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An Experiment on Task Performance Forecasting Based on the Experience of Different Tasks*

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Abstract: Performance in a task is influenced not only by the experience obtained in doing this task, but by how recent it is and by the experience obtained in doing similar tasks. Competence-Performance Approach is used as the theoretical framework. A modified version of Nembhard and Uzumeri learning and forgetting function is proposed to forecast performance by including the experience derived from other similar tasks. An experiment with voluntary students of telecommunication engineering was carried out. The tasks require assembly of electronic circuits. The results fitted well with the proposed model.

Keywords: Learning by doing, Competence-Performance Approach, Work organisation
Categories: J.4

1 Introduction

In production processes today the use of knowledge is increasingly present in all positions. The concept of knowledge worker [Pyöriä, 05] can be extended to almost all jobs. Learning, and particularly learning at work, becomes essential. Needs for current work and needs for learning can be contradictory: performance will be higher when a worker is assigned to a task in which he is experienced, while learning requires him to undertake new tasks. To manage this problem we have to be able to forecast performance for each level of experience. To evaluate the experience we will consider experience doing that task, the time that has passed since it was done and the experience obtained in other similar tasks.

Mechanical and mental tasks have to be distinguished, although both can be considered knowledge tasks. Mechanical tasks are those not involving decisions, while a task becomes more mental as more decisions have to be taken. It has been verified that learning and forgetting processes are simpler for mechanical tasks than for mental tasks [Arazi and Shtub, 97]. The analysis developed here could be applied to any kind of work; however in the experiment developed only mechanical tasks are performed, and thus at the present moment we have results only applicable to this kind of task.

The theoretical basis of our analysis is the Competence-Performance Approach [Korossy, 97]. Forecasting is done by using a modification of the learning and forgetting curve proposed by [Nembhard and Uzumeri, 00]. Previous works applying learning and forgetting models to solve work organisation problems were found in the literature. [McCreery et alt., 04] considers a learning and forgetting model in

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addressing a design problem while [Sayın and Karabatı, 07] includes one in a planning problem. Our contribution is to consider a wider range of factors and to carry out an experiment to test the model that we propose.

2 Theoretical basis

The dependence of performance of a task on experience obtained in performing other tasks is supported by the Competence-Performance Approach [Korossy, 97]. A distinction is made between competences – understood to be unobservable constructs representing "pieces of knowledge"– and performance of a task – a measurable outcome. To define the concept of knowledge structure two more elements have to be considered: relations of precedence and states of knowledge. 'Precedence' means that the acquisition of some competences precedes the acquisition of others. A state of knowledge is the situation of a worker in relation to competences, and is formed by the set of pieces of knowledge learned and known by the worker. Precedence rules determine which states will be feasible and which will not. A state of knowledge that includes a piece of knowledge and not all its precedents will be unfeasible; otherwise it will be feasible. A set of feasible states of knowledge is defined as a knowledge structure [Falmagne et alt., 06].

Knowledge structure leads naturally to the concept of learning path – a sequence of learning experiences. It has been used to describe a situation where competences can be reached by following alternative sequences, as happens in the example we describe later. It has been used to design a lifetime learning path according to the characteristic of the person and his achievements [Karampiperis and Sampson, 06].

	task			
competency	a	b	c	d
1	x	x	x	x
2	x	x	x	x
3		x		
4			x	x
5				x

state	tasks
B	a
C	b; a - b
D	c; a - c
E	d; c-d; a-d; a-c-d
F	a-b-c; b-c
G	b-d; b-c-d; a-b-d; a-b-c-d

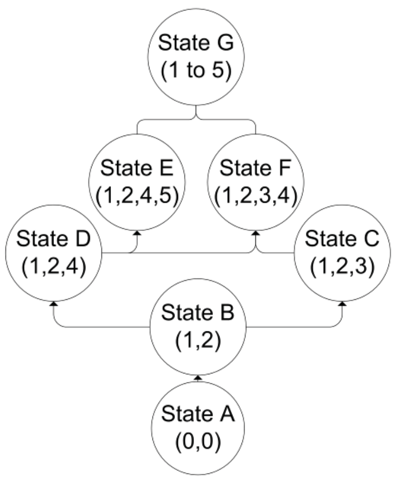


Figure 1:. Example of states of knowledge and precedence.

A simplistic example is illustrated in [Fig. 1] to clarify the model. We consider 4 tasks (a to d) each of which implies the use of several competences (1 to 5). This supposes the existence of 7 states of knowledge (A-G). Effectively, a state consisting in competences 4 and 5, for example, is not feasible because it is not possible to acquire these competences without acquiring 1 and 2. The graphs show the paths that minimize the number of competences to be acquired at each step, and that are thought to be the best ones from the learning point of view. The other steps will be penalized by longer learning time and lower performance.

This theoretical approach has been applied to a methodology to assess underlying competences [Ley and Albert, 03]. Here we use it to define the states of knowledge and justify the differences between time and performance according to previous experience. In real cases the changes from one state to another may not be complete, but in any case the model is applicable because we can easily use states representing partial acquisition of competences.

To apply the Competence-Performance Approach to the performance at work requires us to consider a set of employees and a set of tasks where all tasks can be assigned to any worker. This situation corresponds to the case of a team or a category of workers, for example. Requirements for the job, such as personal traits and offline training, have to be tested previously. The worker's performance when doing a task is experience-dependent, and then it is a learning-by-doing approach, where competences are acquired by working. As competences are acquired, performance in the task will increase. When the new state of knowledge has only a limited number of new competences, the learning process is expected to be faster [Borthick et alt., 03]. Then the time of learning – the time required to acquire the competence – and performance in the transition between states of knowledge will depend on the path followed.

In this situation the acquisition of competences depends on the work to be done and their assignment to the workers. The work to be done is not determined by the needs for learning but by the needs of production. Contradiction between these needs has been analysed in the case of apprentices, where learning is mandatory [Brooker and Butler, 07]. The sequence of work is thus conditioned to the needs of work. This limits the number of possible learning paths to use at each moment. Forecasting of performance and final knowledge goals can be used to support the decision between the remaining options.

3 Learning and forgetting model

We intend to forecast task performance according to experience of the task, the time that has passed since this experience and experience in other similar tasks. A learning and forgetting model modified to include experience in other similar tasks has to be defined.

A learning curve is an equation that shows the relation between experience and performance. Learning curves are based on the premise that people increase their performance in a task as they repeat it. A measure of the experience in doing the task has to be taken into account in any learning curve, while other variables can be included or not. Next the model that we propose is defined in three steps.

3.1 Model depending on repetitions

In a comparison of a total of 11 alternative learning curve models, a three parameter hyperbolic model is found to give the best approximation [Nembhard and Uzumeri, 00]. In [Eq. 2] y_x is a measure of the productivity with x the number of times that the task has been done, p the prior expertise in the task, k the limit of y_x as x approaches infinity – i.e. productivity when learning has been completed – and r a parameter that determines the slope of the curve.

$$y_x = k \cdot \left(\frac{x+p}{x+p+r} \right), \qquad with \quad y, p, k, x \geq 0; p + r \succ 0 \tag{1}$$

3.2 Model depending on repetitions and forgetting

The model has been extended by introducing a forgetting factor. [Shafer et alt., 01] defines a measure of recency [Eq. 2] – i.e. how recent the experience is. Here x is the number of times that the worker did the task and t_i is the moment when the repetition number i of the task is performed – with t_0 the initial moment and t_x the last moment the worker did the task. The more recent the experience is, the closer R_x is to 1; the less recent it is, the closer it is to 0. The resulting learning and forgetting model has proved to be efficient when applying it to real data [Shafer et alt., 01].

$$R_x = \frac{\sum_{i=1}^{x} (t_i - t_0)}{x \cdot (t_i - t_0)} \tag{2}$$

The factor Rx is then introduced to the model [Eq. 3]. The factor Rx makes the performance forecast higher the more recent the experience is. In addition a factor α is also introduced. Factor α depends on the degree to which the individual forgets the task.

$$y_x = k \cdot \left(\frac{x \cdot R_x^{\alpha} + p}{x \cdot R_x^{\alpha} + p + r} \right), \qquad with \quad \alpha, y, p, k, x \geq 0; p + r \succ 0 \tag{3}$$

3.3 Model depending on repetitions, forgetting and experience of other tasks

Next, the model is modified so that when we examine the performance of a task we consider the experience of other tasks. This effect is included by modifying the parameter p by the expression defined in [Eq. 4], where p_j represents the previous experience useful to do task j that has been gained by doing other tasks, j belongs to a group of indices of tasks K, $q_{j,j'}$ are parameters and $x_{j'}$ is the number of times that the task j' has been done. Over a certain threshold more experience of task j' does not provide any advantage for doing task j; in this case x_j takes the value of this threshold.

$$p_j = q_{j,0} + \sum_{j' \in K, j' \neq j} q_{j,j'} \cdot x_{j'} \tag{4}$$

The parameter p is substituted in [Eq. 3] by the expression that has been defined, resulting in the model defined by [Eq. 5].

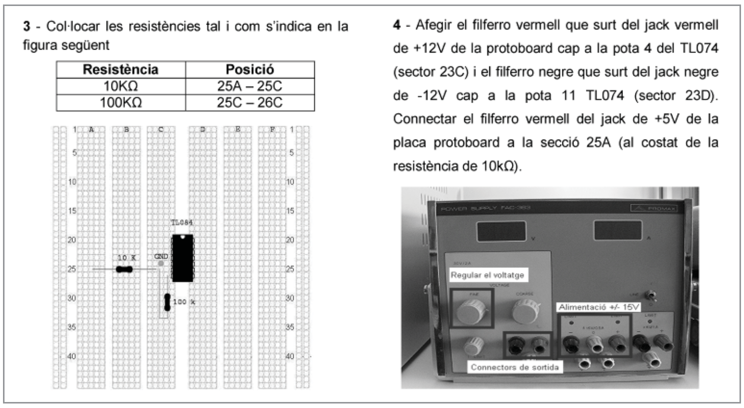
$$y_{j,x} = k \cdot \left(\frac{x_j \cdot R_x^{\alpha} + q_{j,0} + \sum_{j' \in K, j' \neq j} q_{j,j'} \cdot x_{j'}}{x_j \cdot R_x^{\alpha} + q_{j,0} + \sum_{j' \in K, j' \neq j} q_{j,j'} \cdot x_{j'} + r} \right), \tag{5}$$

$$with \quad \alpha, y, p, k, x \geq 0; p + r \succ 0$$

4 Experiment

We developed an experiment to test the validity of the model to explain the performance in a mechanical task. The experiment consists of the assembly of electronic circuits by 12 volunteers, students of telecommunications engineering. The parameters of the model are estimated by using nonlinear regression, and performance forecasted by the model and real data are compared.

The electronic circuits were composed basically of amplifiers, resistors and transistors. Different tasks with different levels of difficulty were prepared. Finally three tasks A, B, C were selected. Task A consists of assembling an inverse amplifier. The material used is an electrical supplier, a functions generator and several electronic components such as resistors, amplifiers and wires. The subjects have to assembly the elements and verify the result with the use of an oscilloscope. Task B is very similar to A but the circuit is more complex. Finally, task C uses the same material as in the other experiments but an intermediate accumulator is used and a transistor is added.



3 - Col·locar les resistències tal i com s'indica en la figura següent

Resistència	Posició
10KΩ	25A – 25C
100KΩ	25C – 26C

4 - Afegir el filferro vermell que surt del jack vermell de +12V de la protoboard cap a la pota 4 del TL074 (sector 23C) i el filferro negre que surt del jack negre de -12V cap a la pota 11 TL074 (sector 23D). Connectar el filferro vermell del jack de +5V de la placa protoboard a la secció 25A (al costat de la resistència de 10kΩ).

Figure 2: Example of task standard.

A standard of work has been defined for the three tasks. All the volunteers must follow the same steps and operations so that their work is homogeneous and they obtain results independent of any individual's methods or ideas. Everybody thus does the same task in the same way. The standard contains all the information about the correct position of each component, the configuration of the appliance and the sequence of operations. Instructions are simple to understand for a telecommunications engineering student. [Fig. 2] shows two steps of the standard for task A.

Sequence 1:	A A A A A A A A A A B B B B B B B B B B C C C C C C C C C C
" 2:	B B B B B B B B B B C C C C C C C C C C A A A A A A A A A A
" 3:	C C C C C C C C C C A A A A A A A A A A B B B B B B B B B B
" 4:	A A A B B B A A A B B B A A A B B B A A A B B B A A A B B B
" 5:	C C C A A A C C C A A A C C C A A A C C C A A A C C C A A A
" 6:	B B B C C C B B B C C C B B B C C C B B B C C C B B B C C C

Table 1: Sequences of task in the experiment

We defined six sequences of work, show in [Tab. 1]; these provide a sample of the possible situations. Two volunteers followed each sequence of work. The tasks were done by the subjects in more than one day, and not always on consecutive days. To take the important effect of these interruptions into account the factor of recency (R_x) has been calculated in days from the first day a task was done, whichever this task was.

	Parameter	Estimated value	Standard deviation	95% confidence interval lower limit	upper limit
Task A	k	114.636	24.604	65.896	163.376
	$q_{A,0}$	6.456	2.832	.845	12.067
	$q_{A,B}$	.110	.034	.042	.177
	$q_{A,C}$	.010	.011	-.011	.032
	r	-6.456	2.653	-11.713	-1.200
	α	.548	.073	.403	.694
Task B	k	167.014	26.518	114.482	219.546
	$q_{B,0}$	4.949	2.079	.832	9.067
	$q_{B,A}$	.241	.061	.120	.361
	$q_{B,C}$	.000	.083	-.164	.164
	r	-4.949	1.866	-8.645	-1.253
	α	.287	.113	.062	.511
Task C	k	73.341	40.153	-6.202	152.884
	$q_{C,0}$	13.702	11.473	-9.026	36.430
	$q_{C,A}$	.000	.054	-.107	.107
	$q_{C,B}$	.138	.043	.053	.223
	r	-13.620	11.193	-35.793	8.554
	α	.613	.116	.382	.843

Table 2: Results of the experiment.

Prior to the experiment the volunteers answered a questionnaire about their personal situation and character (Situational Personality Questionnaire). With these test special situations that could affect the results were discarded.

The results were used to estimate, for each task (A, B and C), the parameters of the model defined above in [Eq. 6]. SPSS 14 nonlinear regression module was used. The complete results are show in [Tab. 2]. The parameters representing the influence of the experience on one task to the performance of another were basically those we expected. A and B are similar tasks and thus experience in A influences performance in B and conversely, as values of $q_{A,B}$ (influence of the experience of B when doing A) and $q_{B,A}$ show. The coefficients of determination have also been calculated and are show in [Tab. 3]. The model explains the results of the experiments to a good extend. The difference between the results when including 'experience of other tasks' and when not including it indicates the suitability of the inclusion of this factor in the model.

	Forecasting of performance of task		
Experience in other tasks	A	B	C
Included	78.24%	69.26%	62.60%
Non-included	66.72%	29.05%	38.53%

Table 3: Coefficients of determination (R^2).

5 Conclusions and further research

We have addressed the problem of forecasting performance in a task by considering the experience in this task, how recent this experience is, and the experience in similar tasks. An experiment with voluntary students gave us data for testing the efficiency of the model we proposed. The results obtained give us a reasonable confidence in the adequacy of our proposals and thus justify further work to corroborate the model. Data from more experiments and, especially, from real work situations has to be analysed to validate the model.

In addition, developments to take advantage of the model are proposed. The Competence-Performance Approach justifies why the performance of one task is influenced by the experience of other tasks. The consequence of this phenomenon is that the set of prior experiences affects the rate of improvement of the performance – i.e. the rate of learning. Learning at work is thus path-dependent. The order in which the tasks are done influences the performance and the process of learning. This can be used in planning to increase the rate of improvement of the performance, increase the volume of acquired skills at the end of one period, or both. We foresee, then, developing a planning model that takes into account the relations between experience and performance and that includes learning objectives.

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