Human and Robot Collaborative Assembly Manufacturing: Trust Dynamics and Control

Behzad Sadrfaridpour
Dept. of Mechanical Engineering
Clemson University
Clemson, S.C. 29634
Email: bsadrfa@g.clemson.edu

Jenny Burke
Boeing Research & Technology
North Charleston, SC 29418
Email: jennifer.l.burke2@boeing.com

Yue Wang
Dept. of Mechanical Engineering
Clemson University
Clemson, S.C. 29634
Email: yue6@clemson.edu

***Abstract*—Human and robot collaboration is attracted lots of attention in manufacturing assembly. In such environments, human and robot work with each other as coworkers. The key question is what are the proper strategies for manipulating the robot(s) during this collaboration in order to have the best outcomes considering both human factors and overall system performance. For repetitive tasks in assembly lines, the human's dynamic trust to robot can be used as a criterion for adjusting and updating the robot parameters and attributes. In our work, we propose a model for dynamic trust of human to robot based on the robot performance and the human performance. The human performance model consists of physical and cognitive parts. The human physical performance is inspired the human muscular fatigue and recovery model. The cognitive human performance is based on mental work load needed for performing a task collaboratively. The robot performance indicates its capability to adjust speed in order to keep up with the human coworker. In this paper, we explain the human performance, robot performance and trust. Moreover, we demonstrate our model by simple simulation when the human adjusts the robot manually. For future work, we will focus on adjusting the robot autonomously. Moreover, we seek to find the switching signal for switching between manual and autonomous mode.**

I. INTRODUCTION

Despite the advance in computer-integrated manufacturing system (CIMS), assembly lines remain highly labor intensive [1]. Recent developments in automation have allowed collaboration between human workers and robots so that some of the repetitive assembly tasks can be performed by robots [1]. In such settings, a human worker and a peer human-friendly robot partner work side-by-side with each other for higher product quality, improved ergonomics, and lower cost [3, 14]. However, improper human-robot interaction (HRI) may cause counter effects such as misuse, overuse, or abuse of machine and/or safety issues [10]. Hence, there arises a need for investigating HRI in smart manufacturing, especially, intelligent assembly. It is possible that many factors may influence HRI [4], in this paper, we focus on human's trust to manufacturing robot. Automation reliability and the operator's trust in automation are major factors influencing human's decision to use (or not to use) automation [11].

Extant works in trust from human factors and artificial intelligence have concentrated on human machine interface design and empirical measurements of trust [3, 4]. Statistical tools have been used to provide design guidance [15]. However, there is a lack for analytical study of the dynamic evolution of trust which hinders the systematic prediction of system performance and human experience. Our main objective is to find real-time analytical model of trust in automation. In [13], inspired by [6], we utilize the concept of trust among people to study trust in automation. In the human robot collaborative mode, when a human worker observes a discrepancy between his/her own performance and his/her expectations from the robot partner, the trust to the robot decreases accordingly. When the robot performance matches human expectation, the human's trust to robot increases. In this paper, we improve our model of trust by considering how both robot and human action will affect each other. Then, we demonstrate our simulation results for the case that the human adjusts the robot manually.

II. HUMAN PERFORMANCE

Workload refers to the total amount of work that a person or group of people is to perform over a given period of time [12]. Mental workload is the amount of mental work or effort necessary to perform a task in a given period of time [12]. In work setting, human performance will decrease due to performing repetitive tasks. Moreover, the performance may suffer if the mental workload is too high or too low [12]. In other words, human performance depends on both the individual's physical states and cognitive workload. We introduce rigorous mathematical formulations for both performances in this section.

A. Human Physical Performance

We adopt the muscle fatigue and recovery model proposed in [9, 2] for the physical performance. Such a model, explains how a muscle or group of muscles get fatigued or recovered when performing physical tasks. The maximum human physical performance occurs at the situation when a human is not subjected to any fatigue, and the minimum performance occurs when the human is experiencing the maximum level of fatigue. The details of the muscle fatigue and recovery model and the corresponding human performance model are presented in our previous work [13]. Next, we briefly introduce the major models used in this work.

When a muscle applies some force for an amount of time, the maximum isometric force that one can produce, $F_{max,iso}(k)$, decreases. The initial maximum isometric force one can generate at rest, is called Maximum Voluntary Contraction (MVC). When the muscle does not apply any force, it gets recovered [8]. Denote the real-time applied force as $F(k)$. Both the fatigue and recovery processes are functions of time and MVC [7, 9]. We use a discrete-time fatigue and recovery model to represent the dynamic evolution of the maximum isometric force [2]

$$F_{max,iso}(k) = F_{max,iso}(k-1) - C_f F_{max,iso}(k-1)\frac{F(k-1)}{MVC} + C_r(MVC - F_{max,iso}(k-1)), \tag{1}$$

where C_f is the fatigue constant and C_r is the recovery constant, having different values for different persons. Equation (1) has an equilibrium point at which the fatigue and recovery balance out. This point is the lowest limit (threshold) of the $F_{max,iso}(k)$. This threshold force, F_{th}, can be calculated by assuming $F_{max,iso}(k) = F_{max,iso}(k-1)$

$$F_{th} = MVC\frac{C_r}{2C_f}(-1 + \sqrt{1 + \frac{4C_f}{C_r}}).$$

Since the fatigue and recovery model predicts the human muscle status related to physical workload, we present the following model for human physical performance, P_P

$$P_P(k) = \frac{F_{max,iso}(k) - F_{th}}{MVC - F_{th}}. \tag{2}$$

Note that in Equation (2), $F_{max,iso}$ varies between the minimum value F_{th} and the maximum value MVC, therefore it is a normalized value between the minimum physical performance $P_P = 0$ and its maximum value $P_P = 1$.

Using Equations (1) and (2), we have the following dynamic model for the human physical performance $P_P(k)$

$$\begin{aligned} P_P(k+1) &= (1 - \frac{C_f F(k)}{MVC} - C_r)P_P(k) \\ &\quad - \frac{C_f F(k) F_{th}}{(MVC - F_{th})MVC} + C_r. \end{aligned} \tag{3}$$

Assume that for a particular task, the applied force is constant, i.e. $F(k) = F_0$. Thus, we can rewrite Equation (3) as

$$\begin{aligned} &P_P(k+1) = aP_P(k) + b, \\ &a = (1 - \frac{C_f F_0}{MVC} - C_r), \\ &b = -\frac{C_f F_0 F_{th}}{(MVC - Fth)MVC} + C_r. \end{aligned} \tag{4}$$

B. Human Cognitive Performance

Stress comes from variety of causes and may has degradation effects on performance on some tasks [15]. Environmental stressors, psychological stressors, life stress, fatigue and sleep disruption, and workload overload have effects on stress [15]. Most of these parameters should be considered in design level of the line. In fact human cognitive workload has a significant impact on human performance. Based on the Yerkes−Dodson law [16], by increasing the level of arousal, the human cognitive performance increases up to a point known as optimum level of arousal (OLA) and then degrades as the arousal increases further. Moreover the OLA has a higher value for simpler tasks or for more highly skilled human operators [15]. In manufacturing environment, a repetitive action on an assembly line is time-consuming but not particularly demanding of cognitive resources or effort [15]. However, a similar task may demand cognitive efforts in a human and robot collaborative assembly line. In our model, we consider the effect the interaction of human and robot on human cognitive workload. If the robot works with different progress rate as the human, then the human cognitive performance may suffer. For repetitive tasks, progress rate of human and robot can be determined at the end of each task by measuring the corresponding demanded time. In Section III, we will define robot performance as a function of the difference between robot and human progress rate. In order to collaborate with robot, the human may need some efforts if robot performance has a low value. Thus we assume that if the robot performance increases, the level of arousal increases as well. Moreover, we assume that the human performance remains on the left side of the inverted U function of performance and it does not pass the OLA since the task for skilled human worker is less complex. In other words, there is a linear relation with the human cognitive performance and the robot performance. In mathematical form, the cognitive performance depends on previous cognitive performance and the robot adaptation of human behavior, i.e.,

$$P_C(k+1) = cP_C(k) + dP_R(k). \tag{5}$$

where c and d are constant values between 0 and 1 such that $c + d = 1$. $P_R(k)$ is the robot performance at time step k and it is the capability of robot to adjust in order to accommodate human performance. Section III describes the robot performance in details. P_R is between 0 and 1. The initial value of P_C is between 0 and 1 as well. Thus, P_C remain between 0 and 1 at each time step.

C. Human Performance Model

After defining human physical (equation 4) and cognitive performance (equation 5), we can now define the total human performance which is a weighted sum of both performances, i.e.,

$$P_H(k) = K_P P_P(k) + K_C P_C(k), \tag{6}$$

where K_P and K_C are constant values between 0 and 1 such that $K_P + K_C = 1$.

III. ROBOT PERFORMANCE

We define robot performance as its capability to adjust speed in order to keep up with the human co-worker. In other words, the robot performance is deemed high whenever it performs tasks in a similar pace as the human worker. During the collaboration of human and robot, robot speeds can be adjusted either by the human manually or by an autonomous controller.

When the manual mode is activated, the robot performance will increase simply because the human can adjust the robot to accommodate his/her performance.

In order to measure the robot performance, we need to compare the human and robot rate of progress during the task. In assembly lines since we know how we programmed the robot at the first place, and we set the robot different working parameters and attributes (either manually or autonomously), for a given task we can find out the robot progress rate. Human progress can be obtained by feedbacks from task completion. For example, a simple way to measure human progress is to record the time and the number of assembly tasks finished up to the moment. Hence, the dynamical model of robot performance can be described as

$$P_R(k+1) = P_{R,max} - (V_H(k) - V_R(k)), \tag{7}$$

where $P_{R,max}$ is the maximum value of the robot performance. V_H and V_R represent human and robot progress rate, respectively. In the full paper, we will discuss in detail the adjustment of the robot progress rate, V_R, so that a desired trust level can be achieved. For a repetitive task, we update the value of human progress rate, V_H whenever the task finishes. We use this value as a progress rate of a next similar task. There is a fastest progress rate that an individual performs during a specific task. This value determines the corresponding maximum value of V_H. Moreover, V_H cannot be updated sooner than the time that an individual can finish the particular task with the maximum value of V_H.

IV. TRUST DYNAMICS & CONTROL

Trust among people is related to the extent to which that an individual can believe another person will carry out actions that are expected [15]. Trust in automation has similar meaning [5]. Our trust in the agent, whether human or computer, should be in direct proportion to its reliability [15]. We can interpret that human's trust to robot depends on both human and robot performance. Lee et al. [5] found a mathematical relation between trust, system performance and fault occurrence. Inspired by our interpretation of trust and their findings our proposed dynamic model of trust is

$$T(k+1) = K_T T(k) + K_R P_R(k) + K_H P_H(k), \tag{8}$$

where K_T, K_R and K_H are positive constants. The human's trust to robot is high as long as both human and robot performances have high values. In contrast, trust will reach a minimum if neither the human nor the robot works with acceptable performances.

A. *State Space Model of Trust Dynamics*

For the purpose of control design, we show that the human performance, robot performance and trust dynamics can be written into the following state-space representation

$$\begin{bmatrix} P_P(k+1) \\ P_C(k+1) \\ P_R(k+1) \\ T(k+1) \end{bmatrix} = \begin{bmatrix} a & 0 & 0 & 0 \\ 0 & c & d & 0 \\ 0 & 0 & 0 & 0 \\ K_H K_P & K_H K_C & K_R & K_T \end{bmatrix} \begin{bmatrix} P_P(k) \\ P_C(k) \\ P_R(k) \\ T(k) \end{bmatrix} + \begin{bmatrix} b \\ 0 \\ P_{R,max} - (V_H(k) - V_R(k)) \\ 0 \end{bmatrix}. \tag{9}$$

Note that in general, we can adjust the robot manually or/and autonomously. Based on the agent (human or/and robot) that adjust(s) the robot, the robot performance and human performance may evolve differently. In Equation (9), we assume that human and robot performance evolve similarly in both manual and autonomous mode.

TABLE I
PRELIMINARY SIMULATION PARAMETERS

Parameter	Value
C_f	10^{-4}
C_r	2.4×10^{-4}
MVC	200
F_{th}	151.9
F_0	50
a	0.9997
b	1.6×10^{-4}
K_P	0.5
K_C	0.5
c	0.75
d	0.25
K_T	0.5
K_R	0.25
K_H	0.25

V. PRELIMINARY SIMULATION RESULTS

To demonstrate our models, we simulate a collaboration of a human and robot on performing a series of similar repetitive tasks in 9 hours. Finding the correct values of the parameters of our proposed equations requires experimental data. The values used for the simulation are presented in Table I. These values need to be modified after experiments. In this setup, the robot progress rate remains constant during each task, i.e., the human worker can only adjust the robot progress rate at the start of each task. Moreover, if robot collaborates perfectly and the human has highest possible progress rate, $V_{H,max}$, the fastest time the job can be finished is $t_{min} = 15$ (minutes). if the human performs a task with the progress rate $\bar{V} < V_{H,max}$, then the time required to finish the task time, $\bar{t}$, is greater than t_{min}. In general, human progress rate, V_H and human performance, P_H can evolve with different trends. However, it is reasonable to assume that V_H is a function of P_H. In the simulation, we set V_H as a function of human performance,

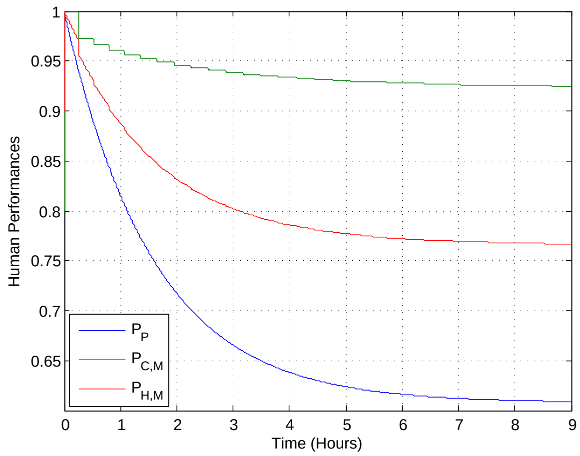

Fig. 1. Evolutions of human physical performance P_P, human cognitive performance P_C and human performance P_H in manual mode.

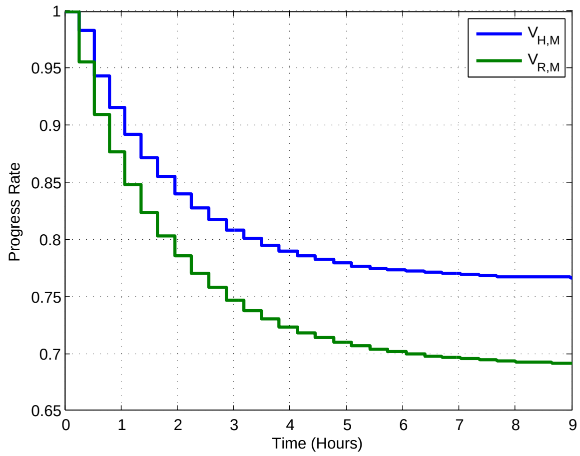

Fig. 2. Evolutions of human progress rate V_H and adjustments for robot progress rate V_R in manual mode.

P_H. In reality, however, the human progress rate can only be determined when the task is finished. In simulation we calculate the time that the human worker spends to finish a task based on his/her average performance $\bar{P_H}$. We only update the value for V_H at the end of each task($V_H = \bar{P_H}$). For the initial value of V_H, we use the initial value of robot progress rate, i.e. $V_H(0) = V_R(0)$. After defining the task parameters, we need to decide how the robot progress rate will be started at the start of each task. In our simulations, we used three different modes for adjusting the robot progress rate including manual, autonomous and collaborative mode. Next we will discuss each of these modes.

A. Manual Mode

We assume that in manual mode, the human worker will adjust the robot performance at start of each task. The human worker benefits the most if the robot performs the task with a progress rate close to his/her progress rate. However, it is hard for human worker to adjust the robot progress rate to be exactly equal to his/her real progress rate value. In our setup of V_R, we assume that the human worker adjusts the robot progress rate to some value close to his/her progress rate but with some small error. Due to the cognitive demands for adjusting the robot progress rate, this error value increases as time passes. Figure (1) and Figure(2) show how human performances and progress rate change respectively in manual mode.

B. Autonomous Mode

In autonomous mode, the robot will adjust its performance at start of each task. Robot tries to set its progress rate close to human worker progress rate. However, similar to manual mode the robot cannot determine the exact value of human progress rate. Therefore, there will be a error. Since at the beginning the human physical performance changes rapidly, the error value is high. However, this value decreases over time. Figure (3) and Figure(4) show how human performances and progress rate change respectively in autonomous mode.

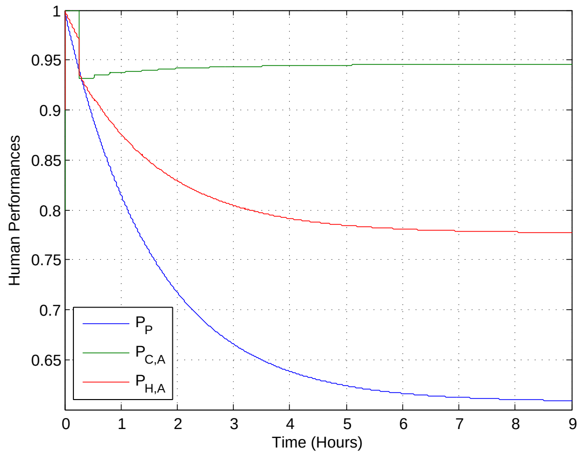

Fig. 3. Evolutions of human physical performance P_P, human cognitive performance P_C and human performance P_H in autonomous mode.

C. Collaborative Mode

Our goal in collaborative mode is to have the best outcome by switching between manual and autonomous mode. One solution is to switch between the manual mode and autonomous mode by determining the error value between human and robot progress rate. At start of each task we check the error value between the human and robot progress rate. If this value is higher than a certain threshold value, that means the human cognitive demands are high. In this case we switch the autonomous mode so the human worker cognitive performance revives. If the error becomes less than the threshold value at the start of the task, we ask the human worker to adjust the robot progress rate. Figure (5) and Figure(6) show how

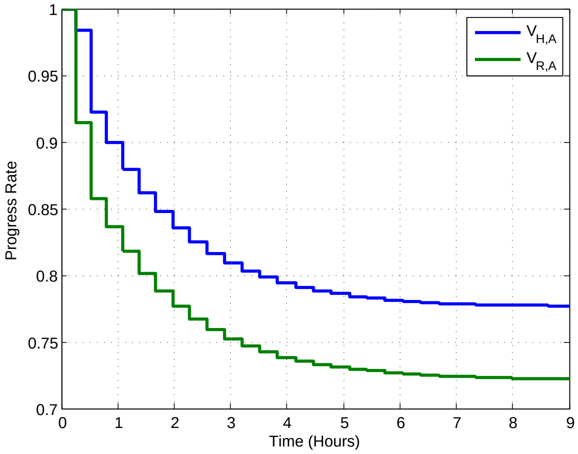

Fig. 4. Evolutions of human progress rate V_H and adjustments for robot progress rate V_R in autonomous mode.

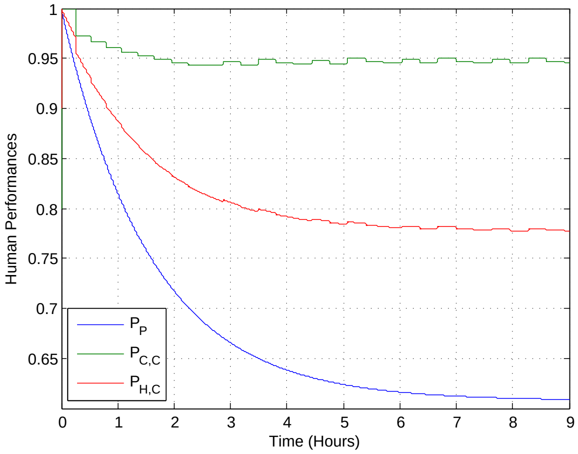

Fig. 5. Evolutions of human physical performance P_P, human cognitive performance P_C and human performance P_H in collaborative mode.

human performances and progress rate change respectively in collaborative mode.

Figure 7 and 8) show how the robot performance and trust changes in different modes. As can be seen in the Figure 8), in the manual mode the trust value is higher compare to the autonomous mode. However, after some point, the trust value becomes higher in the autonomous mode. Moreover, the highest value of trust is achieved in the collaborative mode. Figure 9 shows the switching signal between manual and autonomous modes for the collaborative mode.

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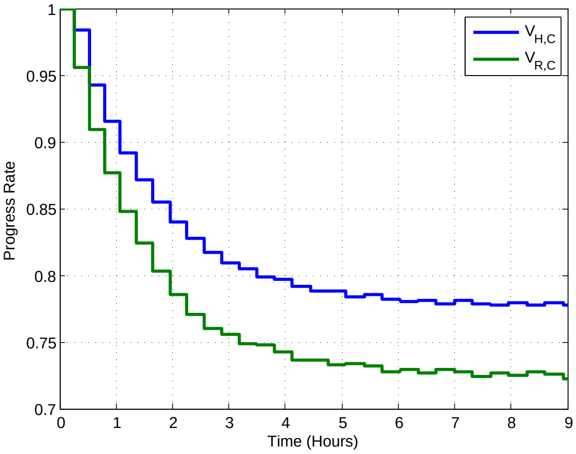

Fig. 6. Evolutions of human progress rate V_H and adjustments for robot progress rate V_R in collaborative mode.

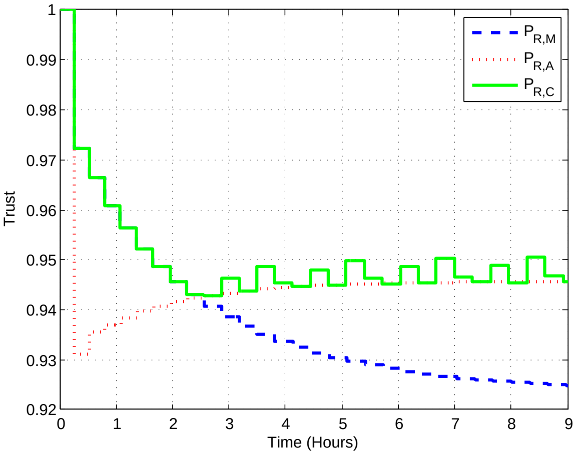

Fig. 7. Evolution of robot performance P_R.

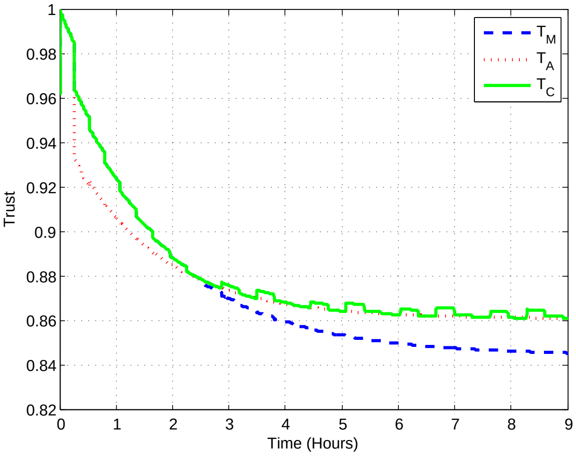

Fig. 8. Evolution of human trust to robot T.

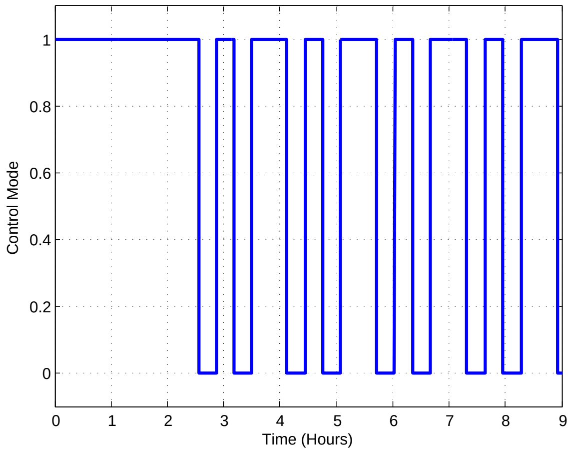

Fig. 9. Control signal; 0: autonomous, 1: manual.

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