Figure 11: The overall variation of amount of two dose parameters

relationships between the rules are easily understood and a systemic inference capability can also be provided. Gogou *et al.*[11] stated that using a FPN to model fuzzy rule based reasoning provides a couple of advantages:

- The visual representation of a FPN can help experts to construct and modify fuzzy rule bases
- A FPN can model the dynamic behavior of fuzzy rule-based reasoning. The token (marking) evaluation is used to simulate the dynamic behavior of the system. The conclusion part of each rule is expressed through the movements of tokens in FPN
- A FPN eliminates the necessity of scanning all the rules. Fuzzy rule based reasoning is improved efficiently by connecting fuzzy rule as a net-based structure
- A FPN can check properties of a modeled system to gain deeper insights into the system.

A FPN is formally defined as 8-tuple, FPN = (P, T, D, I, O, f, α, β).[12] $P = \{p_1, p_2, \ldots, p_m\}$ is a finite set of fuzzy places, $T = \{t_1, t_2, \ldots, t_m\}$ is a finite set of transitions, $D = \{d_1, d_2, \ldots, d_m\}$ is a finite set of properties, I and O are functions of set of where I: P→T is an input function for mapping a bags of places to transitions, O: T→P is an output function for mapping from transitions to a bags of places, f: T→ [0,1] is an association function for mapping from a transition to a real value between zero and one, α: p→ [0,1] is an association function form mapping from places to real values between zero and one and β: p→D is an association function for mapping from places to propositions. This definition is used to model the INS pump in Section 5.

FPN DESIGN OF THE INFUSION DEVICE

As stated in Section 3, a FPN is defined as 8-tuple, FPN = (P, T, D, I, O, f, α, β). All membership functions states of each variable are represented as a place. Figure 12 represents the INS variable as a FPN. According to the INS membership function, shown in Figure 4, it is divided into three levels; accordingly, we use a fuzzy place for each level where a transition is considered for each rule.

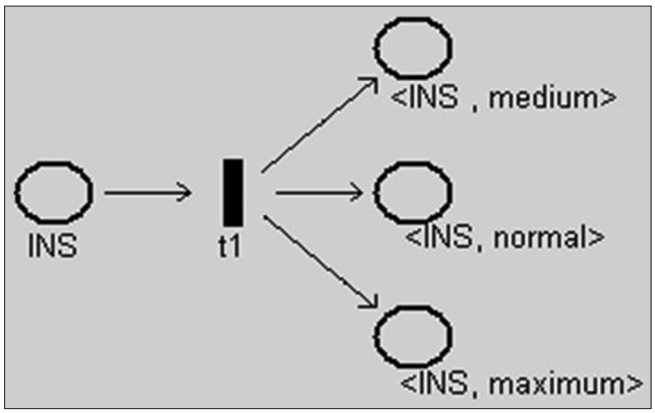

Figure 12: Fuzzy Petri-net for insulin using the membership function

In Figure 12, transition t1 indicates a rule and when it fires, each fuzzy place receives a fuzzy token. The token consisting of a minimum/maximum fuzzy value is sent to the next place. Minimum or maximum fuzzy values depend on disjunction/conjunction between fuzzy variables in rules:

$$OR = \mu(AUB(x)) = \max(\mu A(x), \mu B(x))$$
$$AND = \mu(A \cap B(x)) = \min(\mu A(x), \mu B(x))$$

The maximum/minimum value of tokens is used when a disjunction/conjunction (indicated by OR/AND) is appeared in a rule. For example, consider the following fuzzy rule.

If BS is hyper-danger AND INS is low AND BMI is overweight AND log is less THEN output is very-high.

Where the premise (representing inputs) and conclusion (representing output) parts of the rule consists of 4 and 1 variables respectively. The truth value of tokens (μ_i) is assigned to places. For example, BS in hyper-danger has truth value of 1 ($\mu_i = 1$), INS in low has $\mu_j = 0.4$, BMI in overweight has $\mu_m = 0.6$ and log in less has $\mu_n = 0.7$ [Figure 13a]. Since μ_i, μ_j, μ_m and μ_n are higher than zero, then transition t_n is enabled and it fires. Accordingly, tokens are removed from I (t_n) which are p_i, p_j, p_m, p_n and deposited to O (t_n), which is p_k. The truth value of the output variable is the minimum of truth ones of the input values. It means that $\mu_k = \min(\mu_i, \mu_j, \mu_m, \mu_n) = 0.4$ [Figure 13b].

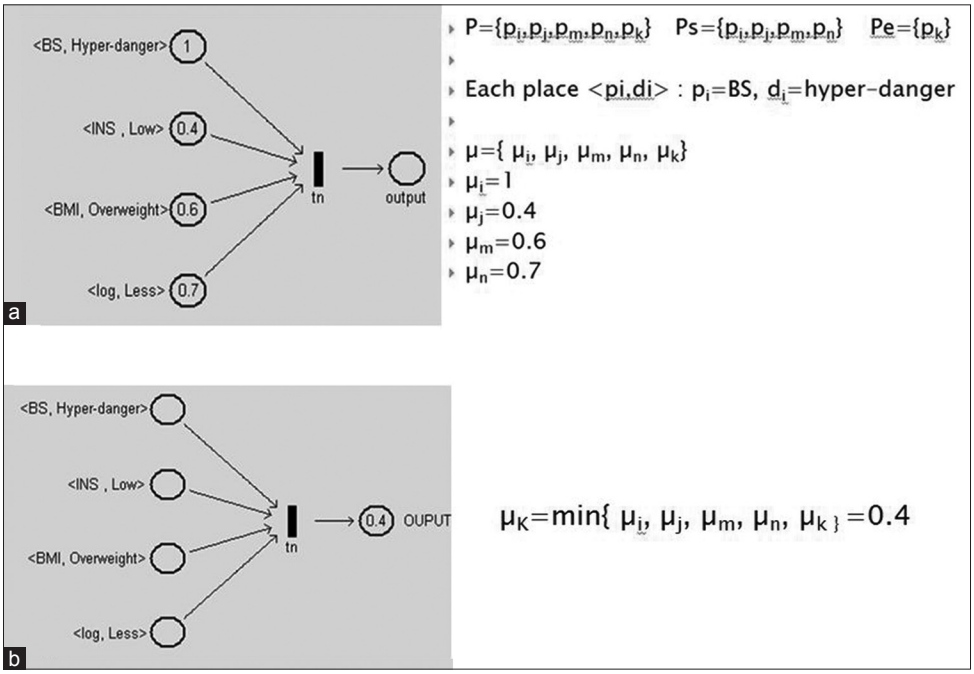

Figure 13: Firing the fuzzy Petri-net (a) Before firing the t_n transition (b) After firing the t_n transition

Figure 14 shows a FPN design of the infusion device that was implemented by PN tools in MatLAB 2012. In this Figure, just 16 rules are shown. As an example, the rule shown as transition R3 is a rule with three inputs: BS is hyper-danger, INS is the minimum and BMI is the normal and the output is the less. All rules were executed and the output of the system was checked against the user's requirements. Figure 14 is used as a reference by the verifier as showing safe paths. When the software is executed, the verifier uses the paths to check if it can find a path that is consistent with the software state. If a path is not found, the verifier concludes the software leads to a hazard and an alarm is raised and the system stops proceeding.

For example, consider input variables that are shown in Figure 15a. After the software executes, rule 4 fires [Figure 15b] and output place has a token [Figure 15c]. All rules are checked and faults and hazards status of the software are determined. To this end, the reachability graph of the system is considered and the system is checked by using the graph. Some advantages of using fuzzy PNs for modeling the behavior of the device are:

- Their graphical representation can help expert to construct and modify fuzzy rule bases
- Fuzzy PNs model reasoning of the dynamic behavior of fuzzy rules and also explain how to reach the conclusions expressed through the movements of tokens
- FPNs do not need to scan all the rules
- The analytical capability of FPNs can check properties of a modeled system in order to gain deeper insights into the system
- A part of state space of Figure 14 has been shown in Figure 16 consisting of 15 states for the BS branch and 63 states for all branches. Due to the complexity, all states have not been shown. Since the INS pump software consists of 110 rules, it is necessary to verify 434 states in static verification. However, using our method at runtime, just one path of the FPN consisting of a small-scale of states is verified

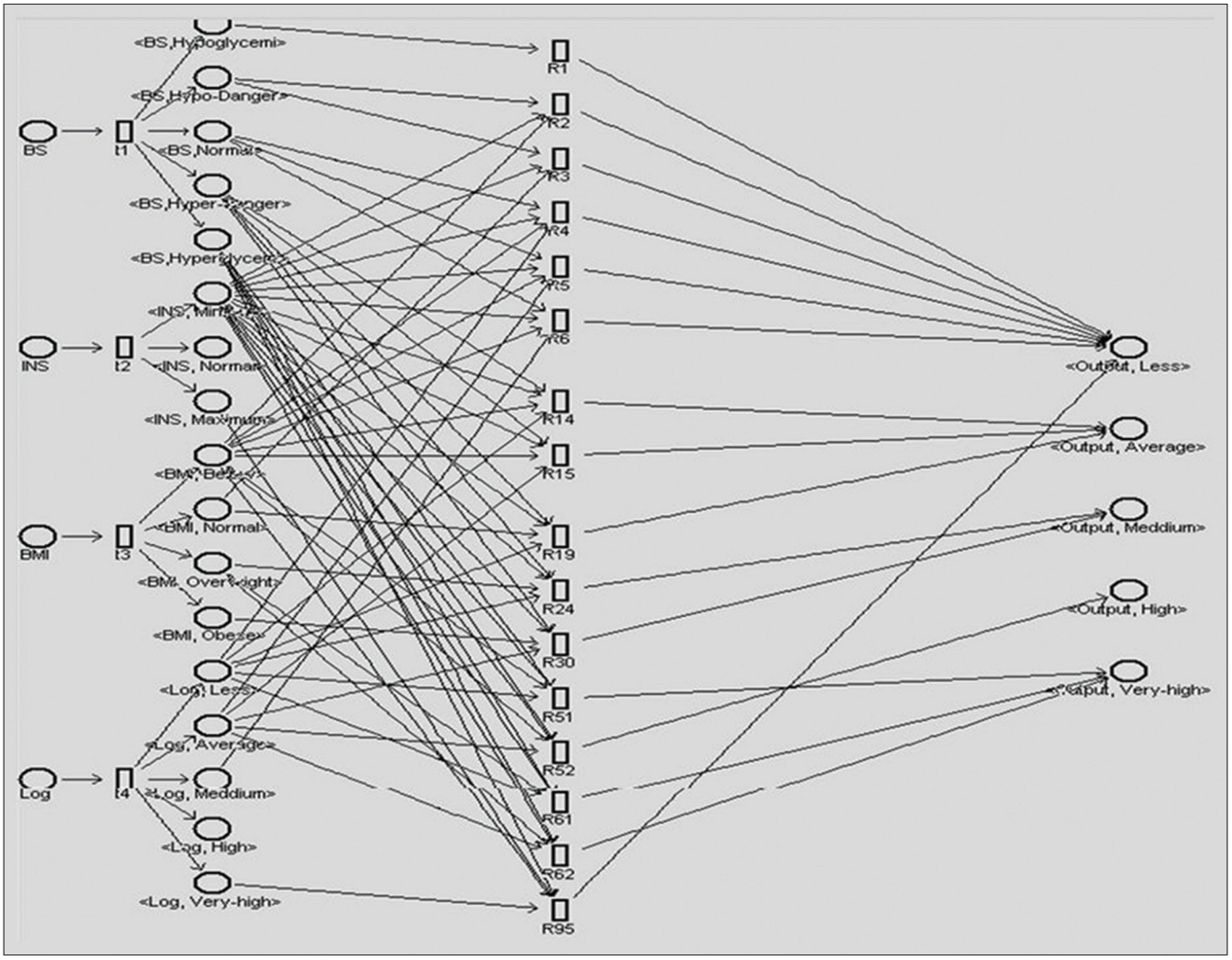

Figure 14: A Petri-net for some rules

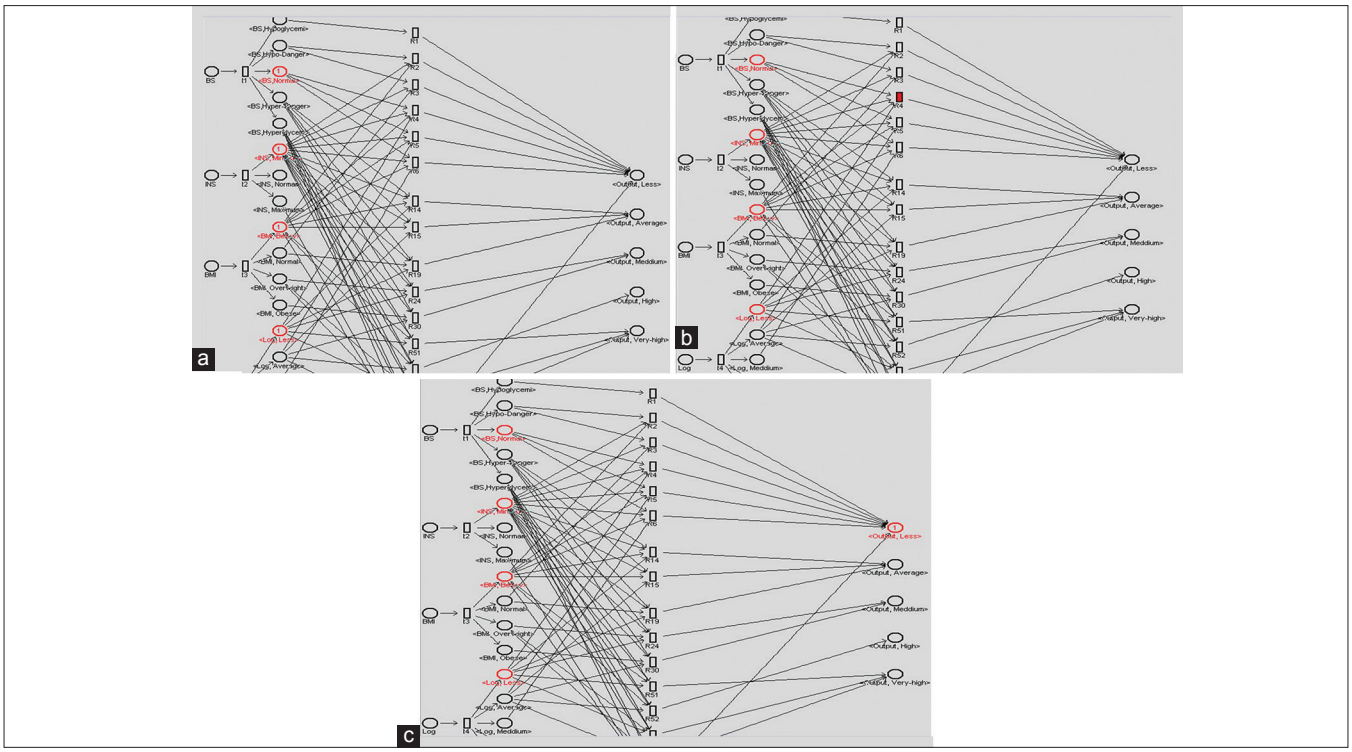

Figure 15: (a) Before firing (b) R4 fired (c) A sample of firing rule

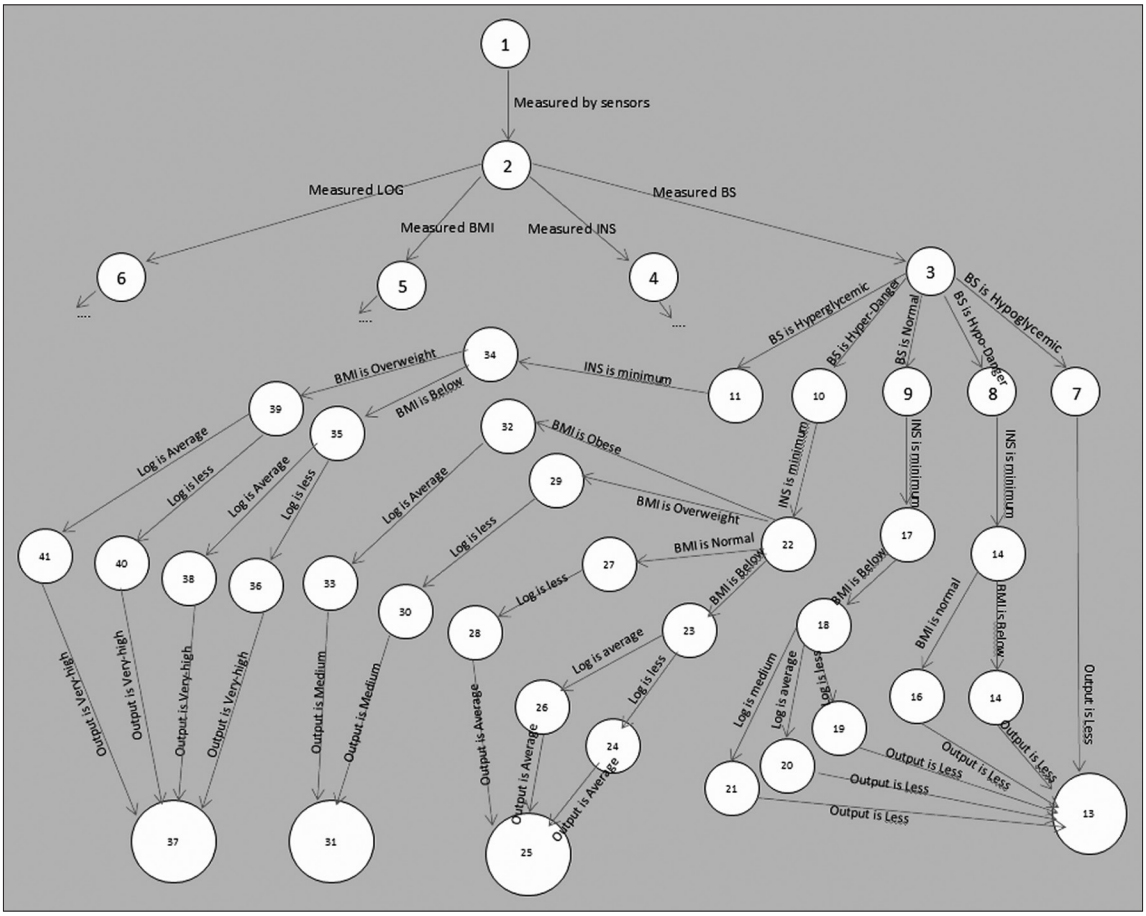

Figure 16: State space of Figure 14

RELATED WORK

In,[13,14] we used PNs to model non-fuzzy behavior of infusion devices. Similarly Maissa *et al*.[15] used timed PNs for formal verification of medical monitoring devices and in,[16] Pantelopoulos proposed a stochastic PN model of a multi-sensor Wearable Health Monitoring System with an implementation of corresponding simulation framework in Java.

Pei-Kuang *et al*.[17] proposed a medical monitoring system for measuring daily physical activity and detecting falls in free-moving patients and the elderly. They used a multi-layer clustering method to classify physical activity of the user. Namayanja *et al*.[18] exploited data mining and clustering to study the measurements in blood glucose and doses of regular INS for a selected number of patients.

Jayaraj *et al*.[6] used the fuzzy reasoning to represent behavior of a system that involves a feedback mechanism and monitors continuous blood glucose and a repository as an artificial pancreas. Chun and Bien[10] used a FPN model for a rule-based decision making system. They perform real-time decision making with applications of control systems and diagnostic systems. Gogou *et al*.[11] used the neural network for an INS administration system to manage the diabetics. Ward and Martin[19] used a fuzzy inference system to propose a glucose regulation model.

Chikh *et al*.[20] used expert systems and artificial intelligence techniques (Artificial Immune Recognition System) in diabetes disease diagnosis. They used diabetes disease dataset in UCI machine learning repository. Jayaraj *et al*.[6] used the fuzzy logic to set the amount of dosage to be delivered to a diabetic and modeled an artificial pancreas by monitoring the continuous blood glucose and the infusion device. Indeed, they introduced a fuzzy infusion system as a controller whose output is fed to the device. However, we proposed a fuzzy system to control and monitor the behavior of the infusion system.

Grant,[21] Khooban *et al*.,[22] Hari Kumar *et al*.,[23] Allam *et al*.[24] and Yasini *et al*.[25] exploited fuzzy concepts in diabetes system. Fuzzy based closed-loop control is an algorithm used for blood glucose regulation using Mamdani fuzzy logic controller. Grant[21] and Yasini *et al*.[25] used fuzzy logic to develop an artificial pancreas for automatic regulation of blood glucose levels using closed-loop feedback mechanism. Bequette[26] addressed challenges and progresses in the development of a closed-loop artificial pancreas. Khooban *et al*.[22] used Particle Swarm Optimization to optimize the fuzzy controller. In addition to software algorithms, hardware mechanisms also have been used to design fuzzy controller for diabetes. Hari Kumar *et al*.[23] used field programmable gate array integrated circuit to synthesize fuzzy controller for the infusion process. Allam *et al*.[24] used: (1) Fuzzy logic controller to determine INS dosage and (2) a recurrent neural network that nonlinearly predicts the effect of each calculated dose on the future of the blood glucose level. They claimed that the prediction leads to excluding severe hyper- and severe hypo-glycemic events.

There are two types of closed loop strategies to control diabetics: (1) Semi closed-loop and (2) closed-loop. In the former, dose delivery rate is adjusted-based on sporadic blood glucose readings; however, the latter plays the role of an artificial pancreas. According to,[21] effectiveness of closed-loop feedback controls should be compared with the conventional ones such as continuous INS infusion control strategies.

SIMULATION RESULTS

To represent the simulation results, we start with calculating the system state space depicted in Figure 16. Nodes 2 and 3 indicating the system inputs and BS states respectively have 4 branches each one. The 1st BS branch (BS is hypoglycemic) has one path and the 2nd one (BS is hypo-danger) has 2 paths after computation of INS for the BMI value. The 3rd BS branch has 3 paths and the 4th one has 6 paths from BMI (just 5 paths were shown in the figure). The 5th BS branch has 112 paths, among them just 4 paths were shown. Similarly, node 4 consists of 3 branches consisting of 2, 6 and 112 paths, respectively. Similarly, nodes 5 and 6 respectively consist of 118 and 112 paths. Totally, the system state space consists of 471 paths without constructing an FPN. However, there are 110 paths when we used the FPN [Figure 14 and its explanation in Section 4] meaning that we have a path reduction of 23.4%, which justifies the performance of our proposed model.

In addition to the state space reduction, another contribution of our proposed model is the enough accuracy, according to the experimental results obtained by the execution of the model. We executed our model 5 times by 100 different random values to evaluate the model where accuracy ranged between 93% and 98% (in average, 95%). Table 5 shows a sample of the results where BS, INS, BMI and LOG values constitute the input values.

Table 5: Some input values and result

BS	INS	BMI	LOG	State in petri-net	Expected reality	Result
30	4	10	1	Output_medium	Between 3 and 5	Correct
200	2	30	1	Output_medium	Between 3 and 5	Correct
74	9.8	15	4	Output_medium	Between 3 and 5	Correct
4	35	1	0	Output_less	Between 1.5 and 2	Incorrect
82	23	14	2.2	Output_medium	Between 3 and 5	Correct
203	30	20	5	Output_medium	Between 3 and 5	Correct
311	11	7	5	Output_average	Between 1.5 and 2	Incorrect
311	35	35	8	Output_less	Between 1.5 and 2	Correct
311	28	35	1	Output_high	Between 4.5 and 6.5	Correct
311	28	35	8	Output_average	Between 1.5 and 2	Correct
254	28	35	8	Output_less	Between 1.5 and 2	Correct

BS – Blood sugar; BMI – Body mass index; LOG – Log insulin dose; INS – Insulin

While other studies such as[27] proposed different techniques for verifying the healthcare devices behavior, they did not use some FPN. Moreover, they did not use fuzzy inference algorithm for calculating INS dose. To reduce these gaps, we proposed a FPN model to represent the system knowledge and the INS pump behavior. This means that our model enjoys the capability of reasoning based on uncertain and fuzzy data.

CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a FPN model to verify behavior of a sample medical monitoring device called continuous infusion INS. We proposed a visual and a mathematical model through which one can verify the device behaviors against user's requirements. This is carried out by determining and device unsafe and hazards statuses.

Considering importance of medical monitoring systems in surveillance of patients, we proposed a model to synthesize a fuzzy verifier for the medical monitoring system. Since in such systems, the obtained data from the input sensors are uncertain, fuzzy values should be supported. This means that the model used for such a purpose should have a capability of reasoning based on uncertain and fuzzy information. This paper introduced a new model for a quintessential sample of a care-working system based on a rule-based system with fuzzy variables. We used FPNs to model the system knowledge and rules, and we showed that the system hazards could be figured out easily by the FPN model.

In comparison with the previous studies, stated in Section 5, we used a visual model to check the INS pump behavior instead. We modeled the infusion device as a rule-based system with 4 fuzzy variables as input and output variables and then the rules were defined. Afterwards, we used FPNs to model the system knowledge and rules.

Our proposed FPN modeled active and deductive rules of INS pump system where functionalities, where were specified using transitions, were used to carry out required computations using input parameters (such as BS, INS). This provided condition-values and action-values. Figure 16 illustrated a part of the system state space where its main disadvantage is the hugeness, called the explosion problem. The explosion causes a time-consuming process because a huge space should be verified for the verification of some property satisfaction by the system. According to[28] such cases cause a serious limitation on the use of state space methods during the analysis of real-life systems. Accordingly, a space reduction helps to reduce the explosion problem.

Our study can be extended in several ways. Currently, the rule base included fuzzy variables and the basic FPN was used. (1) The model can be extended for adaptive FPNs and (2) it can be introduced as a hybrid system whose the knowledge part is represented as rules with a FPNs and then the process model is continued with a Neural network.

ACKNOWLEDGMENTS

Authors like to thank University of Kashan for supporting this research by Grant No. 92/6188.

REFERENCES

1. Otto C, Milenkovic A, Sanders C, Jovanov E. System architecture of a wireless body area sensor network for ubiquitous health monitoring. J Mob Multimed 2006; 1:307-26.
2. Available from: http://www.who.int/mediacentre/factsheets/fs312/en/index.html.
3. Sommervile I. Software Engineering. 9th ed. Harlow, England, Addision-Wesley; 2010.
4. Zhang Y, Jones PL, Jetley R. A hazard analysis for a generic insulin infusion pump. J Diabetes Sci Technol 2010;4:263-83.
5. Boston-Korpeoglu B, Yazici A. A fuzzy petri net model for intelligent databases. Data Knowl Eng 2007;62:219-47.
6. Jayaraj N, Cherian CM, Ganesh Vaidyanathan S. Intelligent insulin infuser. The 3rd IEEE European Symposium on Computer Modeling and Simulation; 2009.
7. Diaz M. Petri Nets: Fundamental Models, Verification and Applications. John Wiley and Sons; 2010.
8. Ouchi Y, Tazaki E. Medical diagnostic system using fuzzy coloured petri nets under uncertainty. Medinfo 1998;9:675-9.
9. Li X, Lara-Rosano F. Adaptive fuzzy petri nets for dynamic knowledge representation and inference. Expert Syst Appl 2000;19:235-41.
10. Chun M, Bien Z. Fuzzy petri-net representation and reasoning method for rule-based decision making system. IEICE Trans Fundam Electron Commun Comput Sci 1993;E76-A:974-83.
11. Gogou G, Maglaveras N, Ambrosiadou BV, Goulis D, Pappas C. A neural network approach in diabetes management by insulin administration. J Med Syst 2001;25:119-31.
12. Motameni H, Ghassempouri T. Transforming fuzzy communication diagram to fuzzy Petri-net. Am J Sci Res 2011;16:63-74.
13. Babamir SM. A framework for specification safe behavior of the CIIP medical system, Software Tools and Algorithms for Biological Systems. Vol. 696. New York: Springer; 2011.
14. Babamir SM. Constructing a model-based software monitor for the insulin pump behavior. J Med Syst 2012;36:829-40.
15. Maissa YB, Kordon F, Mouline S, Thierry-Mieg Y. Modeling and analyzing wireless sensor networks with VeriSensor. International Workshop on Petri Nets and Software Engineering, Germany; 2012.
16. Pantelopoulos A. SPN-model based simulation of a Wearable Health Monitoring System. The Annual International Conference of the IEEE Engineering in Medicine and Biology; 2009.
17. Pei-Kuang C, Yu-Chuan C, Wei-Jay K. Wireless body area network for physical-activity classification and fall detection. The 5th International Summer School and Symposium on Medical Devices and Biosensors; 2008.
18. Namayanja J, Janeja VP. An assessment of patient behavior over time-periods: A case study of managing type 2 diabetes through blood glucose readings and insulin doses. J Med Syst 2012;36 Suppl 1:S65-80.
19. Ward E, Martin T. A fuzzy model of glucose regulation. J Med Syst 2006;30:187-203.
20. Chikh MA, Saidi M, Settouti N. Diagnosis of diabetes diseases using an Artificial Immune Recognition System2 (AIRS2) with fuzzy K-nearest neighbor. J Med Syst 2012;36:2721-9.

21. Grant P. A new approach to diabetic control: Fuzzy logic and insulin pump technology. Med Eng Phys 2007;29:824-7.
22. Khooban MH, Nazari MA, Alfi A, Siahi M, Swarm optimization tuned mamdani fuzzy controller for diabetes delayed model. Turk J Electr Eng Comput Sci, 2012.
23. HariKumar R, Sudhaman VK, Babu CG. FPGA synthesis of fuzzy (PD and PID) controller for insulin pumps in diabetes using cadence. Int J Soft Comput 2012;1.6:2231-307.
24. Allam F, Nossair Z, Gomma H, Ibrahim I and Abdelsalam M. Evaluation of using a recurrent neural network (RNN) and a fuzzy logic controller (FLC) in closed loop system to regulate blood glucose for type-1 diabetic patients. Int J Intell Syst Appl 2012;10:58-71.
25. Yasini SH, Naghibi-Sistani MB, Karimpour A. Active insulin infusion using fuzzy-based closed-loop control. In: Proceedings of the 3rd International Conference on Intelligent System and Knowledge Engineering; 2008. p. 429-34.
26. Bequette BW. Challenges and Recent Progress in the Development of a Closed-loop Artificial Pancreas. Annu Rev Control 2012; 36:255-66.
27. Babamir FS, Norouzi A. Achieving key privacy and invisibility for unattended wireless sensor networks in healthcare. The Computer J 2013; bxt046.
28. Kristensen LM. State space methods for colored petri nets. DAIMI Rep Ser 29, no 546 2000.

How to cite this article: Majma N, Babamir SM. Specification and Verification of Medical Monitoring System Using Petri-nets. J Med Sign Sence 2014;4:181-93.
Source of Support: Nil, **Conflict of Interest:** None declared

BIOGRAPHIES

Negar Majma received her M. Sc. degree in software computer engineering from the University of Shekhbahaie, Isfahan, Iran, in 2010. Currently, she is candidate for PhD degree in software computer engineering in the University of Kashan, Iran and she is faculty member in the Department of Computer Engineering at Naghshejahan Higher Education Institute, Isfahan, Iran. Her areas of interest are software testing, soft computing, fuzzy expert systems and related applications.

E-mail: majma@grad.kashanu.ac.ir

Seyed Morteza Babamir received BS degree in Software Engineering from Ferdowsi University of Meshhad and MS and PhD degrees in Software Engineering from Tarbiat Modares University in 2002 and 2007 respectively. He was a researcher at Iran Aircraft Industries, Tehran City, Iran, from 1987 to 1993, head of Computer Center in University of Kashan, Kashan, Iran, from 1997 to 1999 and haed of Computer Engineering Department in University of Kashan from 2002 to 2005. Now, he is an associate professor of Department of Computer Engineering at University of Kashan, Kashan, Iran. He authored one book in Software Testing, four book chapters, 20 journal papers and more than 40 international and internal conference papers (http://ce.kashanu.ac.ir/babamir/Publication.htm). He is managing director of the Soft Computing Journal, which is publishing under auspices of University of Kashan, Kashan, Iran.

E-mail: babamir@kashanu.ac.ir