**Title**
A Dynamic Neural Network Model of Multiple Choice Decision-Making



**Journal**
Proceedings of the Annual Meeting of the Cognitive Science Society, 21(0)

**Author**
Roe, Robert M.

**Publication Date**
1999

Peer reviewed

# A Dynamic Neural Network Model of Multiple Choice Decision-Making

**Robert M. Roe** (rmroe@indiana.edu)
Indiana University, Department of Psychology, 1101 E. 10th Street
Bloomington, IN 47405 USA

## Abstract

A neural network instantiation of Decision Field Theory (Busemeyer & Townsend, 1993) for multiple choice decision tasks is presented. First it is shown how under certain situations this dynamic model reduces to two well-known static models of choice. Next, model simulations of two well-known findings in multiple choice decision literature are presented. The first is the effect of similarity (Tversky, 1972). Several choice models also predict this effect. However, a more challenging effect, which is not predicted by numerous static choice models is the decoy effect (Huber, Payne, & Puto, 1982). Simulations show that the current model predicts this finding by using the concept of lateral inhibition. Finally, predictions of the model are made about the dynamic nature of the deliberation process in the decoy effect. If empirical results are found to be in agreement with this prediction, it would be a strong test of the model

## Introduction

Preferential choice is a very complex topic that needs to be studied from many different perspectives. Take for example, the relatively simple task of buying a used car. From one point of view, this is a search problem in which a very large set of options is winnowed down to a much smaller set of satisfactory options (Simon, 1955). From another point of view, this is an evaluation problem requiring tradeoffs among multiple conflicting attributes such as safety, quality, performance, and cost (Keeney & Raiffa, 1976). From a third point of view, this is a choice problem which the candidates engage in a competition for the purpose of identifying a winning or best alternative (Thurstone, 1959).

The purpose of this article is to present a general decision theory that encompasses all of these points of view within a single processing framework. The present theory is based on an earlier theory known as decision field theory. Decision field theory was originally developed to explain choice behavior for decision making under uncertainty by Busemeyer & Townsend (1993). Later it was extended to explain the relation between choice, selling prices, and certainty equivalents by Townsend & Busemeyer (1996). More recently, it was extended to account for multi-attribute decision making by Diederich (1997). However, all of these previous developments were limited to choice situations involving only two choice options. This simplification was initially necessary to focus on other issues in more depth such as multi-attribute outcomes and multiple uncertain outcomes. The purpose of this article is to relax this restriction and present an extension of decision field theory to multiple (more than two) preferential choice problems. Many new and complex issues arise with multiple alternative choice problems that do not appear in the simpler binary choice task -- for example, a winnowing search process is unnecessary in the binary choice task.

A very large literature already exists on the topic of preferential choice with multiple options. What is unique about decision field theory is that it provides a detailed description of the dynamic process that ensues between the onset of the choice task and the final selection. This dynamic description permits the theory to explain the systematic relations between choice probability and decision time, and the important effects of time pressure on choice probability.

A second purpose of this article is to build formal connections between decision field theory and other neurally inspired models of decision processes (e.g. Grossberg & Gutowski, 1987, Usher & Zakay, 1993, & Levin & Levin, 1996). More specifically, decision field theory is recast or reinterpreted in terms of a neural network formulation. One key idea borrowed from neural network theorists (e.g., Grossberg, 1988) is the principle of lateral inhibition among competing nodes. This idea turns out to play a critical role in explaining paradoxical findings that have posed serious challenges to a large class of static choice models.

The remainder of this article is organized as follows. First we introduce the basic ideas of decision field theory. In order to do this, a specification of how this theory operates under two different types of task constraints, one called the experimenter controlled choice task, and the other called the subject controlled choice task is needed. Second, it is shown how some earlier static theories of choice can be viewed as special cases of decision field theory. In particular, it is shown how decision field theory can be used to derive a dynamic version of the classic Thurstone choice model for the experimenter controlled task, and it is shown the well known elimination by aspects model can be mimicked for the subject controlled task. Next some basic findings are reviewed from multiple alternative choice including the effects of similarity on choice and the effects of adding asymmetrically dominated alternatives. The latter result is particularly important because it violates a principle of choice called regularity that is satisfied by a large class of previous choice models. Then it is shown how the multiple choice version of decision field theory provides a simple and natural explanation for these paradoxical results. Finally new predictions from the theory are derived for the effects of deadline time pressure on multiple alternative choice. At this point in time, these predictions are unique to newly developed version of decision field theory and provide a strong test of the theory.

## Multiple Cue Decision Field Theory

In order to make the description of the model more concrete, an example of a three option choice task we will be presented and referred to throughout the paper. Consider the case of a new car purchase where after some deliberation the choice set has been reduced to three cars. Also consider that the number of dimensions used to deliberate about these choices has been reduced to two, performance and gas mileage.

Below is presented a neural network interpretation of Multiple Choice Decision Field Theory (MCDFT) for this choice task. The model is expressed with the following linear difference equation:

$$\mathbf{P}(t+1)= \mathbf{S} * \mathbf{P}(t)+ \mathbf{V}(t)$$

where **P** is a 3x1 vector representing the preferences for the three alternatives, **V** is a 3x1 vector of valences which represent the momentary anticipated value of each option, and **S** is a 3x3 constant matrix called the stability matrix that controls the rate of growth of the preferences.

The current model is expressed within a neural network framework as shown in Figure 1. There are three nodes in the system, labeled A, B, and C that represent three options. The nodes in the network are fully connected and have a self-feedback loop. The weights of the connections between these nodes are given in **S** matrix. By choosing the appropriate values in the **S** matrix, the principle of lateral inhibition can be implemented. It turns out that lateral inhibition is a key issue in predicting known findings in the area of multiple choice decision tasks.

The input that drives the system are valences, represented in Figure 1 by **V**'s. Values of the valences for each option change moment by moment as attention is randomly shifted from dimension to dimension in the deliberation process. For example, while deliberating on a new car purchase, attention may be shifting between gas mileage and performance. Therefore, the momentary anticipated value of each option will change depending on what dimension is being attended to. It has been shown that subjects do tend to use a dimension-wise process in many choice tasks (Russo & Dosher, 1983). Because attention is randomly shifting and the value of the **V**'s are fluctuation, they are random variables and are assumed to be independent and identically distributed. The output of the system is the preference, **P**, of each option at time t+1. The option selected in a particular choice task depends on the values of these preferences and the type of choice task.

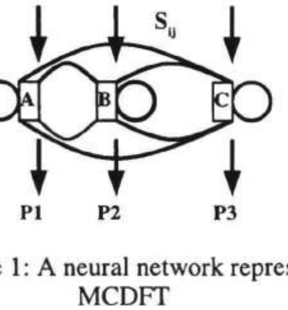


Figure 1: A neural network representation of MCDFT

Given this brief explanation of the model it can now be shown how it maps onto two types of choice tasks, experimenter controlled and subject controlled. In describing these mappings, it will shown how MCDFT can be viewed as special cases of two well-known static theories of choice.

### Experimenter Controlled Choice Tasks

Experimenter controlled choice tasks involve placing a deadline on the choice deliberation time. For example, while deliberating on the purchase of a new car, the dealer may interrupt the deliberation process by forcing an immediate decision. Part of Figure 2 represents this type of choice task for the new car example. The abscissa represents time while the ordinate represents the level of preference of each option. The three lines labeled A, B, and C represent the preferences of each option as they evolve over time. The vertical line to the right represents the choice deadline. The option with the highest preference at deadline is the one chosen. In this case, option C was chosen because it had the highest preference at deadline (the meaning of the upper bound is discussed below).

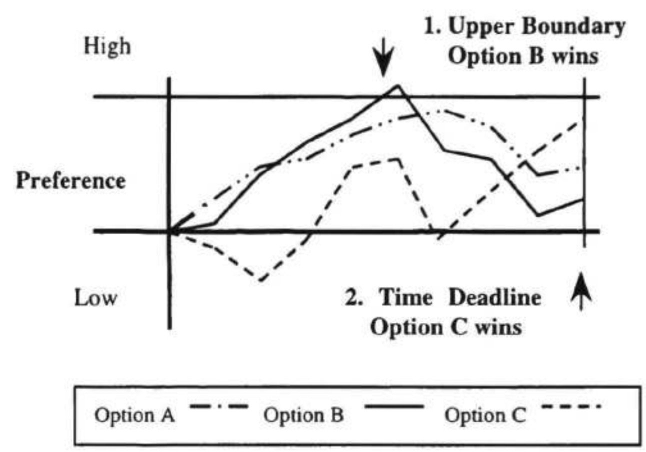


Figure 2: Experimenter and subject controlled tasks

The probability that a particular choice is made at time t, for example option C, is:

$$P(\text{Choose C, AB, at time t}) = P(P_C > P_A \text{ at time t}, P_C > P_B \text{ at time t}).$$

To find the mean and the variance of preferences, we look at the expansion of the model equation given earlier: With $E(V) = \mu$ and $Var(V) = \Phi$ and the fact that the V's are i.i.d. (Therefore their sum becomes multivariate normal), MCDFT reduces to a Multivariate Dynamic Thurstone choice Model with:

$$P(t+1) = \sum_{j=0}^{t-1} S^j V(t-j) + S^t P(0)$$

$$E[P(t)] = (I - S)^{-1}(I - S^t)\mu$$

$$V[P(t)] = \sum S^j \Phi (S^j)^T$$

As can be seen in the above equations, means evolve over time such that at any point in time t, the means can change leading to preference reversals.

By stopping the deliberation process and obtaining a choice response at various points during deliberation, it is possible to study how the deliberation process evolves. A paradigm such as this, known as the response signal method (Reed, 1973), had been used to study many cognitive processes such as recognition memory and lexical decisions (Hintzman & Curran, 1997) and discriminating semantic from episodic associations (Dosher, 1984).

Presently there are no known decision-making studies using experimenter-controlled tasks. However, a model prediction based on this type of task makes a strong test of the model and will be presented below. A second and more frequently used type of choice task is the subject controlled choice task.

## Subject Controlled Choice Task

Subject controlled differ from experimenter controlled choice tasks in that no deadline is placed on the deliberation process. Instead, a choice is made when the preference for an option crosses some threshold. Figure 2 also represents this type of choice task for the new car example. The abscissa represents time while the ordinate represents the level of preference of each option. The three lines labeled A, B, and C represent the preferences of each option as they evolve over time. The horizontal line at the top represents the choice threshold. A choice is made when the level of preference for any option crosses the threshold. In this case, option B is chosen.

Within this type of choice task, MCDFT mimics a well-known model of multiple choice decision, Elimination by Aspects (Tversky, 1972). According to this model, options are eliminated from the choice set based on aspects (or dimensions). However, unlike the subject controlled task presented above, a different choice boundary is needed, a lower boundary to discard options. In Figure 3, the results of a computer simulation of a choice task with five options along three aspects (or dimensions) are shown. The abscissa represents time and the ordinate represents preferences. The lines labeled A through E represent each option. Each vertical line represents a shift of attention from one dimension to another in the deliberation process. As can be seen, while focusing on the first dimension two options, A and E, were eliminated from the choice process. After the shift to the second dimension, no items were eliminated, and while focusing on the third dimension, items B and D were eliminated leaving option C as the option selected.

MCDFT mimics well the Elimination by Aspects model of multiple choice decision. In the sections that follow it sill be shown how MCDFT can qualitatively account for two salient findings in the literature, the effect of similarity and violations of regularity.

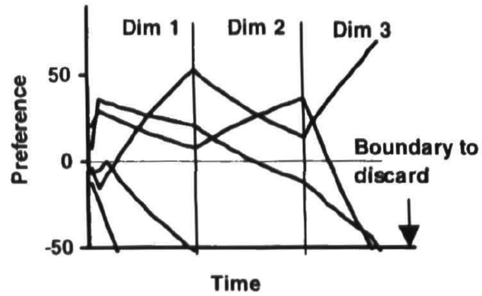


Figure 3: Results of EBA simulation

## Effects of Similarity

The similarity effect is a well-known phenomenon in the area multiple-choice decision-making, (Tversky, 1972). It states that by adding a new item to a choice set that is similar to one already in the set, the probability that the original similar item chosen is lowered relative to the other items in the choice set. In other words, the similar alternative takes more of the market share from items similar to it than dissimilar to it. Part of Figure 4 shows an example of this situation for three options. The three options are represented in a two dimensional space of performance and gas mileage. Options A and B are located such that option A has better performance but poorer gas mileage than B, and option B has worse performance but better gas mileage than A. By adding the third option S which is similar to A, the probability that B is chosen relative to A is increased.

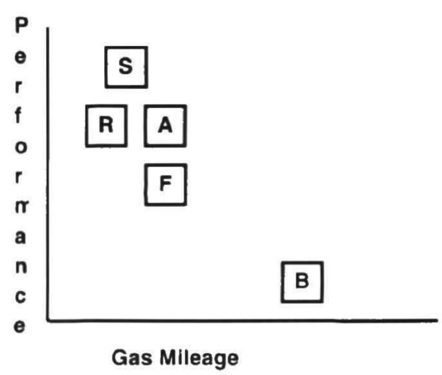


Figure 4: Similarity and Decoy Effects

The similarity effect leads to violations of strong stochastic transitivity. Many static choice models can handle these violations including Elimination by Aspects (Tversky, 1972) and the Edgell-Geisler choice model (Edgell &Geisler, 1980). The dynamic model proposed here can also handle these violations. Computer simulations were run to test model predictions for this finding. Simulations were first run to obtain preferences for two options then a third similar option was added. Figure 5 shows the prediction of the model. The abscissa shows the two possible options A and B while the ordinate shows the probability that an item is chosen. The line connected with the diamonds reflects the probability of each choice when only two options are available. In this case, each option is equally likely to be chosen. The line connected by the squares indicates the effect of adding the similar alternative. As you can see, the probability that A is chosen relative to B is lower when the similar item is added.

This simulation shows that MCDFT can qualitatively reproduce the similarity effect. However, as mentioned above, several static choice models do also. An often more difficult finding to explain is violations of regularity.

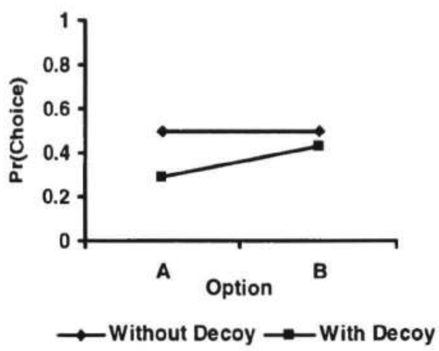


Figure 5: Results of Similarity Effect Simulation

### Violations of Regularity

Violations of regularity, called the decoy effect, have been shown in several studies (Huber, Payne, & Puto, 1982 & Ariely &Wallsten, 1995). Regularity implies that by adding an item to a choice set, the probability of choosing an item already in the set cannot be increased. Formally, for any option $x$ that is an element of set A which is in turn a subset of set B, $x \in A \subseteq B$, the probability of choosing $x$ from A must be greater than or equal to choosing x from B $\Pr(x;A) \geq \Pr(x;B)$.

These violations occur when a new item is added to the choice set which is asymmetrically dominated. An item is asymmetrically dominated if it is dominated by at least one alternative in the choice set but not dominated by at least one other. Figure 4 shows two types of dominated alternatives, or decoys, the range decoy and the frequency decoy. The range decoy R is dominated by A because it has the same performance but worse gas mileage than A. It is called a range decoy because adding it to the choice set increases the range on the gas mileage dimension. The frequency decoy F is dominated by A in that it has the same gas mileage as A but worse performance. It is called a frequency decoy because adding it to the choice set increases the frequency of items below A. Using range and frequency decoys, Huber, Payne, & Puto (1983) found subjects violate regularity and they do more so with range decoys than with frequency decoys.

Computer simulations were run to test model predictions for this finding. Simulations were first run to obtain preferences with two options and then a third option (either a Range or Frequency decoy) was added and another simulation run. Figure 6 shows the prediction of the model. The abscissa gives the probability that the dominating choice is picked (choice A) in the binary condition. The ordinate gives the probability that A is chosen for both two and three option conditions. The line connected by the squares represents the predictions for the probability that A will be chosen without the decoy. The line connected by the circles represents the probability that A will be chosen when the frequency decoy is present. As can be seen, the model predicts that adding the frequency decoy leads to higher probabilities of choosing A across a wide initial range probabilities of choosing A in the binary case. Also notice that the effect is stronger for the range decoy than the frequency decoy

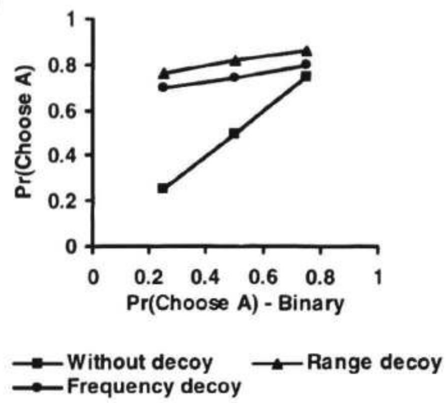


Figure 6: Results of Decoy Effect Simulations

A critical issue in producing this result was the use of lateral inhibition. In the model described here, the S matrix reflects lateral inhibition in which options close together in decision space inhibit each other and this inhibition lessens as distance increases. The S matrix shown below was used in the simulations of the decoy effect for the frequency decoy:

$$S = \begin{array}{c} \begin{matrix} A & F & B \end{matrix} \\ \begin{bmatrix} .95 & -.09 & -.001 \\ -.09 & .95 & -.02 \\ -.001 & -.02 & .95 \end{bmatrix} \end{array} \begin{matrix} A \\ F \\ B \end{matrix}$$

Referring to Figure 4, and this S matrix, we can see that options A and F are closer to together relative to B. Therefore options A and F inhibit each other more relative to B and F. In much the same way as edge enhancement effects can be produced with lateral inhibition, the closeness of A to F enhances the probability that A is chosen. To produce the larger effect for the range decoy, the matrix **S** is simply altered to reduce the inhibition between R and B (because R is farther away from B than F). This allows a greater effect of the inhibition between A and R.

### Effects of Decision Deadline

Because of the dynamic nature of this model, predictions can be made about the effects of deadline time pressure and other time related ideas on the choice process. One prediction of the model is the effect of a time deadline on violations of regularity. As mentioned above, by using the experimenter control method, we can look at the deliberation process at specific instances over time. By stopping the process at various times, the evolution of the process can be studied.

Model simulations of an experimenter controlled choice task were conducted by stopping the choice process at various points in time. The same simulation for the effect of the frequency decoy presented above was used except the time delay was varied.. Figure 7 gives the predictions of the model. The abscissa represents the time deadline with smaller numbers meaning shorter deadline. The ordinate represents the probability of choosing A, the dominating alternative. The line connected with squares represents the probability that A is chosen in the binary choice conditions. Here, no matter what the time cutoff, there is an equal probability that A or B will be chosen. The line connected by diamonds reflects the probability that A is chosen with the decoy present. Notice that with short deadlines, the model predicts that regularity will be satisfied. This can be seen in that by adding the decoy the probability that A is chosen decreases instead of increases. However, as the as the deadline time increases, the model predicts regularity will be violated. This can be seen in that adding the decoy increases the probability that A is chosen. Recall that most static models of choice predict that regularity will always be satisfied even though empirical studies show this is not true. If it is found that with short deadlines regularity is satisfied, it would be a very strong test of the model.

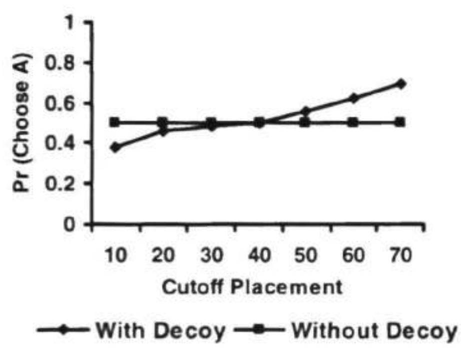


Figure 6: MCDFT predictions for the effect of time pressure

### Conclusion

Under certain choice tasks this neural network instantiation of MCDFT has been shown to reduce to special cases of some well-known static models of choice (e.g., Thurstone's (1959) choice model, and Elimination by Aspects (Tversky, 1972)). Also, MCDFT can account for both the similarity and decoy effects found in the literature on multiple choice decision making. Further, the dynamic nature of this model allows for predictions about time deadlines on the choice process. Specifically it predicts that with very short deadlines, subjects will not violate regularity although it has been found that they do. Due to the fact that most models of choice are static, they make no prediction about this. If this result can be found empirically, it would be a strong test of the model. This is currently being tested in our lab.

### Acknowledgements

This research was supported by an NIMH Post-Doctoral Training Grant F321MH11988-02. For helpful comments on a previous version of this paper, I would like to thank Jerome Busemeyer and Rachel Barkan.

## References

Ariely, D., & Wallsten, T. S. (1995). Seeking subjective dominance in multidimensional space: An exploration of the asymmetric dominance effect. *Organizational Behavior and Human Decision Processes,* 63(3), 223-232.

Busemeyer, J. R., & Townsend, J. T. (1993). Decision Field Theory: A dynamic cognition approach to decision making. *Psychological Review,* 100, 432-459.

Dosher, B. A. (1984). Discriminating pre-experimental (semantic) from learned (episodic) associations: A speed accuracy study. *Cognitive Psychology,* 16(4), 519-555.

Diederich, A. (1997). Dynamic stochastic models for decision making under time constraints. *Journal of Mathematical Psychology,* 41(3), 260-274.

Edgell, S. E., & Geisler W. S. (1980). A set-theoretic random utility model of choice behavior. *Journal of Mathematical Psychology,* 21(3), 265-278.

Grossberg, S. (1988). *Neural Networks and Natural Intellegence.* Cambridge, M.A.:Mit Press.

Grossberg, S., & Gutowski, W. E., (1987). Neural dynamics of decision making under risk: Affective balance and cognitive-emotional interactions. *Psychological Review,* 94(3), 300-318.

Hintzman D. L., & Curran, T. (1997). Comparing retrieval dynamics in recognition memory and lexical decision. *Journal of Experimental Psychology: General,* 126(3), 228-247.

Huber, J., Payne, J. W., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research,* 9(1), 90-98.

Keeney, R. L, & Raiffa, H. (1976). *Decisions with multiple objectives: Preference and value tradeoffs.* New York: John Wiley & Sons.

Levin, S.J., & Levin, D.S. (1980). Multiattribute decision making in context: A dynamic neural network methodology. *Cognitive Science,* 20, 271-299.

Reed, A. V. (1973). Speed-accuracy tradeoff in recognition memory. *Science(Washington, D.C.),* 181, 574-576.

Russo, J. E. & Dosher, B. A. (1983). Strategies for multiattribute binary choice. Journal of Experimental Psychology: Learning, Memory, and Cognition, 9(4), 676-696.

Thurstone, L. L. (1959). *The measurement of values.* Chicago: University of Chicago Press.

Townsend, J. T., & Busemeyer, J. R. (1995). Dynamic representation of decision making. In R. F. Port and T. van Gelder (Eds.) Mind as Motion. MIT press.

Tversky, A. (1972). Elimination by aspects: A theory of choice. *Psychological Review,* 79(4), 281-299.

Simon, H. A. (1955). A behavioral model of rational choice. Quarterly Journal of Economics, 69, 99-118.

Usher, M., & Zakay, D. (1993). A neural network model for attribute-based decision processes. Cognitive Science, 17(3), 349-396.