FUZZY LOGIC APPROACH TO MIMIC DECISION MAKING BEHAVIOR OF HUMANS IN STOCK MANAGEMENT GAME

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Abstract

System Dynamics methodology aims to model real complex dynamic systems for understanding them and coming up with policies to change the problematic dynamic behavior. In most of the dynamic systems of interest, humans play an important role. Hence, human behavior modeling is one of the goals of System Dynamics. This paper proposes Fuzzy Logic to model human behavior. The paper uses the existing data from an experimental study on Stock Management Model and comes up with Fuzzy Logic players to mimic the behaviors of three different types of players. We believe that Fuzzy Logic will be useful in modeling decision making behavior as it also gives an understanding of why humans decide as they do which is in consensus with System Dynamics modeling.

Keywords: System dynamics, Fuzzy logic, Human behavior modelling

1) Introduction

System Dynamics (SD) methodology aims to model real complex dynamic systems for understanding them and coming up with policies to change the problematic dynamic behavior. The real dynamic problems contain feedbacks, delays, and random noise or uncertainties which make them "complex" (Größler 2004). Feedbacks and delays are the main reasons why human decision-making behavior results in unwanted behavior in these systems (Sterman 1989a). In most of the cases, the problems that are which SD is interested in have problematic dynamic behavior usually caused by not optimal decisions of humans. To achieve the aim of making valid models of dynamic systems, SD tries to capture human decision making behavior together with feedbacks and delays which are all endogenously included in the model. In other words, SD models should be able represent 'intended rationality' of human beings (Größler 2004). The words intended rationality or bounded rationality is used to describe the decision making behavior of humans in these complex dynamic systems which are far from optimal. This behavior should not be interpreted as humans acting irrationally (Größler et al. 2004). However, the rationality of decision maker is bounded or limited because of the complexity of many real dynamic systems (Sterman 2000). Thus, the modeler should represent the bounded rationality of the decision maker for the model to be a valid representation of reality.

In order to model human decision-making behavior in a certain system, one must first understand how people behave or decide in that system. Laboratory experiments are conducted where subjects play the role of the decision-maker in the model of the system to capture the behavior of humans. Then their decision behavior is modeled with the help of certain heuristics and rules. Various studies work on generic systems such as stock management problem and use laboratory experiments to come up with decision-making behavior formulation (Sterman 1989a., b., Dogan and Sterman 2000, Barlas and Özevin 2001). Many of these studies base their formulations on anchor and adjustment heuristic which is first proposed by Tversky and Kahneman (1982).

Fuzzy Logic is one of the best tools to model our imprecise and blurred world. The real world is too complicated for precise descriptions to be obtained; therefore approximations (or fuzziness) must be introduced in order to obtain a reasonable, yet traceable, model (Wang 1997). Fuzzy logic is the tool for transforming human knowledge and its decision-making ability into a mathematical formula. In other words, it provides us with meaningful and powerful representation of measurement uncertainties and also with meaningful representation of vague concepts expressed in natural language (Klir & Yuan 1995).

Application of Fuzzy Logic to SD models has been previously demonstrated. Morgan and Ammentorp (1994) uses the qualitative knowledge of experts on financial risk management to determine decision variables, and numeric ranges of these variables such as what value range is low, normal and high. Then their responses to those ranges were obtained to develop fuzzy logic model. Takahagi (1995) applies fuzzy logic modeling to inventory control model with taking sales as the only decision variable. He claims that the behavior of this fuzzy logic model is similar to human behavior without comparison to any real inventory and order behavior. Although human behavior can be modeled by just contemplating on the reasons, it may cause validation problems. A few other applications make use of fuzzy logic to model human behavior. Sousa-Poza et al. (2003) use survey data to build the fuzzy model of how humans determine job satisfaction. Esmaeeli et al. (2006) model electric consumption of low, medium and high income group using fuzzy approach. Ghazanfari et al. (2003) proposes that fuzzy set theory can be applied to model any vague concept in a SD model.

This study proposes fuzzy logic to mimic decision making behavior of humans in Stock Management Problem. The paper uses the existing data from an experimental gaming study on this problem. Three different types of human behavior are extracted from the data (Barlas and Özevin 2004) and hence, three types of fuzzy logic player are proposed. In rest of the paper, we first give a formulation of the problem. Then in the third section, we give the properties of the experimental data used. The fourth section gives a brief definition of FL and how it is used. The section before conclusion is the main part of this paper where we give details of how the decision-makers in stock management problem are modeled by FL.

2) Problem Formulation

In this study, the stock management problem which is a benchmark problem of system dynamics is chosen to work on. The aim in stock management is to keep the state of the system (stock, inventory) at a desired level or at least at a tolerable range. The stock can only be altered by adjusting its inflow and outflow rates. The stock management problem involves a negative feedback loop where the perceived state of the system is compared with the target level. Then the discrepancy is tried to be eliminated by corrective action. Typically, the corrective action involves adjusting the inflow to counteract the disturbances that push the stock away from the target and also to compensate the discrepancy between the perceived state and desired state of the system (Sterman 2000). In this study, a generic stock management gaming is chosen to work on with the objective of keeping the inventory level as low as possible while avoiding any backorders.

Humans act according to certain guidelines and conventions. Generally the corrective actions are a result of these guidelines and conventions. If these guidelines and conventions are explicitly stated, they are referred to as Decision/Policy rules (Forrester 1961). This study tries to state the corrective actions of decision-makers as Decision/Policy rules looking at the experimental data obtained from the subjects in stock management problem.

One method of modeling human decision making behavior in a certain problem is to construct a laboratory experiment and try to understand how people behave. The next step is to model the behavior of players reflecting their reasoning in the model. Sterman proposed the linear anchoring adjustment rule for modeling human decision-making behavior in stock management problem. The study by Barlas and Özevin (2004), gives an extension to Sterman’s articles (1989a., b.) within which the decision patterns are divided into three groups and evaluated the adequacy of different rules in these three groups. Their study illustrates that not all people act similarly; generating certain categories of behavior that covers a greater amount of individuals. We propose FL and its tools to model these three classes of ordering behavior and discuss qualitatively if FL does not only generate the ordering pattern of these classes but also capture the reasoning behind these behavior.

3) Experimental Data

This paper bases its modeling of decision-makers on the stock management simulation game developed by Barlas and Özevin (2004). Therefore, we give a brief overview of the type of experimental data used in the related study. In that paper, the effects of some experimental factors like length of order decision, type of receiving delay, pattern of customer demand on performance of players are analyzed in a stock management simulation game. There are two types ordering decision interval: short and long. In the short game the player receives its order in 4 time units according to the receiving delay type, continuous or discrete. In the long game, the orders are received in 10 time units again with the same delay type options. In this study, we choose arbitrarily to use data from the results of short game because there is no clear difference in the behavior of players between short and long game. There are also two patterns of customer demand, step-up and step-up-and-down customer demand. In step-up customer demand, there is one time increase of 20 units at time 5 for the short game. In step-up-and-down customer demand, demand is increased at time 5 and then decreased at time 25. Also to obtain realistic demand pattern, pink and white noise with standard deviation %15 is added. The initial conditions of the game are as follows: “All games start at equilibrium. The supply line is initially set at 80 in short games… so that no backordering occurs even when the decision-maker does not order goods during the first four decision intervals (at the end of which the disturbance in customer demand causes equilibrium) Inventory level is initially set arbitrarily (at 40 for the short game) so as to satisfy the average initial customer demand for the first two decision intervals (for 2 days in short… game).” In this study, we use data from short games with step-up-and-down customer demand having either continuous exponential or discrete delay.

4) Fuzzy Logic

FL incorporates a simple, rule-based IF X and Y THEN Z approach to a problem rather than attempting to model a system mathematically. The inference mechanism based on these rules makes use of fuzzy sets. Following Zadeh (1965) many sets have more than an either-or criterion for membership. Take for example the set of young people. A one year old baby will clearly be a member of the set, and a 100 years old person will not be a member of this set, but what about people at the age of 20, 30, or 40 years? Zadeh (1965) proposed a grade of membership, such that the transition from membership to non-membership is gradual rather than abrupt. The grade of membership for all its members thus describes a fuzzy set. An item’s grade of membership is normally a real number between 0 and 1. Zadeh (1988) does not give a formal basis for how to determine the grade of membership. The membership for a 50 year old in the set young depends on one’s own view. The grade of membership is a precise, but subjective measure that depends on the context. The membership function is a graphical representation of the magnitude of participation of each input. It associates a weighting with each of the inputs that are processed, define functional overlap between inputs, and ultimately determines an output response. The rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion.

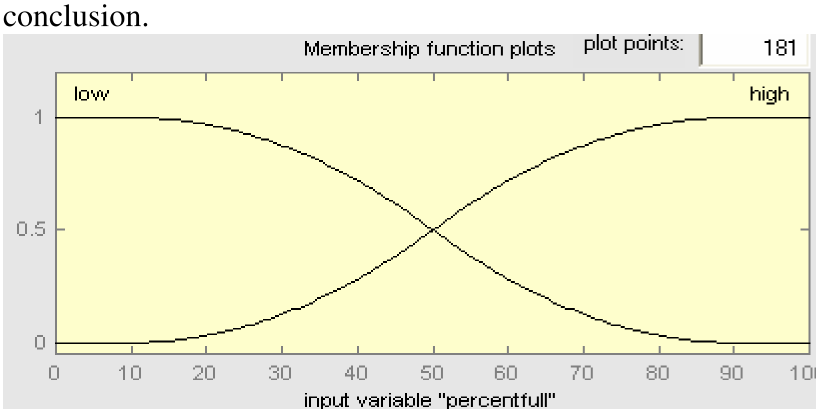

Figure 1: Two terms defining high and low tank levels

One of the most popular models of fuzzy systems is the Takagi-Sugeno-Kang (TSK) models. The TSK models use the linear combination of the input variables to define the “THEN” part of fuzzy rules. Once the functions are inferred, scaled, and combined, they are defuzzified into a crisp output which drives the system.

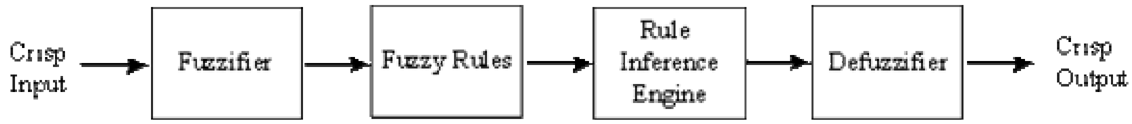

Figure 2: A Block Diagram of a Fuzzy System

5) Fuzzy Logic Approach to Mimic Decision-Making Behavior of Subjects

As mentioned previously, the patterns of ordering behavior of subjects are divided into three basic classes by Barlas and Özevin (2004):

(i) smooth, continuous – oscillatory or non-oscillatory - damping orders,
(ii) alternating large-and-zero discrete orders, like a high-frequency signal,
(iii) long periods of constant orders punctuated by a few sudden large ones.

Anchor and adjustment rule is only a valid representation of (i) type of players. The rest cannot be mimicked by this rule. Then several other decision rules are evaluated to see if they can generate an ordering pattern that belongs to the rest of the classes of interest.

Our study proposes fuzzy logic as an alternative modeling tool for decision-making behavior of humans to commonly used heuristics and rules. We believe that FL provides a valid representation of human behavior in Stock Management Game. Unlike other proposed heuristics, it provides not only the desired pattern, but also provides us with the reasons why humans act the way they do which is in full consensus with SD modeling methodology.

In order to be able to use fuzzy logic in modeling the decision making behavior of subjects, their reasoning should be well understood. For this aim, the game has been played several times, to make the "If...then" rules clear. Clear understanding of "If...then" rules helped to understand what kind of inputs subjects ignore and how they interpret the information that they take into account. In Barlas and Özevin (2004), some rules are only tested with continuous exponential delay and other rules only with discrete delay. In this paper, after different types of ordering behavior is modeled, the models are tested with both delay types. The reason for testing FL models with both delay types is to observe how the logic works on the delay that it is not designed for. Singleton Sugeno type of fuzzy logic has been used to model each class of ordering behavior. Fuzzy Logic modeling is done by utilizing Matlab Fuzzy Toolbox (1995). The orders of the fuzzy logic player are placed in Stella manually and also the inputs to the fuzzy logic players are made manually from Stella. Furthermore, the outputs are in real numbers whereas the orders for the Stock Management Game in Stella could only be adjusted in increments of five. Thus the orders of the Fuzzy Logic player are rounded up to the nearest number, multiple of five. Throughout this section, we use data from the short, step-up-and-down customer demand game with either exponential or discrete delay.

Modeling (i) Type Subjects

The ordering behavior of Type (i) subjects is explained as smooth, continuous-oscillatory or non-oscillatory—damping orders. In this type, the subjects do usually not take the supply line levels into consideration. They try to order as much as the demand so as to keep inventory at the initial level. Even though, subjects order as much as the demand all the time, usually backordering occurs because of exponential delay and step-up in customer demand. When the inventory is below zero, subjects order greater than demand. In this situation, they can not avoid making a peak or an overflow in the inventory level because of both step-down in customer demand and receiving delay. Here is the fuzzy logic model of the subjects with (i) type ordering behavior:

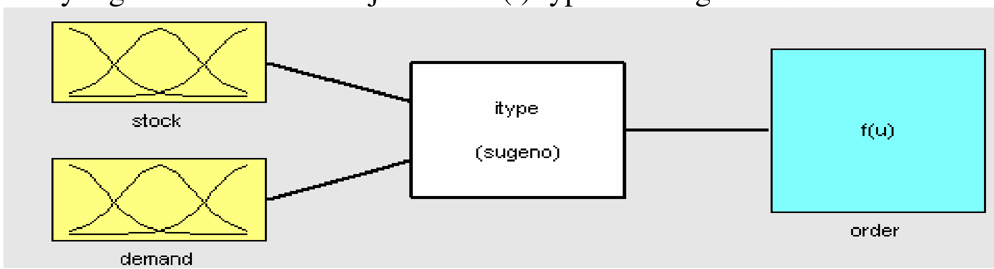

Figure 3: Fuzzy Logic Model for (i) type subjects

The inputs are stock level and demand. Several fuzzy logic models were designed to mimic (i) type decision making behavior and the ones that mimic (i) type players best are the ones that don't take supply line level as a factor in decision making. The ranges of the decision factors are obtained from the experimental data on subjects with (i) type of ordering behavior.

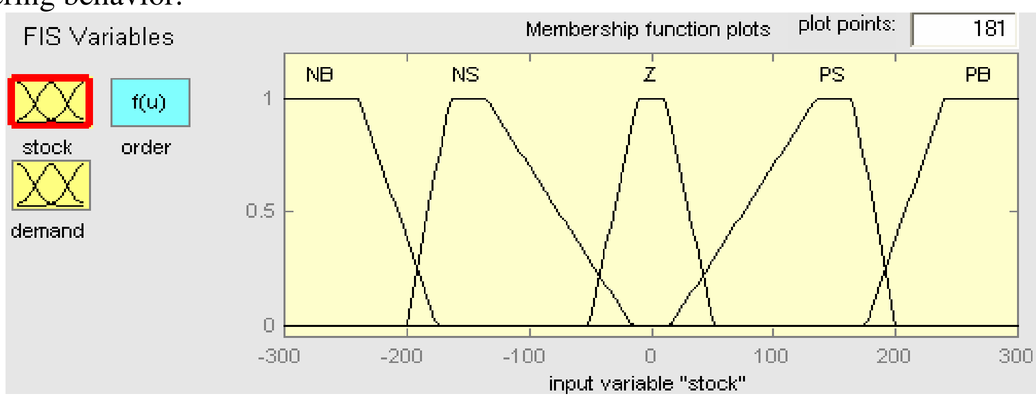

Figure 4: Membership functions of stock level for (i) type subjects

Trapezoidal type membership function is used because in trapezoidal functions, the degree of membership can be made equal to one for some range of values. This is not possible in triangular types. The desired interval of the inventory level is kept around -50 and +50 preferably around 0 and +50 so membership function 'Z' is adjusted accordingly. The effect of 'NS' and 'PS' are very small around the range -50 and +50. Hence, when the inventory level belongs to the 'Z' membership function, the inventory is in the tolerable range and orders are arranged only to compensate demand.

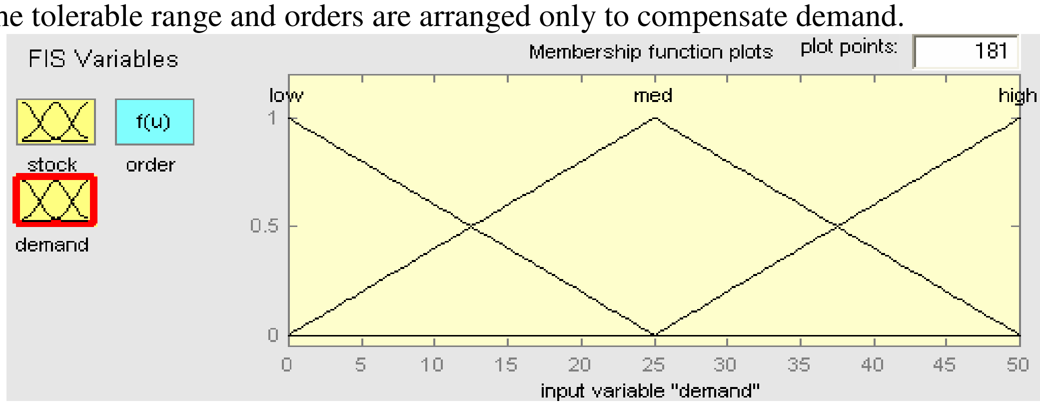

Figure 5: Membership functions of demand for (i) type subjects

The range of the demand membership function is obtained looking at the maximum and minimum levels of the demand under noise during the game.

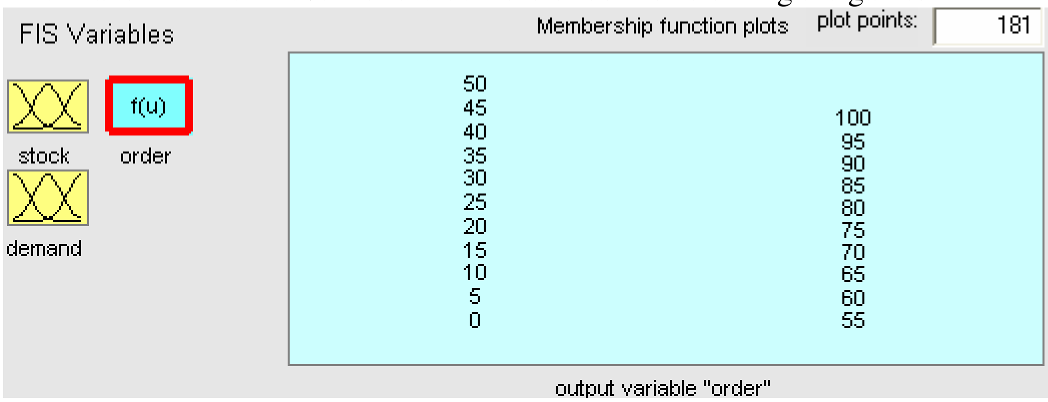

Figure 6: TSK membership functions of order for (i) type subjects

Since a Singleton, TSK type of FL model is implemented, the orders are exact numbers.

Table 1: Inference rule table of the fuzzy logic model for (i) type subjects

1. If (stock is NB) and (demand is high) then (order is 70) (1)
2. If (stock is NB) and (demand is med) then (order is 50) (1)
3. If (stock is NB) and (demand is low) then (order is 40) (1)
4. If (stock is NS) and (demand is high) then (order is 55) (1)
5. If (stock is NS) and (demand is med) then (order is 35) (1)
6. If (stock is NS) and (demand is low) then (order is 20) (1)
7. If (stock is Z) and (demand is high) then (order is 50) (1)
8. If (stock is Z) and (demand is med) then (order is 30) (1)
9. If (stock is Z) and (demand is low) then (order is 15) (1)
10. If (stock is PS) and (demand is high) then (order is 35) (1)
11. If (stock is PS) and (demand is med) then (order is 20) (1)
12. If (stock is PS) and (demand is low) then (order is 10) (1)
13. If (stock is PB) and (demand is high) then (order is 25) (1)
14. If (stock is PB) and (demand is med) then (order is 15) (1)
15. If (stock is PB) and (demand is low) then (order is 5) (1)

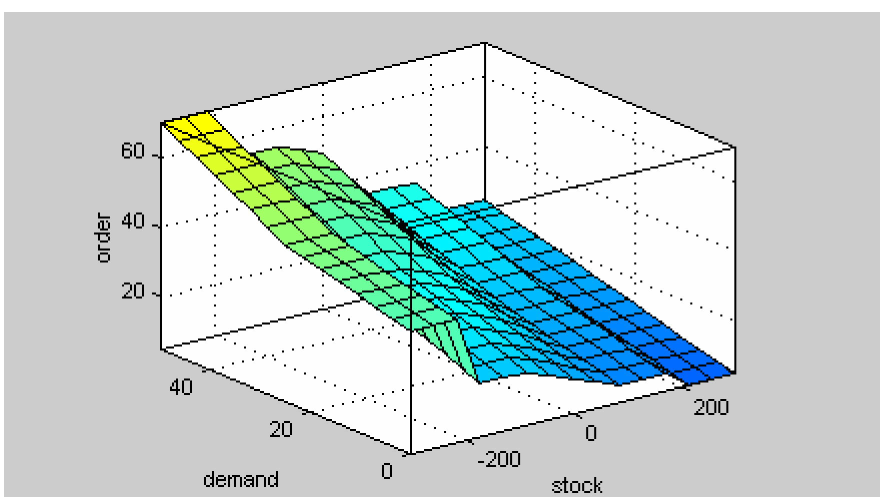

Figure 7: Surface of the fuzzy logic model for (i) type subjects

The ordering response to changes in stock level and demand is smooth. There is a slightly sharper increase in order when the inventory level moves from the membership functions ‘PS’ to ‘PB’ or from ‘NS’ to ‘NB’. Transitions of the inventory level from ‘Z’ to ‘NS’ or ‘PS’ are quite smooth and close to linear. This is obtained by keeping the ranges that membership functions intersect small, at the same time by choosing the output values of consecutive membership functions close.

For example,

IF stock is NS and demand is med then order is 35.

IF stock is Z and demand is med then order is 30.

IF stock is PS and demand is med then order is 20.

Looking at the inference rules given above, when the demand is exactly medium, which is 25, and stock level is exactly zero then the order will be 30. Similarly when the demand is exactly medium, which is 25, and stock level is in NS, which happens between -135 and -165, then the order will be 35. This will cause a gradual increase because of exponential delay.

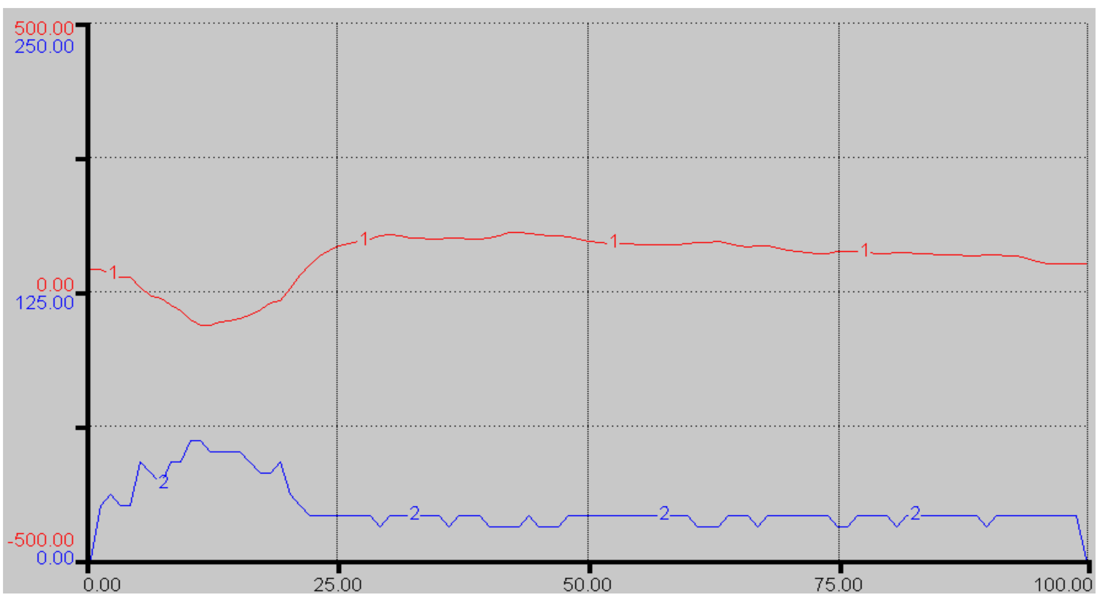

Figure 8: Simulation result of the (i) type fuzzy logic player in short, step up and down in customer demand, continuous exponential delay game

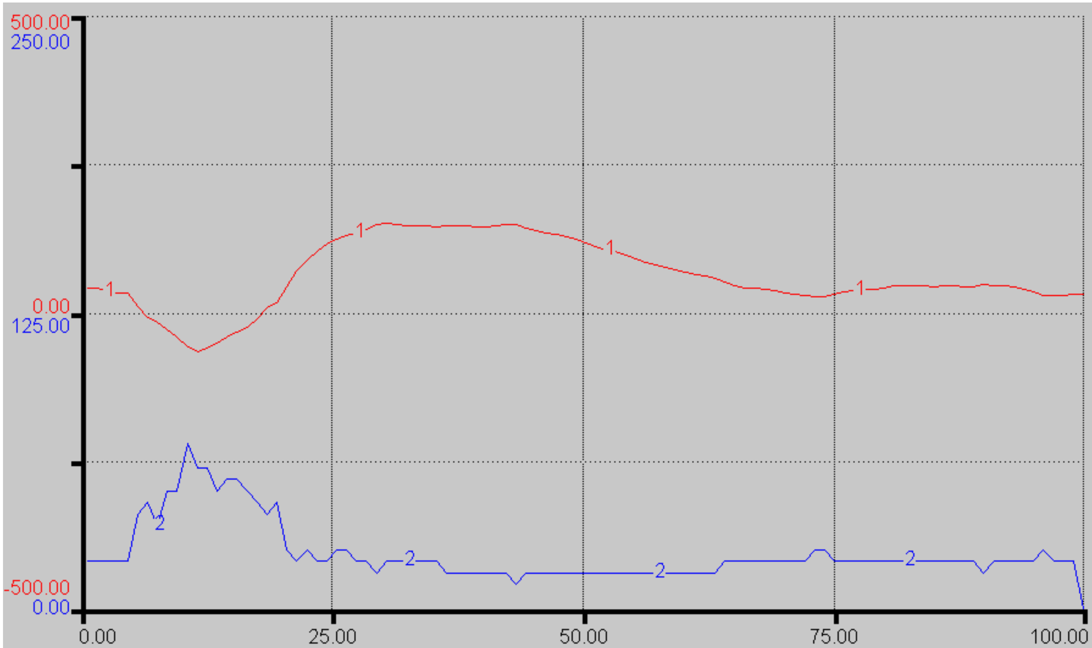

Figure 9: The result of a short, step up and down in customer demand, continuous exponential delay game played by type (i) human player

Both the human and the FL player show the similar ordering behavior and hence stock level behavior (see Figures 8 and 9). Even though the players order as much as the demand, there is a decrease in stock level at the beginning due to the step up in customer demand and exponential delay. Then players order slightly more than demand to counteract the demand and compensate the discrepancy between the desired and actual value of the inventory. However, both players cannot avoid a peak in the inventory level due to step down in customer demand and exponential delay. Later, both players are able to stabilize the stock level when the customer demand is about the same.

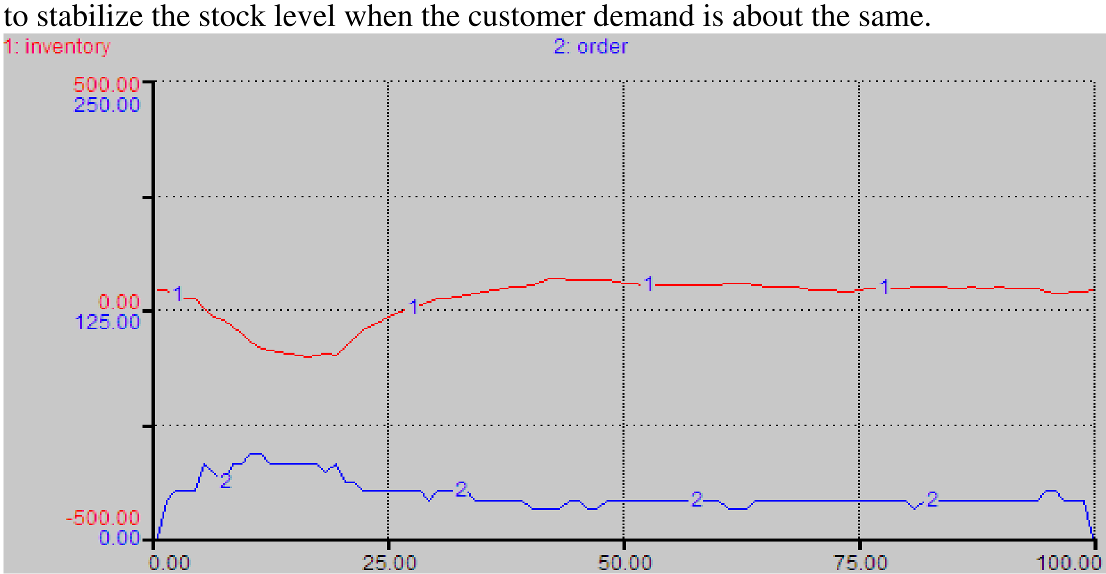

Figure 10: Simulation result of the (i) type fuzzy logic player in short, step up and down in customer demand and discrete delay

This fuzzy logic player mimics the ordering behavior of (i) type of decision maker also in discrete delay. (i) type players can not be the ideal type of players as their decision making process does not consider supply line level.

Modeling (ii) Type Subjects

This ordering behavior is explained as alternating large-and-zero discrete orders like a high frequency signal. (ii) type subjects are usually observed in discrete delay games. In discrete delay the inflow is simply lagged by the given delay time. Hence, in the discrete game, a placed order is received in 4 days as exactly the same amount. In the experimental data, the subjects capture the dynamics of the game as the game unfolds. So an idea about the delay type can quickly be developed by observing supply line level. If the players do not consider supply line level as a decision factor, usually an oscillatory and unstable stock level results. The inventory of the (ii) type subjects usually endures zigzagging stock levels since a large order reaches the inventory after a discrete delay of 4 days. Then the inventory begins to drop gradually till the next large order reaches the inventory.

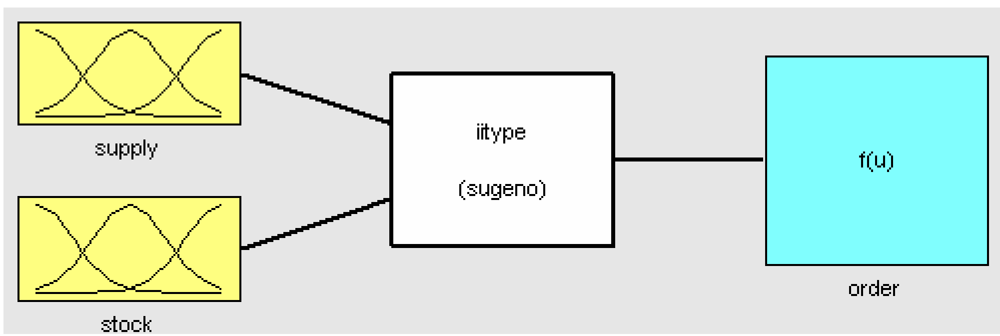

Figure 11: Fuzzy Logic Model for (ii) type subjects

The decision making factors for the model is supply line and stock level. The demand is not considered as decision making factor. Even though the order amount should be the total of four day delays' demand, the subjects usually make the large orders looking at the level of the inventory or randomly.

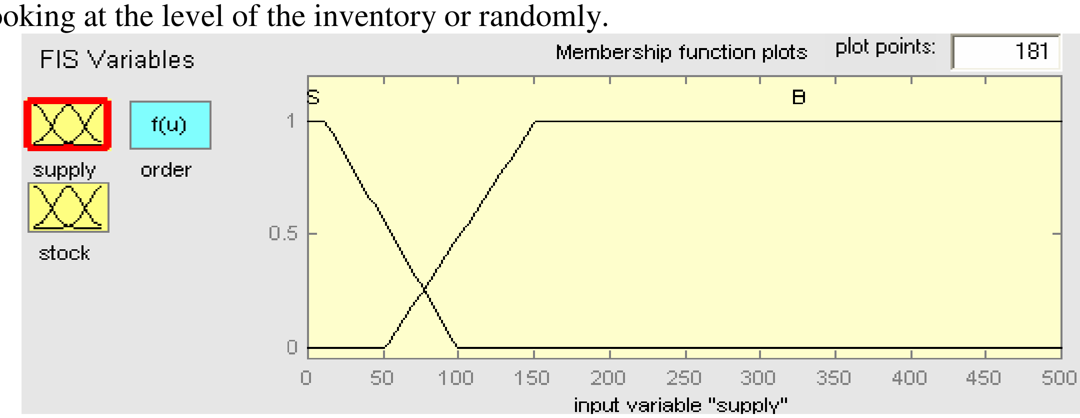

Figure 12: Membership functions of supply line level for (ii) type subjects

The ranges of the decision factors are obtained from the experimental data on subjects with (i) type of ordering behavior. The supply line level is B (Big) if it is over

150. It is S (small) if it is less than 10. Between 50 and 100, the two functions intersect.

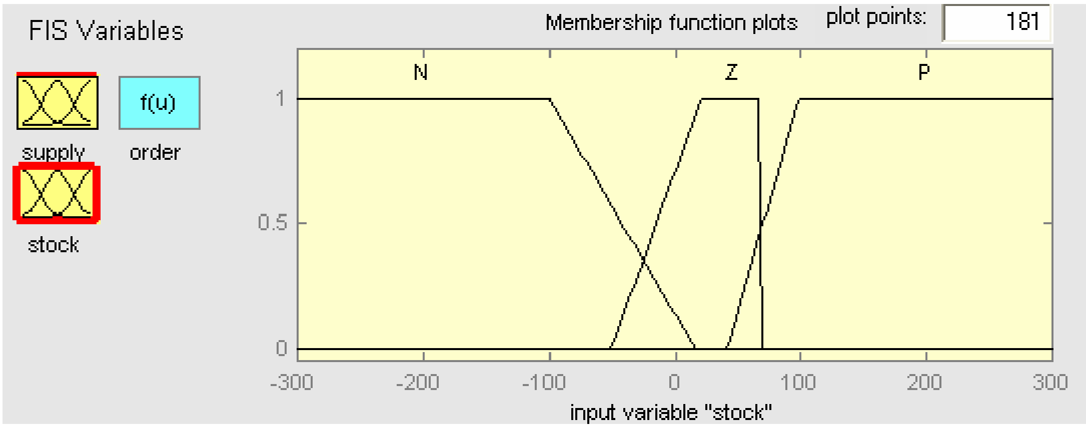

Figure 13: Membership functions of stock level for (ii) type subjects

The inventory level is tried to be kept above zero. So the Z(zero) membership function is not symmetric around zero. It is a bit tilted towards the positive side. To obtain alternating large-and-zero orders membership functions should intervene in small ranges. In other words, a level of inventory or the supply line should usually belong to one membership function. Also the stock range is divided only to three functions because no small adjustments are necessary. A large negative or positive value of the inventory level is 'N' or 'P'. It is not divided to 'NS' or 'NB' and 'PS' or 'PB'. When the stock level is 'N', a large order will be given. And when the stock level is 'P', no goods will be ordered.

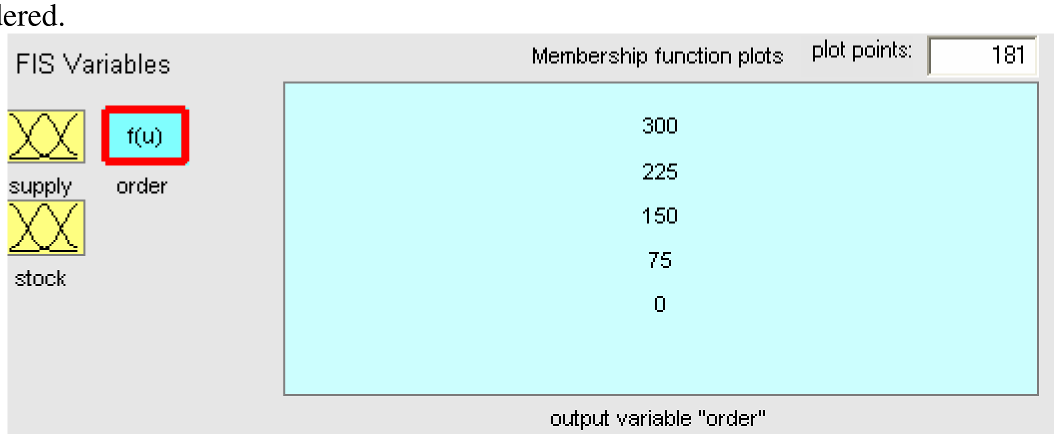

Figure 14: TSK membership functions of order for (ii) type subjects

The order range is between 0 and 300 where the maximum order level is from the experimental data of subjects with (ii) type ordering behavior.

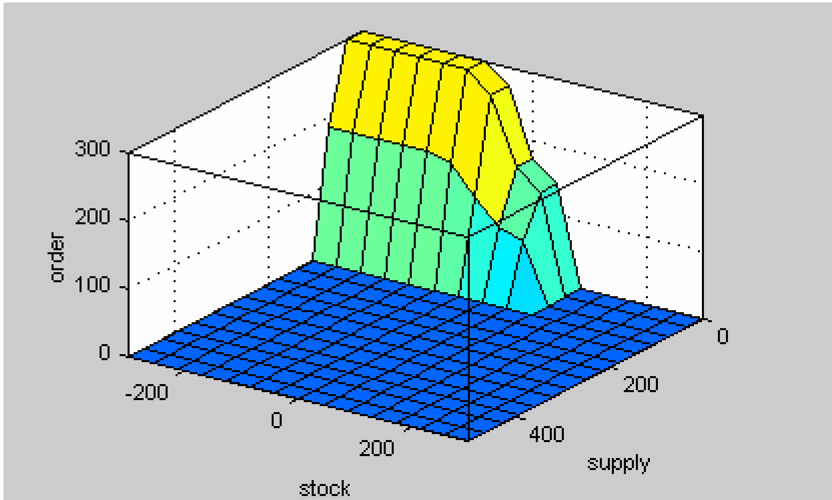

Figure 15: Surface of the fuzzy logic model for (ii) type subjects

The surface is very steep which means the order is zero or a large amount. The inference rules suggest that if stock is ‘P’ or the supply line is ‘B’ then the order is zero. If the supply line level is 0, then it is known, because of discrete delay, there will be no inflow to the stock for at least four days. If the stock level is not too high, the model should avoid supply line level to drop to zero. As soon as the supply line level is ‘S’ and the stock level is not ‘P’, a large order is placed according to the stock level.

Figure 16: Simulation result of the (ii) type fuzzy logic player in short, step up and down in customer demand, discrete delay game

Notice that the figure is scaled between -2000 and 2000 for inventory level and between 0 and 1000 for ordering. So it is a larger scale than the other figures.

The maximum order is 250 when the supply line is ‘S’ and stock is ‘N’. Generally the large orders are around 150. The minimum stock level is -200 and the maximum is about 120. After day 25, when the demand is steady, backordering occurs at the end of each zigzag. To avoid backordering, either the negative end of the membership function

'Z' should be moved a bit to the positive side or the ordering value should be increased, when supply line is 'S' and the stock level is 'Z'. A better fuzzy logic model where no backordering occurs could be achieved; however, this is not the objective of this paper as this fuzzy logic model mimics the (ii) type player. Yet this shows us that what decision makers call normal stock level is actually a low stock level for this game.

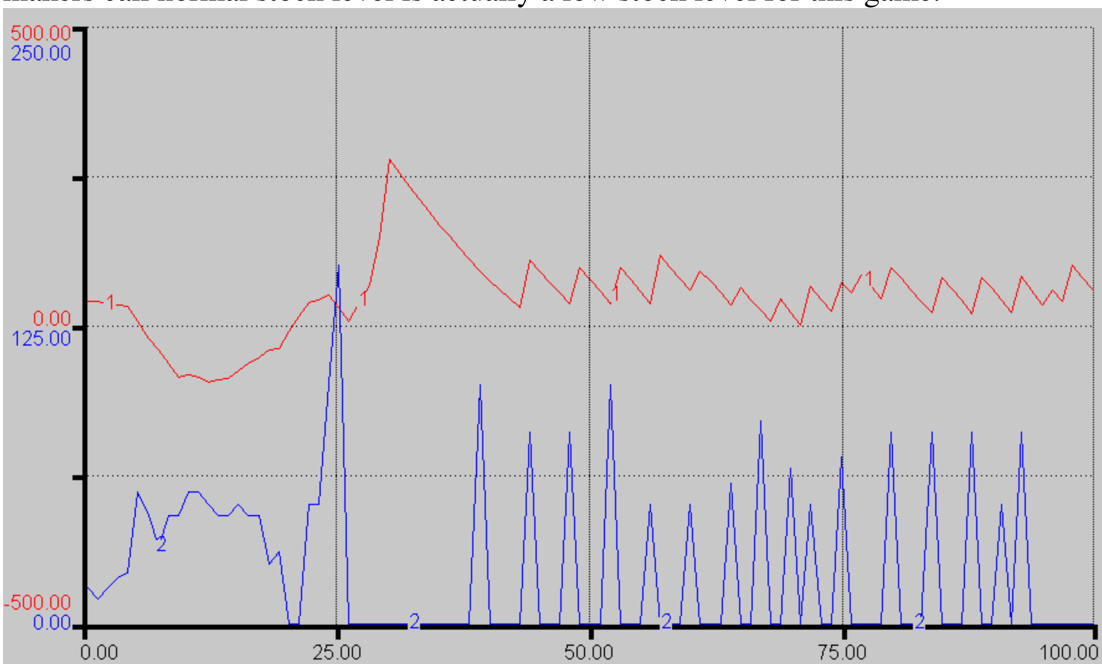

Figure 17: The result of a short, step up and down in customer demand, discrete delay game played by type (ii) human player

The player does not pay attention to the supply line in the beginning so there is a peak in inventory level when a step down in demand occurs. Later, when the demand is about the same, the player is able to keep stock level above zero while avoiding backlog. The minimum inventory level is -42 and maximum inventory level is 282. The human player is better at avoiding backlog while stock level peak is higher than the FL player.

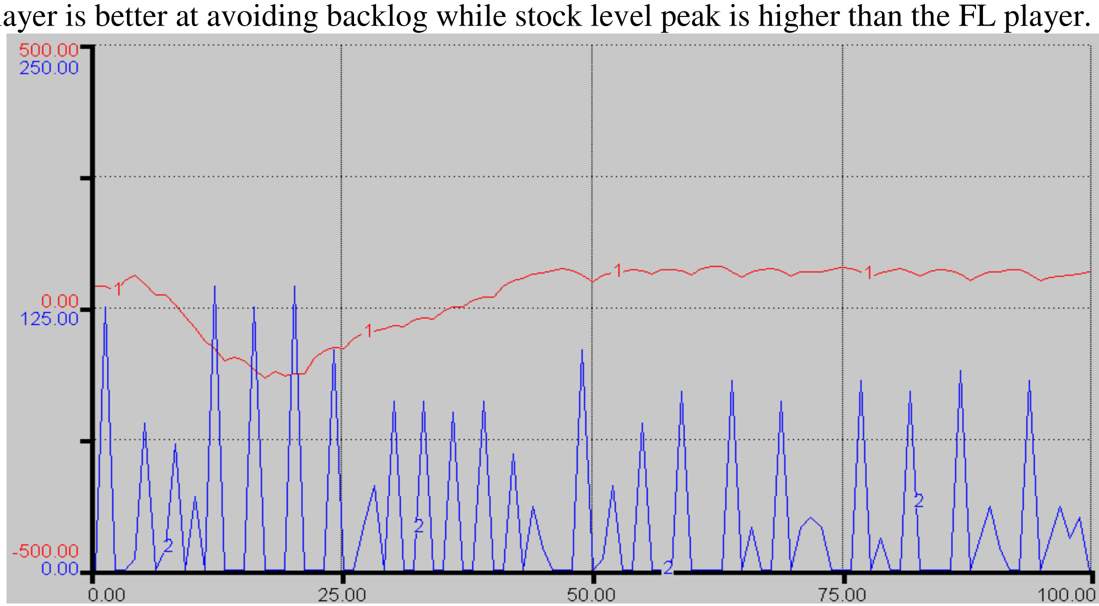

Figure 18: Simulation result of the (ii) type fuzzy logic player in short, step up and down in customer demand and continuous exponential delay

(ii) type fuzzy logic player preserves its ordering behavior in continuous exponential delay. Notice that the zigzagging is lost because of the change in the delay type. Small curves with maximums are observed in this delay type.

Modeling (iii) Type Subjects

This ordering behavior is explained as long periods of constant orders punctuated by a few sudden large ones. This (iii) type subjects are common in continuous exponential delay games. Some players do not order smoothly like (i) type. They order smoothly when the inventory level is around the desired level. When the inventory level is below the desired level, in other words when backordering occurs, subjects tend to give large orders to compensate the discrepancy in the inventory level quickly. Similarly, when the inventory level is above the desired level, they cease ordering.

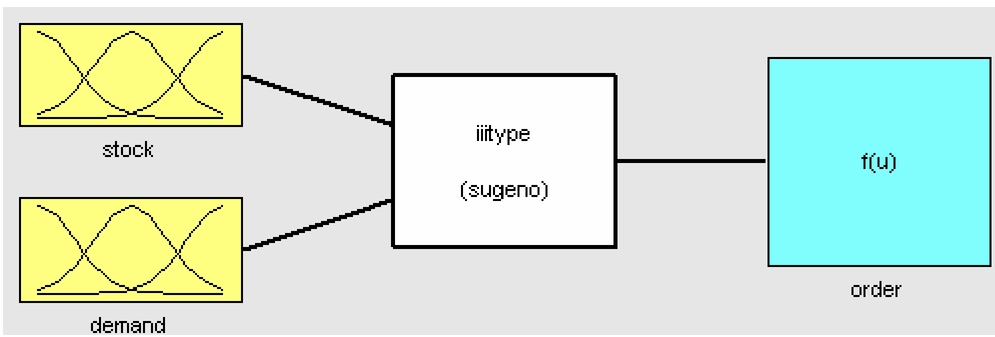

Figure 19: Fuzzy Logic Model for (iii) type subjects

The decision making factors for (iii) type players are stock level and demand. Demand is needed as an input for fuzzy logic model to obtain a smooth ordering around desired range of inventory to counteract the demand. (iii) type players order in high amounts only when backordering occurs or cease ordering only when there is overflow of goods. Hence, supply line is not a decision making factor for this type of players.

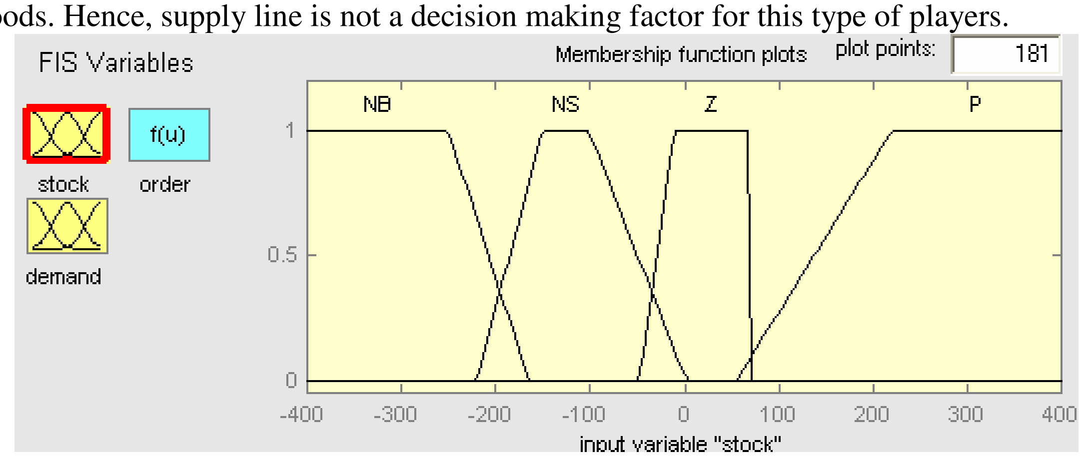

Figure 20: Membership functions of stock level for (iii) type subjects

The ranges for membership functions are obtained looking at the maximum and minimum levels of inventory with (iii) type ordering behavior subjects. The membership function Z (zero) is tilted to positive of zero to keep the level of stock above zero. After the level exceeds 70, those values belong to the membership function P (positive). There are two membership functions at the negative side of the inventory. When the stock level is below a certain negative value, subjects order large. They order just above the demand when the stock level value belongs to 'NS'. These two regions on the negative stock level could be explained as tolerable backordering and not tolerable backordering which should be amended as fast as possible.

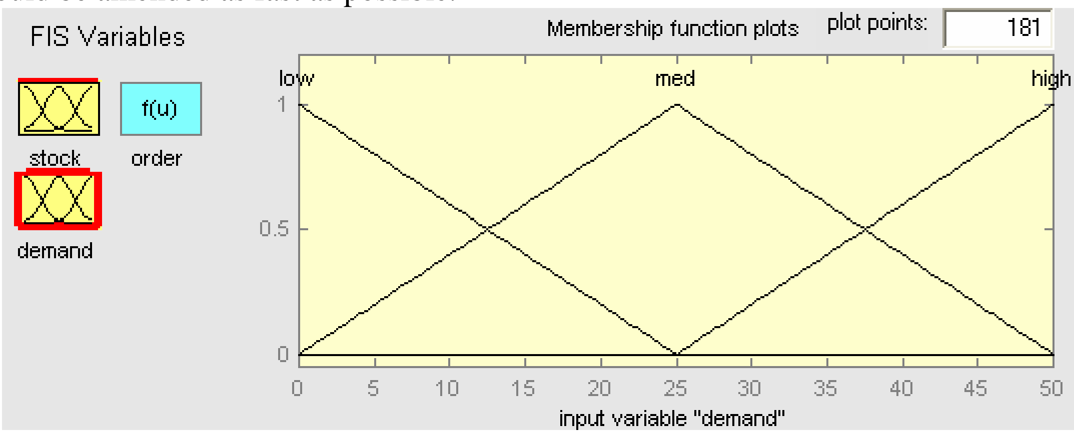

Figure 21: Membership functions of demand for (iii) type subjects

The range of the demand membership function is obtained looking at the maximum and minimum levels of the demand under noise during the game.

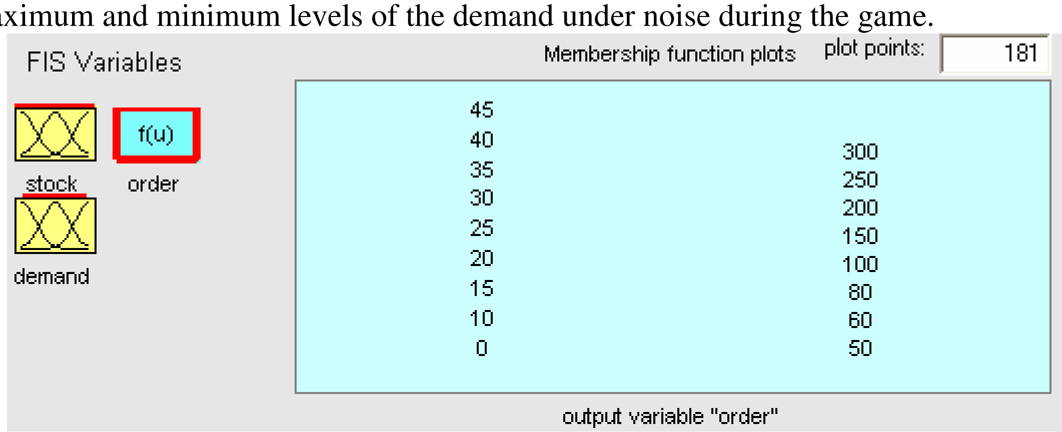

Figure 22: TSK membership functions of order for (iii) type subjects

Because this is a TSK type of fuzzy logic controller, the orders are exact numbers. The range is obtained looking at subjects' maximum peak of orders with (iii) type of ordering behavior. Notice that the range of ordering is like the combination of (i) and (ii) type players.

Table 2: Inference rule table of the fuzzy logic model for (iii) type subjects

1. If (stock is P) and (demand is high) then (order is 10) (1)
2. If (stock is P) and (demand is med) then (order is 0) (1)
3. If (stock is P) and (demand is low) then (order is 0) (1)
4. If (stock is Z) and (demand is high) then (order is 40) (1)
5. If (stock is Z) and (demand is med) then (order is 25) (1)
6. If (stock is Z) and (demand is low) then (order is 10) (1)
7. If (stock is NS) and (demand is high) then (order is 150) (1)
8. If (stock is NS) and (demand is med) then (order is 100) (1)
9. If (stock is NS) and (demand is low) then (order is 60) (1)
10. If (stock is NB) and (demand is high) then (order is 300) (1)
11. If (stock is NB) and (demand is med) then (order is 250) (1)
12. If (stock is NB) and (demand is low) then (order is 200) (1)

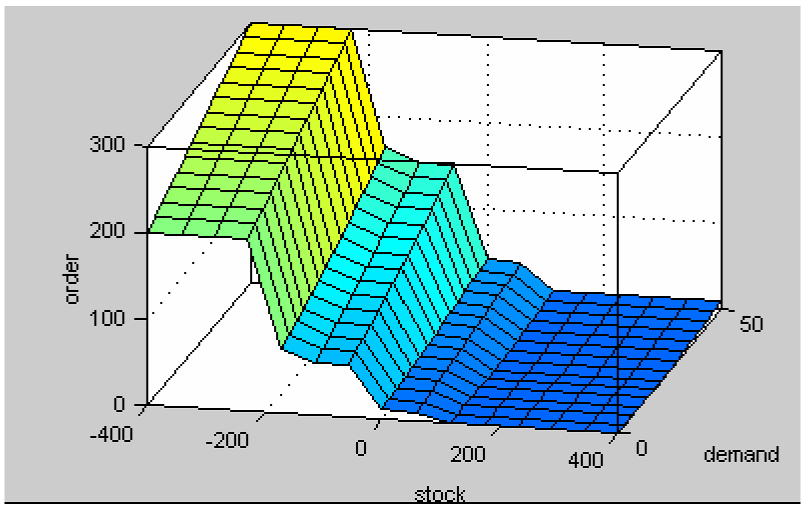

Figure 23: Surface of the fuzzy logic model for (iii) type subjects

Looking at the surface, it is seen that the ordering response to changes in stock level and demand is smooth between 0 and 100. When the stock level is above 100, the model does not order. There is a sharp increase in order when the inventory level moves from the membership functions 'Z' to 'NS' or from 'NS' to 'NB'. The order increases gradually as the demand increases no matter what the inventory level is. Few sudden large orders or the leaps in orders are obtained when the inventory level goes below 0 or below -200.

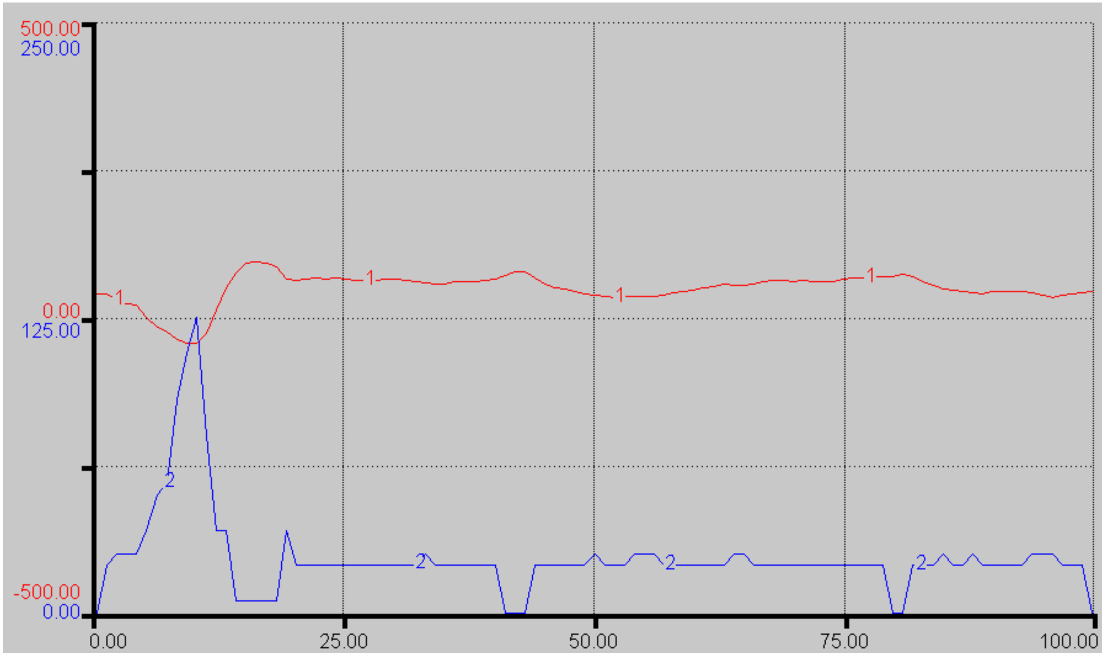

Figure 24: Simulation result of the (iii) type fuzzy logic player in short, step up and down in customer demand, continuous exponential delay game

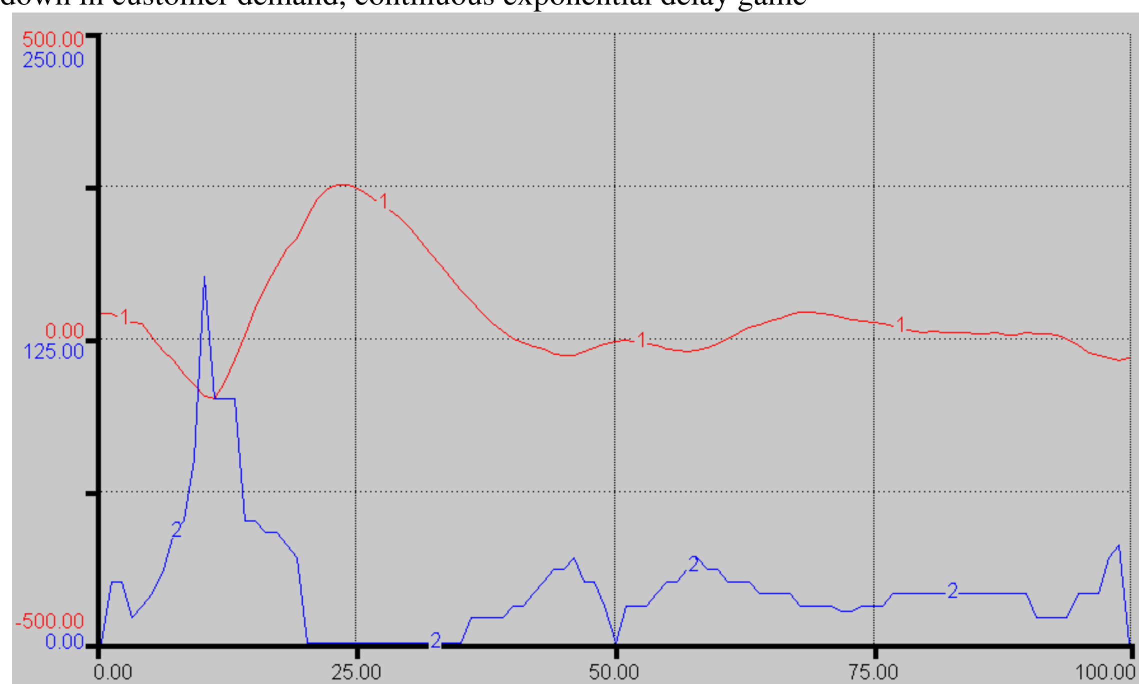

Figure 25: The result of a short, step up and down in customer demand, continuous exponential delay game played by type (iii) human player

Both fuzzy and human player produces a similar kind of ordering and stock level behavior. There is a decrease in stock level at the beginning because even though the players order as much as the demand, the step up in customer demand and exponential delay cause the stock level to go down. Then the players begin to order large amounts of goods to avoid backordering. The difference of (iii) player from (i) type player is that subject orders large amounts to get rid of backlog above certain threshold as soon as possible. But, the step down in customer demand causes a peak in stock level. Also the effect of exponential delay should not be forgotten at the occurrence of a maximum peak. Later, both players are able to stabilize the stock level when the customer demand is about the same.

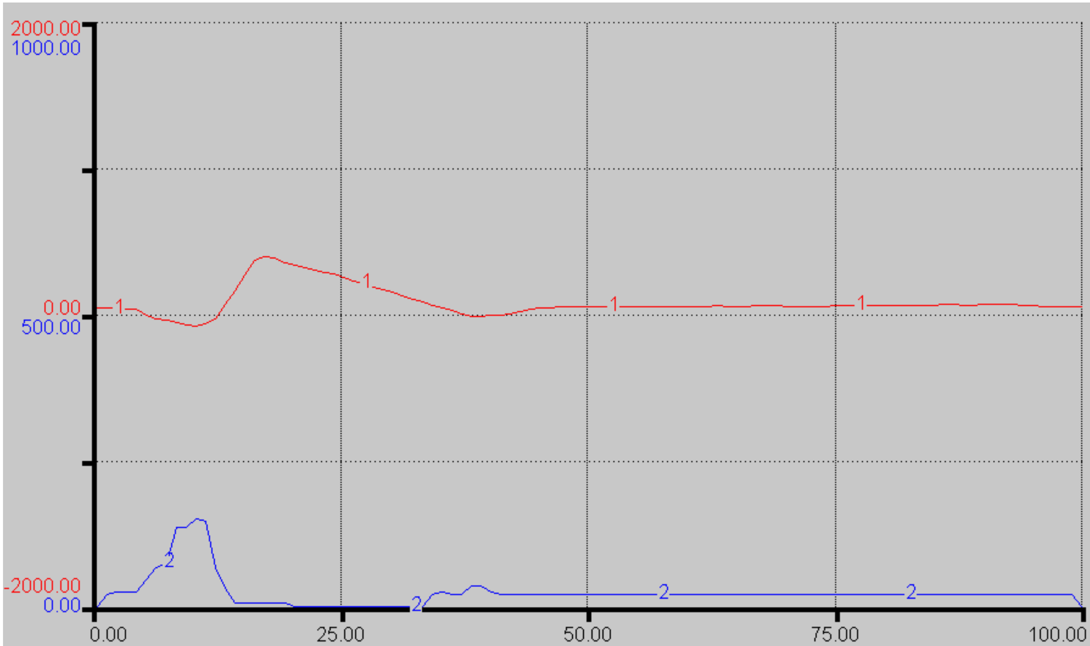

Figure 26: Simulation result of the (iii) type fuzzy logic player in short, step up and down in customer demand and discrete delay

Notice that the figure is scaled between -2000 and 2000 for inventory level and between 0 and 1000 for ordering. So it is a larger scale than the other figures.

(iii) type fuzzy logic player does not change its ordering behavior in discrete delay as expected. The maximum order value is 150. Because the (iii) type fuzzy logic player does not have the input supply line level, the maximum peak of the inventory level at discrete delay is very large. When the inventory level value belongs to 'P' membership function, the player cease ordering. Hence, we observe backordering between days 37 and 42. Although the fuzzy player orders as soon as the inventory level value moves from membership function 'P' to 'Z', the discrete delay causes a backordering for four days. (iii) type player is designed to avoid high volumes of backordering as soon as possible. It can be concluded that, (iii) type fuzzy logic player is a better player than (i) type players if penalty for backordering is much higher than stock cost.

6) Conclusion

Throughout this paper, we give a qualitative explanation of why humans order in certain ways in Stock Management Problem. This explanation enables us to reach our objective of mimicking the human behavior. FL is the tool used to model the qualitative explanation of the behavior. The results show that this approach gives a satisfactory mimic of the three different classes of human behavior. Hence, FL proves to be a useful tool to mimic/model bounded rationality of humans.

It is almost impossible to explain how people think exactly even in particular situations. The most practical way to have an idea about how people generally act in particular situations is to observe a number of individuals' behavior. Before modeling human behavior, which in the literature of SD means explaining why people behave as they do, it is a simpler task to mimic human behavior. FL approach surely provides us with a mimic of human behavior as well as an idea about what humans consider and how they interpret the information provided. This study tries to explore the human reasoning behind the behavior by first interpreting their behavior qualitatively. Then we propose to model this interpretation with the most suitable tool. This is a step towards modeling human behavior since we go beyond mimicking and model our interpretation to the reasoning behind human behavior. It is an essential step towards developing aid in the decision making process.

Further research should be done to integrate FL and SD, as we claim that FL is a useful tool for modeling human behavior. If it is believed or accepted that FL provides us with a valid model of human behavior, finding the optimal player of each different type according to a performance index would be a contribution. The membership functions are formed manually. A search for the best membership function values that mimic the players can be a good way to speed up the modeling process. The decision of which variables humans base their decisions on and the weight of these decision variables is very hard to determine. It is unlikely that a search algorithm result would give a meaningful answer. A survey or questionnaire of decision makers can be a valuable source of information.

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