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The Effect of Job Similarity on Forgetting in Multi-Task Production

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Abstract

For many decades, research has been done on the effect of learning and forgetting for manual assembly operations. Due to the evolution towards mass customization, cycle time prediction becomes more and more complex. The frequent change of tasks for an operator results in a rapid alternation between learning and forgetting periods, since the production of one model is causing a forgetting phase for another model. a new mathematical model for learning and forgetting is proposed to predict the future cycle time of an operator depending on the product mix of his actual assembly schedule. A main factor for this model is the job similarity between the task that is being learned and is being forgotten. In our experimental study the impact of job similarity onto the forgetting effect is measured. Two groups of operators were submitted to an equal time schedule, with other tasks to perform. At first, both groups were asked to perform the same main task. In the subsequent phase, they were submitted to different assembly tasks, each with another job similarity towards the main task, before again executing that main task. After a period of inactivity, the main task was assembled again by every subject. Results confirm that a higher job similarity results in a lower forgetting effect for the main task.

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1. Introduction

Current trend in manufacturing companies is mass customization. This means that a large variety of products has to be produced in the same assembly workspace. This introduced the mixed-model assembly lines where manual assembly operators are challenged more than before because of the high job variance. Since operators ensure the flexibility on the shop floor, they remain the key assets of many manufacturing companies. Due to the increased complexity of the operator's work load, they are more likely to experience stress or to be unsatisfied by the feeling that they are not fit to the job [1]. It is thus important to provide additional support for manual assembly operators in a mixed-model environment. There are many ways to support operators with the cognitive load they experience: online training, offline training [2], providing context-aware instructions [3], etc.

Next to different ways to support an assembly operator, the timing of the additional support is crucial for an optimal effect. In order to plan a training or decide what instruction fits best for a specific operator-job combination, the skill level must be estimated. To do so, learning and forgetting curves can be used to predict the cycle time of the operator. Furthermore a similar model could be used to estimate the quality of assembly. The learning and forgetting effect of manual assembly operators have been studied for a very long time already. The main purposes of these studies are: line balancing problems [4], optimal lot size predictions, strategical job assigning [5] and labor cost estimations [1]. At this point, many different curves are presented including a large number of factors [6]. For learning, the experience of the worker and the complexity of the task are reported to be important factors. More experienced workers learn faster, but forget quicker as well. A more complex task will slow down the learning process and increase the forgetting effect of a task. Other factors affecting the forgetting effect are the duration of interruption and experience on the job at the beginning of the interruption. There are also factors on which different studies do not agree. The forgetting rate, for example, is not depending on the learning rate according to different studies [7], while other research claims the opposite [8,9].

Despite the great amount of publications on this topic, there is no learning and forgetting model for the specific case of a mixed-model assembly environment. Focusing on the forgetting effect, the present models assume an interruption of a repetitive task. However, in a mixed-model assembly environment, operators are supposed to assemble different kinds of products at the same assembly line and while assembling one model, another model is not learned and moreover forgotten. This means that forgetting not only occurs when a repetitive task is interrupted, but this same effect will also show up when another task is performed. The circumstances of these two forgetting phases are not equal. In this study, the authors investigate the influence of job similarity onto the forgetting rate.

Some theoretical background on learning and forgetting is pointed out in section 2. The urge of further studies on the effects in a mixed model environment is demonstrated. An experiment was conducted to get more insights in this phenomena and is described in section 3. Next, the results of the experiment are summarized in section 4. At last, the discussion of the results and a view on the next steps in this research are given in section 5.

2. Theoretical background

2.1. LFCM (learn- forget curve model)

There are a lot of different models for the prediction of learning and forgetting. Most of the learning curves are log-linear, exponential or hyperbolic models [10]. A commonly used learning and forgetting model is the LFCM of Jaber and Bonney [11]. The model has shown a good performance on empirical data and it is easy to implement by the low level calculations and the high flexibility [12]. Therefore this model will be adapted to fit the needs of a mixed-model environment for cycle time prediction. The main principle of the LFCM is that there are two phases that can be distinguished, a learning phase and a forgetting phase. During the learning phase, the assembly time decreases by an exponential function as introduced by Wright [13], with following equation:

$$T_x = T_1 \cdot x^{-l} \tag{1}$$

with T_x as the time to produce the x^{th} unit and l as the learning coefficient. This is the learning model which is most frequently used to predict assembly cycle times.

During the forgetting phase, a similar curve is used. The main difference is that in that case, the forgetting coefficient is applied to the equation and is not negative. Furthermore it is not possible to count the assembly iterations during the forgetting phase. Therefore the model uses the amount of units that could have been produced during the forgetting time to predict the first assembly time of the next learning cycle. To have a realistic prediction at all times, the forgetting curve must intersect with the learning curve at the last unit that is produced in the antecedent learning phase. The form of the forgetting curve is as followed:

$$\hat{T}_x = \hat{T}_1 \cdot x^{f_{LFCM}} \tag{2}$$

With $\hat{T}_x$ as the predicted cycle time after an interruption and x the equivalent amount of items that could have been produced if no interruption occurred. $\hat{T}_1$ represents the equivalent time for the first unit of the forgetting curve. f_{LFCM} is the forgetting coefficient which indicates how fast the tasks are forgotten. This coefficient can be calculated with:

$$f_{LFCM} = \frac{l(1-l)\,log(q)}{log\left(1+\frac{t_B}{t_q}\right)} \tag{3}$$

where l is the learning coefficient, q the amount of products that could have been made without the interruption. Furthermore, t_B is the minimal duration needed for total forgetting and t_q is the time that would be needed to produce q products using the learning curve.

2.2. Mixed-model application

The main difference between the purpose of the LFCM and the cycle time prediction in a mixed-model environment is that there is no real interruption of assembly in the last case. The forgetting phenomena is not only caused by the interruption of a learning period, but also by the interruption while performing another job. Because of this difference, it is assumed that the effect of forgetting will not be equal in both cases.

When looking to two extreme situations within a mixed-model assembly line, this assumption can be clearly verified. The variable for these situations is the job similarity between the task which is being forgotten and the task that is performed during this forgetting phase. For instance when the "in-between-job" is totally different from the main job, the job similarity would be equal to 0 and the normal forgetting curve of the LFCM could be applied since there is nothing going on that has any relation to the main job.

The opposite situation is when the "in-between-job" is (nearly) equal to the main job. This would result in an extension of the learning process and so forgetting will not occur, or as you want, negative forgetting will occur. This situation could be described as a forgetting phase where the forgetting coefficient is equal to the negative learning coefficient. The forgetting curve would then just be the extension of learning curve. Based on this theory, a new equation could be introduced to calculate the forgetting coefficient:

$$f = \frac{l(1-l)\cdot log(q)}{log\left(1+\frac{t_B}{t_q}\right)} - k(j)\cdot l\left[1+\frac{(1-l)\cdot log(q)}{log\left(1+\frac{t_B}{t_q}\right)}\right] \tag{4}$$

where $k(j)$ is a function of the job similarity, j. This function varies between 0 and 1, depending on the job similarity. If this function is equal to 0, last term drops and the initial calculation for the forgetting coefficient will be used. If the function is 1, the outcome will be equal to $-l$ and the learning curve will be applied. The function $k(j)$ can have

different forms such as linear, quadratic, exponential, etc.
A critical value for the forgetting coefficient is 0. Once the coefficient becomes negative, learning will occur instead of forgetting. With the aid of this equation, the critical value of the job similarity could be calculated and equals to:

$$k(j)_{critical} = \frac{f_{LFCM}}{l+l \cdot f_{LFCM}} \qquad (5)$$

If the job similarity between tasks is higher than this critical value of $k(j)$, the operator will improve for the two tasks while performing one of them.

In this study, the authors wanted to test if there is indeed an effect of job similarity onto the forgetting effect. Therefore an experimental approach has been used to get a first indication about the correlation of the forgetting coefficient and the job similarity between jobs.

3. Experimental setup

3.1. Assembly tasks

In order to check the effect of job similarity on the forgetting rate in a mixed-model setting, an experiment has been conducted. During this experiment, different assembly tasks needed to be performed by different subjects. The production of a case product was created to have a logical division of different assembly jobs. The end product consisted of a socket, installed on a wooden plank and wired to a luster clamp. The end product is shown in Fig. 1**Error! Reference source not found.**.

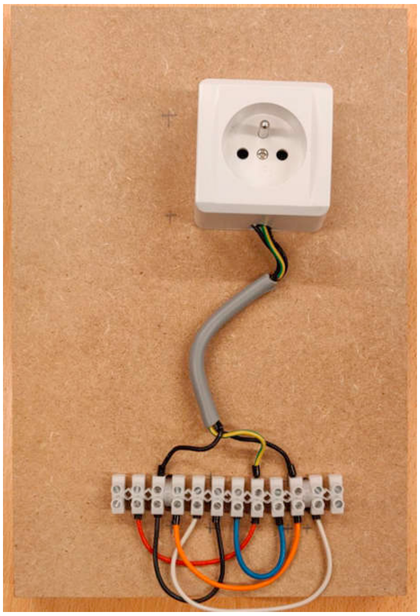

Fig. 1: Case product

A flowchart of the production is presented in Fig. 2. The assembly operations are all related to industrial tasks such as drilling holes, wiring and stripping cables. The operations are grouped into different jobs to make sure there are clear differences and similarities between the jobs. This was necessary regarding the purpose of the experiment. The factors that are causing the (dis)similarity are the use of common parts and tools, the same working place and the application of the same type of operations. The main task in this research is job A. The job was made cognitively difficult enough in order to ensure a forgetting effect occurs. This was achieved by imposing a specific wiring combination. Next to the wiring, the assembly of the socket cover onto the base is part of job A. The relation between job A and the other jobs is thus important. Job B1 is assumed to be less similar to this main task in comparison to job B2. The only factors that are similar between job A and B1 are the use of 2 common parts. Job B2 has much more parts in common with job A and further, the same tools and operation types are found in both jobs.

Although the job similarity is not yet quantitatively defined, this difference in job similarity is assumed to be large enough to make this statement. A uniform framework to score the job similarity between assembly tasks is an interesting topic for further research as this could be implemented in equation 4.

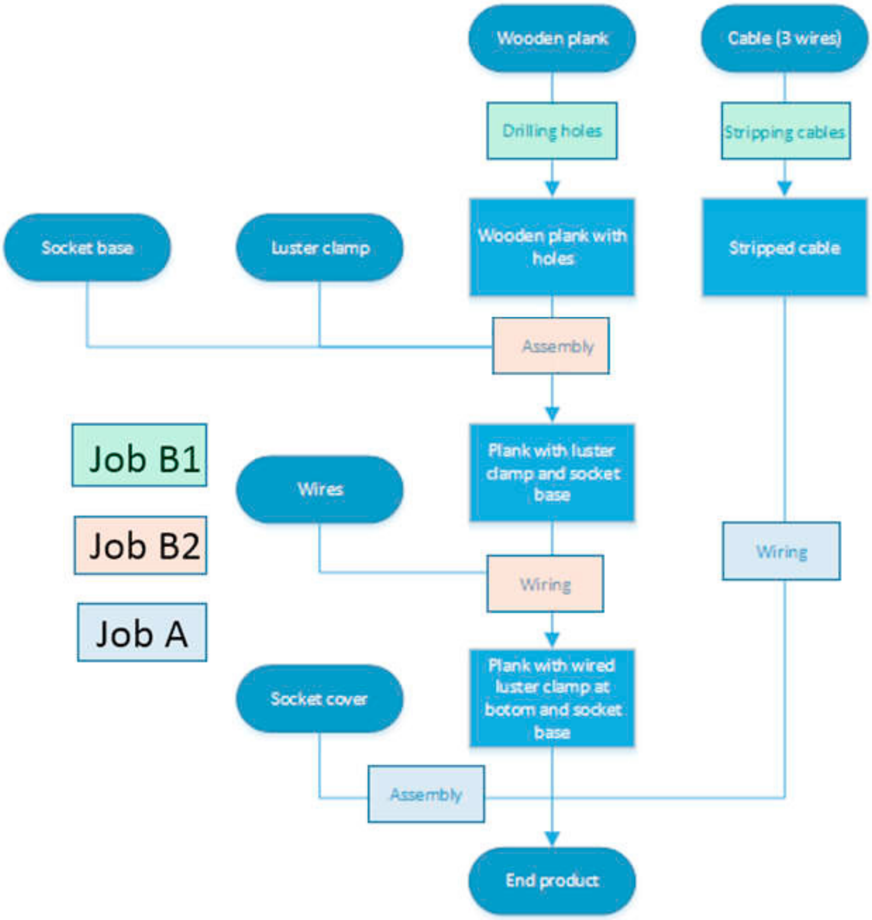

Fig. 2. Flowchart of the product assembly

3.2. Procedure

Two groups of 17 students each were assigned to a specific sequence of the presented jobs. This sequence can be separated in three stages. In the first stage, all subjects of both groups performed job A 4 times. This period will further be addressed as the learning phase. The purpose of these assembly iterations was to compose all subject's learning curves for this particular task.

In the second phase, further referred to as the forgetting phase, the subjects performed one of the other jobs 4 times as well. Group 1 had to perform job B1 during the forgetting phase, group 2 did job B2. In the third phase, the second learning session, the main task needed to be performed again, twice. Based on the last assembly of the learning phase and the first assembly of the third phase, the actual forgetting curve of every subject could be derived. After one week, the subjects were asked to perform job A again in order to check their forgetting coefficient during a normal interruption, this is further indicated as f_n.

4. Results and discussion

All job's assembly times are registered to analyze the differences and similarities. Based on the assembly time of the learning phase, a learning curve with constructed. Similarly, a forgetting curve for the main job was determined, based on the duration of the last assembly of the learning phase and the first assembly of the second learning session. In Table 1. Learning and forgetting curves the coefficients for both curves of group 1 are given for each of the 17 subjects, a similar overview of group 2 can be found in Table 2.

Table 1. Learning and forgetting curves of group 1

Subject number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Mean
T_1[s]	249	242	257	275	479	564	313	271	264	266	299	334	286	281	202	307	404	311
l	0.40	0.25	0.54	0.94	0.69	0.83	0.47	0.19	0.39	0.24	0.38	0.53	0.30	0.30	0.37	0.65	0.84	0.49
$\hat{\hat{T}}_1$	98	149	111	70	128	146	131	146	128	163	176	129	165	225	83	61	77	129
f	0.27	0.098	0.066	0.22	0.25	0.15	0.15	0.26	0.14	0.11	0.01	0.16	0.10	-0.14	0.27	0.52	0.36	0.18
f_n	0.021	0.038	0.052	0.039	0.057	0.085	0.006	0.087	0.016	0.039	0.096	0.006	0.077	0.061	0.045	0.049	0.00	0.046

Table 2. Learning and forgetting curves of group 2

Subject number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Mean
T_1[s]	321	404	318	419	488	539	431	305	342	374	374	187	440	321	236	221	422	360
l	0.21	0.52	0.47	0.77	0.47	0.58	0.50	0.49	0.42	0.38	0.81	0.16	0.48	0.40	0.69	0.12	0.60	0.47
$\hat{\hat{T}}_1$[s]	314	141	158	98	465	242	171	117	174	236	109	158	284	160	69	289	190	198
f	-0.19	0.23	0.04	0.29	-0.40	0.002	0.10	0.20	0.07	-0.10	0.08	-0.06	-0.15	0.11	0.24	-0.26	-0.02	0.03
f_n	0.050	n.A	0.081	0.052	0.084	0.060	0.083	0.064	0.010	0.079	0.089	0.062	0.060	0.067	0.036	0.045	0.036	0.057

Through an independent sample t-test, the learning and forgetting coefficients of the two groups were compared to each other. All statistical tests are performed and analyzed with a confidence interval of 95%. The learning coefficient is supposed to be equal for both groups. This means that on average, the groups improved similarly during the learning phase. Since the subjects of the groups are randomly divided into two groups and the subjects have similar backgrounds, this is a logical outcome. The p-value of the test was equal to 0.837 and thus much higher than the critical value of 0.05. Subsequently, the learning coefficient of both groups are not significantly different and can be assumed to be equal. The high p-value indicates a high probability of equality.

The same test for the forgetting coefficient of both groups gives the opposite result. A p-value of 0.006 is found which means that both groups are significantly different. This implies that both groups did not forget the main task at the same rate. The forgetting rate during the week of interruption (f_n) is not found to be significantly different. The p-value for this parameter was 0.125. These results indicate that the activity during a forgetting phase does in fact influence the rate of forgetting.

In previous models, the forgetting coefficient is given as a function of different parameters. Amongst these parameters, the learning coefficient is sometimes used. However, there is a lot of disagreement in literature if the learning rate affects the forgetting rate. To evaluate the influence of the learning coefficient on the forgetting of both groups, a two-way ANOVA test was performed. The forgetting coefficient was used as dependent variable, the group number and the learning coefficient as independent variables. The test checks if the independent variables are a moderator for the dependent variable. The learning coefficients were divided into 4 categories. Each category covers a quartile of the total sample size. So all subject's learning rates are listed and the subjects were divided based on their learning rates. This has been done to represent a clear overview of the effect.

In this experiment, there is a statistically significant interaction between the forgetting and learning coefficient (p-value = 0.003), meaning that the rate of learning affects the rate of forgetting. In general, someone who learns quicker, will forget this task quicker as well. This outcome confirms the theory that is used in the LFCM. Jaber and Kehr show that the forgetting slope f increases with the learning rate l in the range $0 < l \leq 0.5$ [14]. An explanation for this correlation can be that someone who does not perform a task very well the first iteration, will have a higher learning rate.

There is also a significant interaction between the groups and the forgetting coefficient. This implies that it does matter which task an operator performs during the forgetting phase to predict the forgetting effect of this operator. The main effect of the learning coefficient and the group number (= task during the forgetting phase) is shown in Fig. 3. In this figure, *LCcat* represents the different levels of learning coefficients, each group consist of one quartile. A similar trend is visible for both groups, concerning the forgetting rate. This indicates the clear interaction between the learning rate and the forgetting rate of the subjects. Since the independent t-test did declare a statistically significant difference in forgetting coefficient between the groups, the difference between both curves indicates that there is an interaction between the activity while interrupted and the forgetting coefficient. Intuitively, the more similar task causes a decrease of forgetting in comparison with the dissimilar task.

Another tendency that is visible in Fig. 3 is that the impact of job similarity is larger for operators who have a lower learning rate. However, this cannot be statistically substantiated due to the low number of subjects.

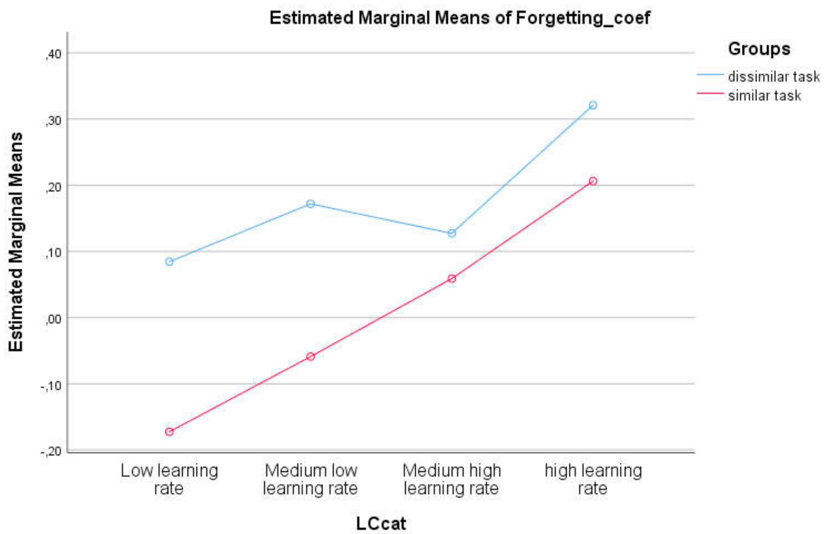

Fig. 3. Effect of groups and learning rate on the forgetting rate

5. Conclusion and future research

In this paper, the forgetting phenomena is analyzed in a mixed-model assembly environment. More specific the influence of different activities that are done while a forgetting phase occurs for a certain job. The study confirms earlier findings that there is a correlation between the learning rate and forgetting rate of a certain operator for a certain job. This correlation is already described and implemented in several learning and forgetting models. The models that can be found have the aim to predict the cycle time of an operator after an interruption of the assembly process. This differs drastically with the aim of this research.

The aim of the authors is to predict the cycle time of an operator for a specific job after a period of assembling different other models. The data of the conducted experiment show that the activity that has been done during the forgetting phase, does affect the level of retention. A more similar job results in a better retention of the reference job. Therefore the forgetting curves in a mixed-model environment should be adapted and this factor should be taken into account. A first adaptation of the LFCM is already presented in this paper. With the aid of industrial data, different mutations of the presented form could be validated. In order to optimize the model, also other factors that can affect the forgetting effect, such as the assembly complexity, should be investigated.

In future work, the authors want to develop a framework to score the job similarity between jobs and implement this score in the presented modified model. This should be an optimization of the model and must enhance the prediction of cycle times of a specific operator-job combination, given the work schedule of the operator in a mixed-model environment. The applications of this model can be used for different purposes such as planning of training sessions for the operator on the particular job, rescheduling for optimal efficiency, etc.

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