Control-Theoretic Results on Dynamic Decision Making

S. Y. Xu
Peking University
College of Engineering
100871 Beijing
CHINA
xushiyun@pku.edu.cn

Z. P. Jiang
Polytechnic University
Department of ECE
Brooklyn, NY 11201
U. S. A
zjiang@control.poly.edu

Y. Yang
Peking University
College of Engineering
100871 Beijing
CHINA
yy@water.pku.edu.cn

L. Huang
Peking University
College of Engineering
100871 Beijing
CHINA
hl35hj75@pku.edu.cn

D. W. Repperger
Air Force Research Laboratory
Wright-Patterson Air Force Base
Dayton, Ohio 45433-7022
U. S. A
Daniel.Repperger@WPAFB.AF.MIL

Abstract: Several approaches to learning in dynamic decision making tasks are developed in this paper on the basis of the application of feedback control theory to the case study of the Sugar Production Factory task. Previous experimental models are not robust to workload change and require a large amount of information to be stored. The control model presented here not only avoids such shortcomings, but also significantly enhances the system efficiency, adaptivity and robustness. On the other hand, as trust and self-confidence are closely linked to the capacity of automation and manual control in a supervisory control system, it behooves us to develop a dynamic model to assist the operator in gaining a better understanding of capacities. A quantitative model of trust in automation is then proposed to accurately characterize operator's reliance on automation. Those results are demonstrated through simulation within a framework of a Sugar Factory supervisory control system.

Key–Words: Control theory, Dynamic decision making, reliance on automation, Sugar Factory task, supervisory control.

1 Introduction

Dynamic decision making tasks include important activities such as stock trading, air traffic control, and managing continuous production processes. In these tasks, decision makers make multiple recurring decisions to reach a target, and they receive feedback on the outcome of their efforts along the way (see [11, 18, 20] and the references therein).

A transfer of insights from other related domains makes it possible to develop a formulation of learning building on the application of control theory to the study of human performance in dynamic decision making [19]. Brehmer uses control theory [3, 4] as a framework to analyze the goal-directed behavior in dynamic decision-making environments, who emphasizes the decision makers' understanding of the environmental model. People who use less sophisticated environment models are able to learn to improve their performance only when feedback is timely and continuous [3, 4]. Jordan and Rumelhart [20, 22] address similar issues in the area of motor learning. A key idea of their approach to dynamic decision making is to divide the learning problem into two interdependent subproblems. A broad set of topics including feedback control, feedforward control, delay and learning algorithms are then introduced into this area [21]. Gibson [17] inherits Jordan's connectionist network and applies online learning in parallel distributed processing, or a neural network control model to illustrate the Sugar Factory (SF) Task [16].

The SF model is a simple dynamic decision-making task in which decision makers are expected to learn from experience [1, 16, 10]. It is of interest to computational organization theorists, and there have been various kinds of tests conducted on it. A typical phenomenon arising from these experiments is that while participants progressively improve their capacity to control the system, they remain unable to describe how the system works or how does it reach the target value, leading to large amounts of repetitive work and low efficiency. Upon such backgrounds, an automatic design is required and presented as a reference.

Automation can improve the efficiency and safety of complex and dangerous operating environments by reducing the physical or mental burden on human operators [30]. Despite this fact, it is always a critical distinction whether or not automation is engaged, and the operator's role has to be changed from controllers directly involved with the system to supervisory controllers [24]. In such supervisory control systems, operators monitor the performance of automation during normal operations, and intervene to take manual control when necessary.

Studies have shown that operator's use of automation reflects automation reliability, and inappropriate reliance associated with misuse and disuse partly depends on how well trust matches the true capabilities of the automation [34]. In order to guide design, evaluation and training to enhance human-automation partnerships as well as high specificity of trust are required, and through which misuse and disuse of automation can be mitigated [25]. Consequently, a better operator knowledge of how automation works and the automation design philosophy are both required for more appropriate use of automation [29].

The operator's choice plays such an important role in the automated system performance that the allocation of functions is becoming a critical decision making process, and to optimize this process will be of great importance [26]. A dynamic approach capitalized on the power of the DFT (Decision Field Theory) has been developed to characterize operators' reliance on automation in a supervisory control system by describing a quantitative model of trust in automation, and an EDFT (Extended DFT) model is proposed [15]. As trust and self-confidence are closely associated with the capacity of automation and manual control separately [23, 35], it behooves us to improve the existed model in order to help the operator gain a better understanding of capacities.

In the first instance of the following sections, a control approach is introduced to produce the desired output in the SF task, with the response of one specific input being available at the next time step. Since the information of capacity on automation is conveyed to the participants specifically, a good estimation of the automation control capability will thus be presented. It will be found that automatic control provides a clear guidance to participants for better decision making. Secondly, we will propose a framework to modify the EDFT method based on theoretical analysis. A more satisfying result is derived through a computer simulated Sugar Factory supervisory control scenario, which presents an effective demonstration of our proposal.

The rest of this paper is organized as follows. The next section gives a detailed description of the Sugar Factory task. A control model for the SF task is proposed, in which two cases are discussed. Also simulation results are presented corresponding to both cases respectively to show the feasibility of our method. The modified EDFT method in supervisory control system is described in detail in Section 3. Also in this section, theoretical analysis to the EDFT model and modified approaches are proposed, as well as simulation results via the SF supervisory control system. In Section 4, some concluding remarks and future work are given.

2 Motivation: Sugar factory task

The Sugar Factory (SF) task was first investigated to see how participants learn to operate complex systems through a computer simulated scenario. Two kinds of computational models have been proposed to explain the behavior of participants: the D&F model [10] and the W model [33]. Over a series of trials within a training set, subjects repeatedly specify a new workforce and observe the resulting production level, attempting to achieve the prespecified production goal. Almost all of the experiments carried out within the SF paradigm adopted the same value as 9,000 tons of sugar [1, 2, 10], but there are still exceptions of considering what would happen if such a value is varied by assuming, for instance, that the participants should reach and maintain a production of 3,000 tons [9]. Changing a target value needs another series of repetitive trials, and a large amount of information has to be stored.

2.1 Mathematical Description

By choosing discrete-time computational steps, the actual output of production $p(k)$ is governed by the following equation (which is unknown to subjects):

$$p(k+1) = 2w(k+1) - p(k) + \varepsilon \qquad (1)$$

where $p(k+1)$ represents the new production at time $t+1$, $w(k+1)$ is the input specified at $t+1$, and ε is a uniformly distributed random error term, taking the values of -1, 0, or 1.

Both $p(k)$ and $w(k)$ are chosen as a discrete-value state from 1 to 12, and they are multiplied in the actual computer simulation by 1000 and 100, respectively. So values within ± 1000 of the production goal are also considered to be on target.

Although the task appears fairly simple as presented in Equation (1), it exhibits hard constraints that are challenging to handle. First, the input signal $w(k)$ at each trial only takes discrete values, and moreover, $100{*}w(k)$ must be an integer by taking account of the actual meaning. Second, the signals $w(k)$ and $p(k)$ are both bounded. Particularly, due to the lag term $p(k)$, two interdependent inputs are required at both time steps k and $k+1$ to reach steady-state production. The authors of [32, 17] observe that maintaining a steady-state workforce at nonequilibrium values leads to oscillations in production. However, this could be solved by formulating the control model as introduced in the next section, by which stability of the system could be guaranteed. Also, the system is allowed to change autonomously due to the random term, forcing participants to exercise adaptive control [1, 32]. A measure of performance is the participant's ability to accurately predict how the factory's production will respond next period to a new workforce value given this period's production [1, 2, 5]. As a result, an accurate automation-oriented approximation is required as a reference, which is demonstrated in the following section. We will find later that this new model is also robust to workload change.

2.2 Control Model of SF

As it is well known, using a feedback controller can not only correct error at the current time step, but is also likely to diminish error at the following time step. The performance of such a controller is not so sensitive to the exact value of the gain as other types of controllers (e.g. open-loop feedforward controller). Under the circumstance of existence of unanticipated disturbance in the system, a feedback controller, if suitably designed, will yield robustness of stability.

Based on these merits, we apply the feedback control theory to the analysis of the Sugar Factory task to present a relatively accurate reference to participants. As for the type of controller, PI (Proportional plus Integral) control is chosen to eliminate or diminish the error signal $e(k)$, which is the difference between the actual production $p(k)$ and the target production p^*. The primary reason for the integral part is to reduce or eliminate steady-state errors by considering all previous errors in [12], yielding

$$\eta(k) = \eta(k-1) + e(k) \tag{2}$$

where $e(k)$ is as previously defined:

$$e(k) = p^* - p(k) \tag{3}$$

Let the output from the controller be $u(k)$, which is counted to be twice the input $w(k)$ in the SF model (1).

$$u(k) = 2w(k) = 2[k_p e(k) + k_i \eta(k)] \tag{4}$$

Through these slight adjustments, the whole system could be expressed as a standard state-space formulation in control theory. In the following subsections, we will consider two kinds of circumstances separately.

(A) Ideal Case($\varepsilon = 0$)

For the sake of simplicity, first let us consider the ideal case of no stochastic disturbance existing in the system, which means that the last term ε in equation (1) is ignored. After adding (4) to the equation, the whole system is given as follows:

$$p(k) = u(k-1) - p(k-1) \tag{5}$$

Define state variables as $x(k) = \begin{bmatrix} \eta(k) \\ e(k) \end{bmatrix}$ to express the system in the state-space form, and let p^* and $p(k)$ be the system input and output separately. Then the equations could be rewritten in a more compact form [13]:

$$\begin{aligned} x(k+1) &= Ax(k) + Bp^* \\ p(k) &= Cx(k) + Dp^* \end{aligned} \tag{6}$$

where

$$\begin{aligned} A &= \begin{bmatrix} 1-2k_i & -2k_p-1 \\ -2k_i & -2k_p-1 \end{bmatrix}; \quad B = \begin{bmatrix} 2 \\ 2 \end{bmatrix} \\ C &= \begin{bmatrix} 0 & -1 \end{bmatrix}; \quad D = [1] \end{aligned} \tag{7}$$

After the control design is completed, ensuring the stability of the obtained closed-loop system is a crucial issue in control engineering. Also, stability of a linear system ensures state variable converge to its equilibrium, which is $x(k) = \begin{bmatrix} \eta_e \\ 0 \end{bmatrix}$ in our case. Consequently, if system (6)-(7) is stable, then $e(k)$ and $\eta(k)$ will converge to zero and η_e respectively as time k goes to infinity. In other words, the limit of $p(k)$ is exactly that of p^*, and this is just the case we desire.

So next we shall focus on the linear system stability criterion. For the SISO(Single-Input Single-Output) linear discrete systems to be stable, the poles of the closed-loop pulse-transfer function (derived by z-transformation) or the roots of the characteristic equation must lie within the unit circle. Any closed-loop pole outside the unit circle makes the system unstable. As for MIMO(Multi-Input Multi-Output) linear discrete systems, we can express them in the form of state space equations. The concept of pulse-transfer function is extended to the pulse-transfer-function matrix of a state space representation. Under this circumstance, stability requires all roots of

$$|zI - A| = 0 \tag{8}$$

lie within the unit circle [28]. Then the actual outcome $p(k)$ in system (6) will converge to the desired target value p^* in a certain number of time steps, if we choose proper k_i and k_p satisfying either of the following inequalities:

$$\text{(a)} \qquad \begin{cases} (k_p + k_i)^2 + 2k_p + 1 \geq 0 \\ k_p < -0.5k_i < 0 \end{cases} \tag{9}$$

or the inequalities:

$$\text{(b)} \qquad \begin{cases} (k_p + k_i)^2 + 2k_p + 1 < 0 \\ -1 < k_p < -0.5 \end{cases} \tag{10}$$

The above conditions can be derived as follows. Substituting the state matrix A in (7) into characteristic equation (8), one derives the expression of eigenvalues as

$$z = -(k_i + k_p) \pm \sqrt{(k_i + k_p)^2 + 2k_p + 1}. \tag{11}$$

Two cases appear, as shown below:
Case (a) $\quad (k_i + k_p)^2 + 2k_p + 1 \geq 0$.
This is the situation that all roots of (8) are real, then stability condition requires the following expressions:

$$\begin{cases} -(k_i + k_p) + \sqrt{(k_i + k_p)^2 + 2k_p + 1} < 1 \\ -(k_i + k_p) - \sqrt{(k_i + k_p)^2 + 2k_p + 1} > -1 \end{cases} \tag{12}$$

Case (b) $\quad (k_i + k_p)^2 + 2k_p + 1 < 0$.
In this case, the poles are complex. Inequalities below ensure the stability of the whole system.

$$|z|^2 = (k_i + k_p)^2 - [(k_i + k_p)^2 + 2k_p + 1] < 1. \tag{13}$$

Simple transformations of (12) and (13) lead to (9) and (10) directly. Thus, the proof is completed.

The following simulations demonstrate the effectiveness of our method by choosing different pairs of parameters (k_p and k_i) that satisfy the above conditions. In Figure 1, the solid line represents the actual

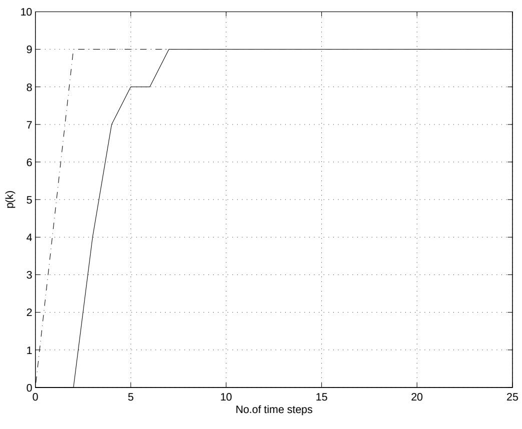

Figure 1: Invariable target value for the ideal case

sugar production output, which reaches the invariable target production value of 9000 tons of sugar (dashed line) in less than seven time steps. As for the variable target from 3000 to 9000 shown in Figure 2, it demonstrates the adaptivity to workload change of the control model. Both of the charts have presented good illustrations of obviously enhanced effectiveness to the SF task.

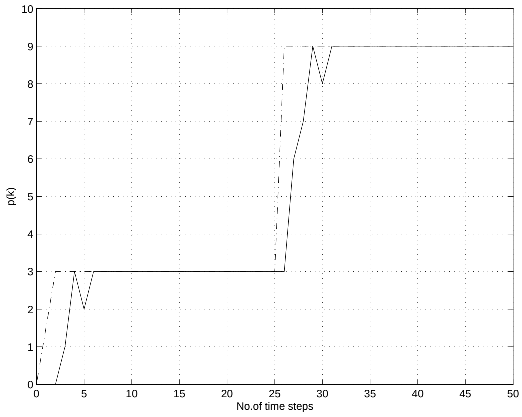

Figure 2: Variable target value for the ideal case

We remark here that the process of choosing the type of controller is crucial. If the proportional control method is chosen without the integral part, which is the so-called P control, then the main result as stated above will not hold.

(B) Practical Disturbance Case ($\varepsilon \neq 0$)

This case can be addressed by studying disturbance $\varepsilon \neq 0$, or in other words, the external stability. By *external stability*, we mean that for every Bounded Input, it should have a Bounded Output. This is also called *BIBO stable*. Using linear system theory [12], if all poles are inside the unit circle, the system with rational transfer function is BIBO stable. As we have already proved in the previous part that for parameters k_i and k_p satisfying conditions (9) or (10), system (6)-(7) has all poles inside the unit circle or is internally stable) when no disturbance exists in the system. Therefore, if we choose parameters based on these conditions, output $p(k)$ will also be bounded, accordingly when the disturbance ε is considered as the input. The following simulation results validate our conclusion. Here ε is chosen to be a group of stochastic numbers. By adding this disturbance term to the dynamic equation, it is getting closer to the actual model. One can intuitively see from Figure 3 that after several time steps, the actual production $p(k)$ (plotted in the solid line) keeps oscillating around the desired production 9000t (dashed line) in a small region, from which robustness of the control model is validated.

Figure 3 can be viewed as a reference of choosing the input number of workforce $w(k)$. Nevertheless,

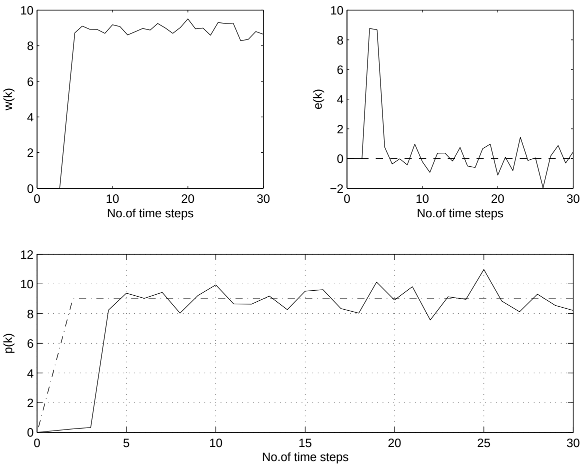

Figure 3: Disturbance case (invariable target value)

we hope that the control model we propose may help participants make better decision. One of the effective ways is that, if the oscillation is within the region of ± 1, the operator just input the number of workforce $w(k)$ as shown in the figure; if not, they adjust the number slightly according to the simulation result. Through the application of the human-machine interface, effectiveness will be enhanced greatly.

In Figure 4, the solid line denotes the actual production value due to the desired production change, which is in the form of dashed line. This figure shows the transition process of desired production from 3000t to 9000t, from which adaptivity is also well demonstrated.

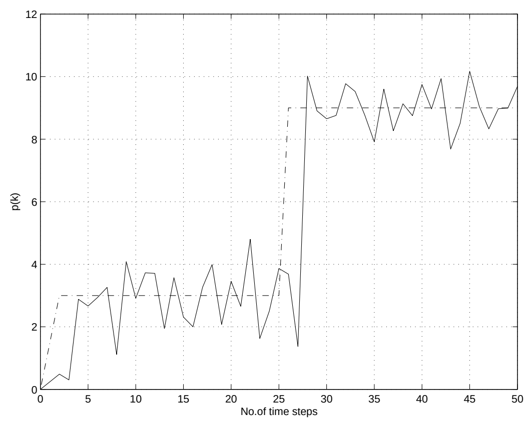

Figure 4: Disturbance case (variable target value)

3 Extended Decision Field Theory: Some preliminary results

3.1 Problem Statement

Due to the complexity and variability of automation performance, the operator's choice between automatic and manual control in supervisory control situations can be considered both a preferential choice problem and a decision-making process described by Decision Field Theory (DFT) [7, 8]. The standard elementary DFT model used to investigate decision making under risk or uncertainty could be described through a straightforward example in supervisory control. Suppose one is facing the problem of choosing whether to rely on automation (A) or to intervene with manual control (M), as shown in the following chart. In Figure

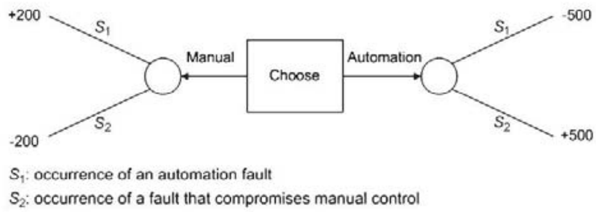

Figure 5: DFT choosing model in a supervisory control situation [15]

5, S_1 and S_2 are two interdependent uncertain events, one of which may occur at a certain time point. S_1 denotes the occurrence of an automation fault and S_2 represents the incidence of a fault that compromises manual control. During the course of decision making, the valence of an action V_i (i = A or M) is defined as the subjective expected payoff for each action also fluctuates from sample to sample, which is relevant to the subjective probability weight $W(S_j)$ and the utility of the payoff [6]. The preference state at sample n is derived based on the accumulated valence difference:

$$\begin{aligned} P(n) &= (1-s) \times P(n-1) + [V_A(n) - V_M(n)] \\ &= (1-s) \times P(n-1) + [d + \varepsilon(n)]. \end{aligned} \tag{14}$$

Let C represent the true capability of the automation (C_A) or manual control (C_M). The former symbol describes the reliability of the automation in terms of fault occurrence and general ability to accomplish the task under normal conditions, while the latter one describes how well the operator can manually control the system in various situations. B_C denotes the belief or estimation of the capability of automation (B_{CA}) or the operator's manual capability (B_{CM}). In the EDFT model, sequential decision processes are linked by dynamically updating beliefs regarding the capability of automation or manual control based on previous decisions in order to guide the next decision as follows [15]:

$$B_C(n) = B_C(n-1) + \frac{1}{b_1}(C(n-1) - B_C(n-1)). \quad (15)$$

The value b_1 ($b_1 \geq 1$) represents the level of transparency of the system interface, describing how well information is conveyed to the operator when capability information is available. $b_1 = 1$ means the information is perfectly conveyed to the operator. The larger b_1 is, the more poorly information is conveyed to operator.

There is a formulation depicted in [14] that beliefs represent the information base that determines attitudes and then attitudes determine intentions and consequently behaviors. Under the circumstance of supervisory control, trust and self-confidence are both attitudes that depend on beliefs, while at the same time, they determine preference and reliance. Take T and SC as the denotation of trust and self-confidence, which are updated by B_{CA} and B_{CM} as the new input respectively. Preference of A over M is defined as the difference between trust and self-confidence at time step n in the EDFT model, denoted by $P(n)$ [15]:

$$\begin{aligned} P(n) = T(n) - SC(n) &= [(1-s) \times T(n-1) \\ &+ s \times B_{CA}(n) + \varepsilon(n)] - [(1-s) \times SC(n-1) \\ &+ s \times B_{CM}(n) + \varepsilon(n)] = (1-s) \times P(n-1) \\ &+ s \times [B_{CA}(n) - B_{CM}(n)] + \varepsilon_P(n). \end{aligned} \quad (16)$$

Here the difference between C_A and C_M corresponds to d, and $P(n)$ combined with other factors such as time constraints will determine whether to actually rely on automation or not.

3.2 Model Modification

In a supervisory control system, operators are sensitive to the ability of predicting the capacity of automation or manual control, and previous findings suggest that operator's trust is closely linked with the capacity of automation [27]. More specifically, people's trust on automation may vary according to the change of discrepancy between the operators' expectation and the true behavior (the capacity) of automation. Consequently, though it is useful to get to know the influence of capacity C on trust, it is necessary to examine whether the expectation of capacity is close to the practical situation if we are to develop a predictive model of trust in automation and intervention behavior. Improving the accuracy of operators' perception to the system capacities will also greatly enhance the appropriateness of their trust in automation. Based on this, it is necessary to develop a modified model that can better reflect appropriate trust.

One of the effective ways to modify the EDFT model is to consider the discrepancy between the capacity of two sequential time steps. Accordingly, belief is expressed as:

$$\begin{aligned} B_C(n) &= B_C(n-1) + \frac{1}{b_1}(C(n-1) - B_C(n-1)) \\ &+ (1 - \frac{1}{b_1})(C(n-1) - C(n-2)). \end{aligned} \quad (17)$$

By transposing (17), we will get:

$$X(n-1) = (1 - \frac{1}{b_1})X(n-2), \quad (18)$$

where $X(n-1) = B_C(n-1) - C(n-2)$. Equation (18) constitutes a contraction mapping, from whose definition we know that $X(n-1)$ converges to 0 for a enough large n. Consequently, $B_C(n-1)$ will eventually converge to $C(n-2)$ as time step n increases.

Modifying the generation of belief in pattern of (17) enables operators to generate their belief much closer to the true capacity, and it provides a better understanding of how automation works. As a result, the operators' trust in automation will grow, and thus lead to more appropriate reliance on automation. The effectiveness is demonstrated through simulation in the next subsection.

3.3 Simulation Results

Some work on designing an automated aid to simulate the actual production output of the Sugar Factory has already been done in Section 2. Since operators play an important role in this system to decide whether to adopt automation or not, this model can also be considered as a supervisory control system. In this part, we will take this general case for example.

The capability of automation is commonly manifested by its ability to achieve the goals of the operator in a consistent fashion. It is a critical parameter that describes the automation and should not be randomly selected. Under the circumstance of the SF supervisory control task, we can treat the error signal between actual output and desired output as a measure of automatic ability, that is the system's true capability of automation C_A. By using the EDFT model, the belief or estimation of the automation B_{CA1} is generated by equation (15), while B_{CA2} is generated by using our modified EDFT model (17). Depending on whether there exists random noise in the system, we simulate separately to compare these two beliefs.

Figure 6 presents the comparison result under the non-disturbed circumstance with $b = 2$, while Figure 7 corresponds to the similar situation with $b = 100$. As it is defined previously that the parameter b represents the transparency of the system interface, one could straightforwardly find that the beliefs derived by our modified approach are closer to the original capacity of automation C_A than those updated by the EDFT model in both cases. This phenomenon becomes more distinct as b grows larger, which is the circumstance that information is not well conveyed to the operator. Thus the predominance of our approach is verified.

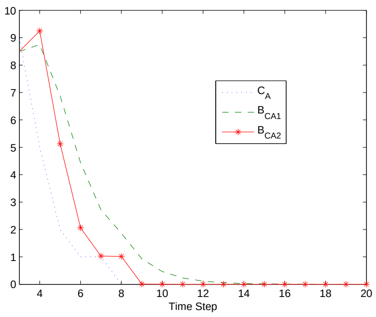

Figure 6: Comparison of B_{CA1} and B_{CA2} when no disturbance exists $(b = 2)$

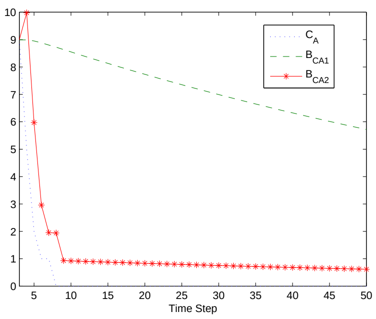

Figure 7: Comparison of B_{CA1} and B_{CA2} when no disturbance exists $(b = 100)$

As for the disturbance case, one can get a more obvious understanding of the superiority to the modified EDFT approach. Figure 8 shows the case in which stochastic disturbance exists, from which we can see that the original EDFT model just make belief fluctuate randomly without any inhibition on disturbance. On the other hand, the modified approach enables belief to match the capacity of automation quite well in a short period's time.

We could also combine trust and self-confidence with other factors of attitude like perceived risk and mental workload to form the intention of preference. In such cases, it comes to the multiple choice problem

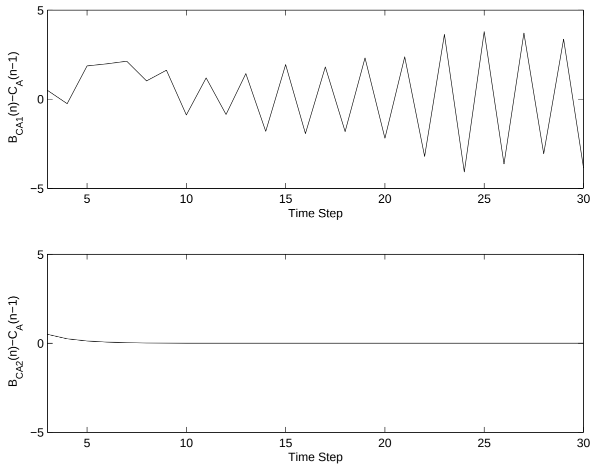

Figure 8: Difference between $B_{CAi}(i = 1, 2)$ and C_A in the disturbance case $(b = 2)$

in a dynamic decision making task. In order to solve such problems, a MDFT (multi-alternative DFT) formulation [31] is required to be extended as an EMDFT model.

4 Conclusions and Future Work

This paper presents a control-theoretic approach to learning in dynamic decision making tasks to the study of Sugar Factory task. By constructing a control model, it presents a fairly good estimation of automation control capability to participants. Also, the model provides an accurate approximation and a reliable reference to participants through the demonstration of simulation. Aiming at enhancing appropriate trust in automation in a supervisory control system, a modified approach to the previous EDFT model is proposed to provide a more accurate approximation of trust. Feasibility is demonstrated by both theoretic analysis and simulation through a Sugar Factory supervisory control system. The model becomes robust to disturbance irrespective of the fluctuations after modification, and the effectiveness is demonstrated.

Currently, we are working towards improving the proposed control model from the following aspects:
(1) Addressing the above-mentioned constraints on the number of workers $w(k)$ and the production value $p(k)$;
(2) Optimal choice of parameters for improved performance;
(3) Other types of high-level control method like nonlinear control for further performance improvement.

As for the modified EDFT model, experiments should be conducted to further verify the effectiveness of the modified approach in the future.

Acknowledgements: This work is supported in part by the U. S. Air Force Office of Scientific Research. This work was done when the first author was visiting the Polytechnic University under a Fellowship from the China Scholarship Council. Also, the authors thank Feng Ma (Graduate Assistant) for help in simulation.

References:

[1] D. C. Berry and D. E. Broadbent, On the relationship between task performance and associated verbalizable knowledge, *Quarterly Journal of Experimental Psychology* 36A, 1984, pp. 209–231.

[2] D. C. Berry and D. E. Broadbent, The combination of explicit and implicit learning processes in task control, *Psychological Research* 49, 1987, pp. 7–15.

[3] B. Brehmer, Strategies in real-time, dynamic decision making. In R. Hogarth (Ed.), *Insights from decision making*, Chicago: IL: University of Chicago Press, 1990, pp. 262–279.

[4] B. Brehmer, Dynamic decision making: Human control of complex systems, *Acta Psychologica* 81, 1992, pp. 211–241.

[5] A. Buchner, J. Funke and D. C. Berry, Negative correlations between control performance and verbalizeable knowledge: Indicators for implicit learning in process control tasks, *Quarterly Journal of Experimental Psychology* 48A(1), 1995, pp. 166–187.

[6] J. R. Busemeyer, Decision making under uncertainty: A comparison of simple scalability, fixed-sample, and sequential-sampling models, *Journal of Experimental Psychology* 11, 1985, pp. 538–564.

[7] J. R. Busemeyer and J. T. Townsend, Decision field theory: A dynamic cognitive approach to decision making in an uncertain environment, *Psychol. Rev.* 100(3), 1993, pp. 432–459.

[8] J. R. Busemeyer and A. Diederich, Survey of decision field theory, *Math. Soc. Sci.* 43(3), 2002, pp. 345–370.

[9] D. Fum and A. Stocco, Instance vs. rule based learning in controlling a dynamic system, *Proceedings of the international conference on cognitive modelling*, Universitats-Verlag Bamberg, Bamberg, Germany, 2003, pp. 105–110.

[10] Z. Dienes and R. Fahey, Role of specific instances in controlling a dynamic system, *Journal of Experimental Psychology: Learning, Memory, and Cognition* 21, 1995, pp. 848–862.

[11] S. Farrell and S. Lewandowsky, A connectionist model of complacency and adaptive recovery under automation, *Journal of Experimental Psychology: Learning, Memory, and Cognition* 26(2), 2000, pp. 395–410.

[12] G. F. Franklin and J. D. Powell and M. L. Workman, *Digital Control of Dynamic Systems*, Addison-Wesley Publishing Company, Inc. 1992

[13] G. F. Franklin and J. D. Powell, *Feedback Control of Dynamic Systems*, New Jersey: Pearson Prentice Hall 2006

[14] M. Fishbein and I. Ajzen, *Belief, Attitude, Intention, and Behavior*, Reading, MA: Addison-Wesley 1975

[15] J. Gao and J. D. Lee, Extending the Decision Field Theory to Model Operators' Reliance on Automation in Supervisory Control Situations, *IEEE Trans. Syst., Man, Cybern. A, Syst., Humans* 36(5), 2006, pp. 943–959.

[16] F. P. Gibson and D. C. Plaut, A connectionist formulation of learning in dynamic decision-making tasks,*Proceedings of the 17th Annual Conference of the Cognitive Science Society* , 1995, pp. 512–517.

[17] F. P. Gibson, The Sugar Production Factory– A Dynamic Decision Task, *Computational and Mathematical Organization Theory 2:1*, 1996, pp. 49–60.

[18] F. P. Gibson, M. Fichman and P. Plaut, Learning in dynamic decision tasks: computational model and empirical evidence, *Organizational Behavior and Human Decision Processes* 71(1), July, 1997, pp. 1–35.

[19] R. M. Hogarth, Generalization in decision research: The role of formal models, *IEEE Transactions on Systems, Man, and Cybernetics* 16, 1986, pp. 439–449.

[20] M. I. Jordan, Constrained supervised learning, *Journal of Mathematical Psychology* 36, 1992, pp. 396–425.

[21] M. I. Jordan, Computational aspects of motor control and motor learning, In H. Heuer, and S. Keele (Eds.), *Handbook of perception and action: Motor skills*, New York: Academic Press 1997

[22] M. I. Jordan and D. E. Rumelhart, Forward models: Supervised learning with a distal teacher, *Cognitive Science* 16(3), 1992, pp. 307–354.

[23] J. D. Lee and N. Moray, Trust, control strategies, and allocation of function in human-machine systems, *Ergonomics* 35(10), 1992, pp. 1243–1270.

[24] J. D. Lee and N. Moray, Trust, self-confidence, and operators' adaptation to automation, *Int. J. Human-Comput. Stud.* 40(1), 1994, pp. 153–184.

[25] J. D. Lee and K. A. See, Trust in Automation: Designing for Appropriate Reliance, *Human Factors* 46(1), Spring 2004, pp. 50–80.

[26] B. M. Muir, Trust in automation 1: Theoretical issues in the study of trust and human intervention in automated systems, *Ergonomics* 37(11), 1994, pp. 1905–1922.

[27] B. M. Muir and N. Moray, Trust in automation 2: Experimental studies of trust and human intervention in a process control simulation, *Ergonomics* 39(3), 1996, pp. 429–460.

[28] K. Ogata, *Discrete-time Control Systems*, New Jersey: Prentice-Hall 1987

[29] R. Parasuraman and V. Riley, Humans and automation: Use, misuse, disuse, abuse, *Hum. Factors* 39(2), 1997, pp. 230–253.

[30] D. W. Repperger and C. A. Phillips, The Human Role in Automation, *Handbook of Automation*, Springer –Verlag, April 2008

[31] R. Roe, J. R. Busemeyer and J. T. Townsend, Multialternative decision field theory: A dynamic connectionist model of decision-making, *Psychol. Rev.* 108(2), 2001, pp. 370–392.

[32] W. B. Stanley, R. C. Mathews, R.R. Buss and S. Kotler-Cope, Insight without awareness: On the interaction of verbalization, instruction, and practice in a simulated process control task, *Quarterly Journal of Experimental Psychology* 41A(3), 1989, pp. 553–577.

[33] N. A. Taatgen and D. Wallach, Whether skill acquisition is rule or instance based is determined by the structure of the task, *Cognitive Science Quarterly* 2, 2002, pp. 163–204.

[34] A. C. Wick, S. L. Berman and T. M. Jones, The structure of optimal trust: Moral and strategic, *Academy of Management Review* 24, 1999, pp. 99–116.

[35] R. E. Wood and A. Bandura, Impact of conceptions of ability on self-regulatory mechanisms and complex decision making, *Journal of Personality and Social Psychology* 56, 1989, pp. 407–415.