THE TRAINING EFFECT IN MECHANICAL TUNNELLING

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ABSTRACT: Productivity losses caused by the training effect can play a major role for the economic success of a project. The major factors influencing learning can be divided into three groups; analysing these factors helps to develop preventive measures for reducing productivity losses. There are two methods for analysing and quantifying the training effect; these will lead to estimations for learning curve parameters and for the duration of the training period.

1 INTRODUCTION

In stationary industry, the training effect is a much-discussed topic on which there is a large amount of information, in particular because of the easily defined basic conditions. In building construction, the effect of familiarisation is of minor importance since the basic conditions are subject to frequent changes.

Tunnelling, however, is an exception to this; due to the frequent repetition of identical work steps, the effect of familiarisation is easy to see. So far, there have been only few investigations on the extent and the process of familiarisation.

This paper tries to improve that state and to provide a closer look to the training effect during mechanical tunnel driving.

2 STARTING SITUATION

Observing the daily advance rate of a tunnel boring machine (TBM) over working days, there is often an increase in performance. One explanation for this increase is the effect of familiarisation, provided that there are no geological reasons.

Figure 1 shows a typical course of daily advance rates over construction time. In addition to the general increase in performance, the large fluctuation of advance rates is also evident.

In the following, some major points on the training effect will be investigated:

- analysis of factors influencing learning
- modelling the training effect
- options for prediction

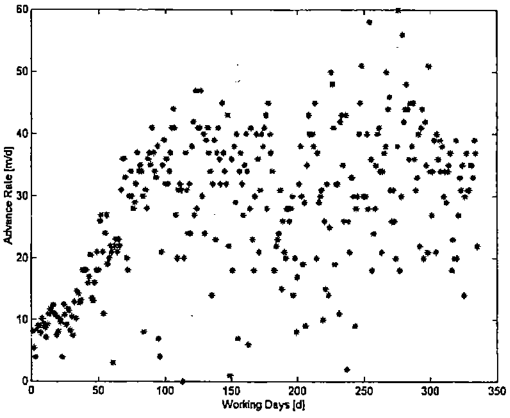

Fig. 1: Course of the daily advance rate of an open TBM observed over working days

3 MAJOR INFLUENCING FACTORS WITH TBM ADVANCES

The increase in performance can be explained by learning. Psychology, which is regarded as the origin of learning science, has developed models and theories describing and explaining learning processes in a general way. Learning is thus defined as a process by which an activity comes into being or is modified as a result of reactions of an organism to an environmental situation [1]. I will refrain from going into further detail on this way of modelling and the explaining of learning processes in this place.
A definition of the concept of learning can be deduced for company learning processes from all these considerations. According to Henfling [2], learning can be defined as follows:

- A dynamic process, in which
- information is processed, which leads to a
- modification of company structures and processes.

There is a close connection between the concept of learning and the concept of the creation of knowledge. These theories provide descriptions of the processes that lead to the creation of company knowledge [3]. They try to describe the processes that lead to already internalised (obtained) knowledge of a person being externalised, i.e. being made available to the organisation, so that other parts of the organisation can convert it into own knowledge (internalisation). They try to create organisational processes that accelerate learning and thus the training effect.

The familiarisation period can thus be regarded as a phase of creation of knowledge on all organisational levels of a construction site. It should be stressed that during that time, an organisational framework must be created that makes it possible to implement the creation of knowledge, leading to a positive influence on the training effect. This applies in particular to the top performers, the heading crews, whose abilities have a direct influence on advance performance.

The major factors influencing learning can be divided into three groups; however, the amount of influence exerted by individual factors on learning behaviour cannot be determined.

- **Man**
  - Qualification and motivation
  - Construction site organisation
  - Communication on the construction site
- **Machine and support system**
  - Machine type
  - Adaptation measures
  - Condition of the driving system
  - Condition of the back-up system
  - Type of support system
- **Geology**
  - Geological formation
  - Hydro-geological conditions
  - Changes between sections of homogeneous geology

Among these influencing factors, man turns out to be the carrier of learning; it is his qualification and motivation as well as the organisational environment that is crucial for progress in learning. The technology of machine and support system is subject to a learning process that is not crucial on a single construction site, but has an effect over several sites. In addition to these, the machine and the support system set conditions the construction site team has to cope with. The influence of geology represents another factor one must learn to deal with in the individual case.

In the production planning of TBM advances, there is a high interest in being able to estimate the effects of learning, that is, the training effect. The following comments are dedicated to that question.

4 MODELLING THE TRAINING EFFECT

Before being able to discuss the modelling of the training effect, one must first define a suitable measurable variable, for one can only measure the effects of learning, not learning itself.
Suitable measurable variables are:

- effort spent per units produced
- units produced, effort amount being constant
- cost

Effort spent includes the following measured variables:

- working hours
- machine hours

- standstill hours
- repair hours
- man-hours, etc...

Considering that the measured variable should be easy to ascertain on the one hand and a common measure on the other hand, the daily advance rate is used as the measured variable for tunnel driving. This ensures the direct application in performance predictions.

There are basically two ways to model the training effect:

- Adjustment of learning curves
- Analysis of the familiarisation period on the basis of the advance data

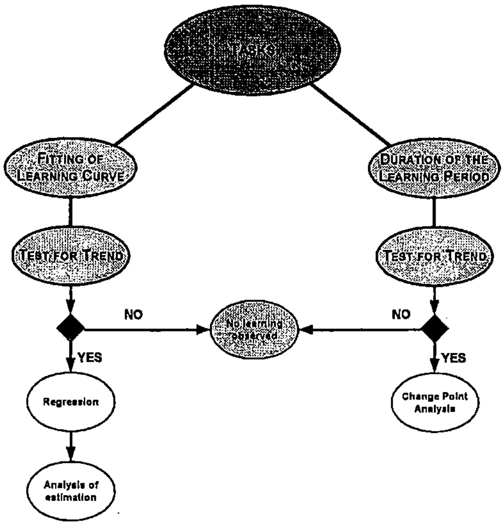

Figure 2: Tasks in modelling the training effect

For modelling the training effect, various statistical tools are needed to evaluate the data:

- **Test for trend:** Before one can start evaluating the data under the aspect of learning, it is necessary to find out if there is a significant trend. This can be done by way of a test for trend in daily advance rates.
- **Regression analysis:** It is necessary to perform a regression analysis in order to fit a learning curve to the data and ascertain corresponding parameters. The fitted curve has the lowest total of squared deviations.
- **Change point analysis:** In order to statistically ascertain a significant change in the data (jump, change of slope of regression line, etc.), the statistical test theory must be used with tailored test variables.

5 LEARNING CURVES

The concept of learning curves originates from the 1930s and was originally used in production planning and control in the aeronautical industry [4]. That model is a power function (1); it is based on a decreasing amount of factor-related effort spent with an increasing number of repetitions.

$$y = a \cdot x^{-b} \qquad (1)$$

Legend:

y	effort spent (hours spent, etc)
a	effort spent for the unit produced first
x	accumulated amount produced
b	slope parameter of learning curve

As a result of various applications of the learning curve concept, a number of learning curve approaches have been developed and adjusted to the special behaviour of the respective case of application. In literature, some summaries and comparisons can be found (cf. Henfling [2] and Hieber [5]). Learning curve models have also been used for purpose of construction operations; an overview over various learning curve approaches is given by Everett [6].

A comparison of different applications shows that there are two dominating types of function; first, the classic power function approach and second, an exponential function approach. Both functions have the advantage of easy handling; an argument for using a power function is the fact that the curve can be fitted by linear regression; an argument for using an exponential function is the clear plateau area the power function lacks.

When applying learning curves to conventional tunnel driving (cf. Platz [7] and Schmidberger [8]), exponential approaches are used in both cases, although the form used is different in the two. In both cases, different measured variables have been defined.

An exponential function approach is proposed for analysing the training effect with mechanical tunnel driving. Daily advance rates are used as a measured variable over working days. A three-parameter learning curve of the following form is fitted to these data records (2):

$$L(t) = a - b \cdot e^{-c \cdot t} \qquad (2)$$

Legend:

L(t)	daily performance [m/WD]
a	sustained performance [m/WD]
b	reduced performance at the beginning of the advance [m/WD]
c	learning ability
t	number of working days [WD]

The function proposed here has turned out to be the most favourable modelling option from a variety of variants.

Since the data are subject to large fluctuations, it is sensible to use methods for smoothing the data material. This is obtained by forming the cumulative sum, which has the advantage that the data remain interpretable. Furthermore, this is a usual form of display in tunnelling and for other linear construction activities.

The learning curve model can be obtained by integrating the learning curve with respect to daily performance, taking into account the daily advance rates (3):

$$S(t) = a \cdot t + b' \cdot e^{-c \cdot t} - b' \qquad (3)$$

Legend:

S(t)	cumulative curve [m]
a	sustained advance rate [m/WD]
b'=b/c	reduced performance at the beginning of the advance
t	number of working days [AT]

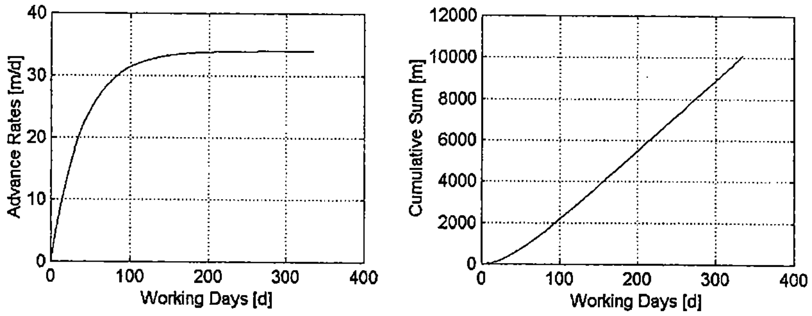

Figure 3 Comparison of the two learning curve models

In Figure 3, the two learning curve models have been displayed graphically. Figure 4 shows the results of an evaluation of a number of advances with DS-TBMs in the form of a box plot. These are four advances with DS-TBMs, one advance displaying a re-training effect. The following parameters could be found:

- a=27,93 m/WD
- b=21,62 m/WD
- c=0,1284

Two advances are available for analysing open TBM tunnel driving, one of these being unsuitable for investigating familiarisation. The following parameters could be found with the other advance:

- a=22,95 m/WD
- b=20,85 m/WD
- c=0,0086

In determining the parameters, all standstill days that could not be clearly attributed to the familiarisation phenomenon were removed from the data records evaluated. It is of particular interest to note that the determined parameters contain all conditions under which advances were carried out, which in particular includes the geological and staff conditions. This means that the evaluated parameters are not directly comparable and only represent individual values providing a scale.

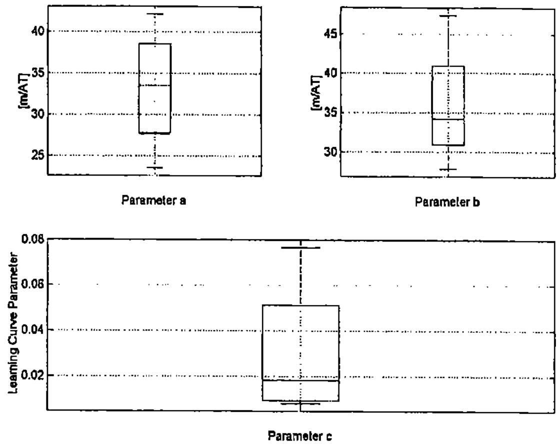

Figure 4 Evaluation results of learning curve parameters DS - TBM

6 EVALUATION OF THE FAMILIARISATION PERIOD

Another way to model the training effect is to determine the familiarisation period. This means looking for the point in time from which it can be assumed that the advance has been familiarised. From that time, we have regular operation. One has to look for a significant change (jump or kink) in the data records of daily advances. Various procedures are available for this:

- **Sequential testing:** Using a regression line, it is tested (T-test, F-test) if there is a significant trend in the data material. Then, data records are removed from the familiarisation period until no trend can be found. This marks the end of the familiarisation period.
- **Pettit Test** [9]: In this test, one looks for the presence of two different mean values - one mean value for the familiarisation period and one mean value for regular operation.
- **Huskova Procedure** [10]: In this procedure, two different regression lines are fitted to the data material, and the time of change is shifted until the residues are at a minimum.

These procedures are well suited to determine the familiarisation period for a project. It is necessary that the data for the whole advance are available; evaluation cannot be performed while the advance is still in progress.

Figure 5 shows the evaluation results for the familiarisation period (left above and below) and for the days lost (right above and below) for the same four advances with DS-TBMs. The lower graph is a box plot display. The following values could be determined for the advance with an open TBM:

• familiarisation period:	120 WD
• days lost:	60 WD

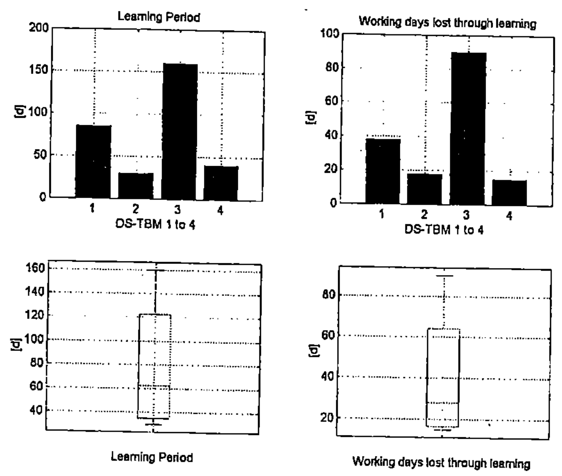

Figure 5 Familiarisation period, evaluation results

Based on the familiarisation period determined, additional evaluations can be made:

- **Determination of days lost:** To do this, a permanent advance rate is determined that does not show any training effect. This equals the advance rate achieved after the familiarisation period. Using that advance rate, the optimal period of construction can be found. If one subtracts that period of construction from the actual time (without standstill days), one gets the number of days lost through learning, that is, the working days lost as a result o the training effect.
- **Determination of the advance rate percentage during the familiarisation period:** This evaluation is also based on determining a permanent advance rate without familiarisation as described above. Then, the average advance rates per time period (month, week, etc.) are put in relation to that permanent advance rate without familiarisation.

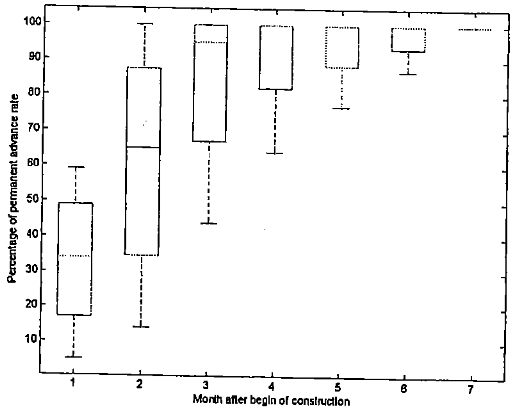

Figure 6 Advance rate during the training period

Figure 6 shows a summary of the results of the advance rate evaluations during the familiarisation period for the four DS-TBMs. Percentages have been calculated for mean daily advance rate per month.

7 OPTIONS FOR PREDICTION

A major issue in discussing the training effect is the possibility of predicting it for the purpose of production planning and controlling. Basically, there are two types of prediction:

- **Type 1 - Before starting the advance:** Only the possible basic conditions are known (staff, driving machine, etc.).
- **Type 2 - Advance has just started:** The basic conditions and a few first advance rates are known.

The evaluation results described above are individual results that include all conditions under which the advance was performed. The parameters are only valid for the respective special case. To be able to make general statements, it is necessary to remove the influence of variables from the data or to quantify the influence they have. The major influencing factors are man, machine, and geology.

The factor of geology has a direct effect on the advance rate via the penetration rate that can be achieved and an indirect effect on the advance rate due to the heading class, which is of particular importance with open TBMs. The influence geology has on advance rates can be directly quantified; the influence of the penetration rate on the advance rate can be estimated just like the influence of the rockmass class. This information can be used to develop filter functions which, when applied to the current advance data, makes the advance run in fictitious, quasi-homogeneous ground. What remains is the influencing factors of man and machine in the heading data, which can be evaluated as described above.

The procedure used with the influencing factor of geology cannot be applied to the other two factors. Here, it is advisable to determine and classify the basic conditions in the form of ratings, assessing them in a first approach as "favourable or "unfavourable". Later, mathematical methods or empirical data can be used on the basis of standard familiarisation parameters to determine modifiers to these parameters in order to take into account unfavourable influences on man and machine. Thus, the influence of staff and machine can at least be coarsely quantified.

$$c = c_0 + c_1 \cdot \alpha_1 + c_2 \cdot \alpha_2 \qquad (4)$$

c	learning ability	
c_0	standard learning ability	
c_1	influence of staff	
α_1	staff toggle variable:	0...favourable 1...unfavourable
c_2	influence of machine	
α_2	machine toggle variable:	0...favourable 1...unfavourable

With type 1 predictions, the objective is to assess what losses the training effect will cause for a future project. For this, the learning curve model is simplified to the form shown in (5) and (6); this is admissible because the determined parameters show that in most cases a = b. On the basis of the procedure described above, the possible conditions can be estimated and the valid learning curve parameter c can be determined. Taking into account the influence of geology over an average advance rate, the progress of advance (5) and the duration of construction (6) can be estimated.

$$L(t) = a \cdot (1 - e^{-c \cdot t}) \qquad (5)$$

$$S(t) = a \cdot \left(t + \frac{1}{c} \cdot e^{-c \cdot t} - \frac{1}{c} \right) \qquad (6)$$

The objective of type 2 predictions is to verify and update the assumptions of type 1 predictions. The basic situation is the type 1 prediction described above and a number of daily advance rates corresponding to the time of the advance. An adjustment of the model by regression is not possible because the amount of data at an early stage of the construction site is too low; the regression curve would not even approach the values to be expected. This is due to the fact that at that time, no high advance rates have been reached, and the curve determined by regression is the curve showing the minimum error square sum; i.e. this method cannot predict the high advance rates achieved at the end of the advance.

This makes it obvious that a sensible prediction depends on the management setting suitable preconditions. Therefore, parameter $\underline{a}$ must be estimated, and then parameter $\underline{c}$ is determined by regression. Using this procedure, very good results for learning ability $\underline{c}$ can be achieved at a relatively early time of advance (20 working days – 40 working days). Only the permanent advance rate a must be determined in a plausible way (such as by calculation). It is advisable to make parameter studies for a resulting in various values for c. These parameters can be compared with the database for c and analysed, and then the effects on construction time can be investigated. Fuzzy methods can be used to increase meaningfulness.

8 FINAL NOTES

These comments are supposed to give an overview over possible sources and thus the possibilities for influencing learning behaviour with mechanical tunnel driving. Using the methods presented, it is possible to analyse the results of the training effect and to take it into account for future projects. Under equal conditions, the training effect leads to degressive costs, i.e. the higher the number of repetitions under the same conditions, the lower the amount of hours spent per tunnel meter driven.

In the case of undisturbed construction, the risk of the training effect basically falls into the contractor's sphere, since it is he who is in the best position to influence the major influencing factors, that is staff and machine. The costs caused by the training effect must be considered in the estimation of cost.

Disturbances in construction, such as by

- longer interruptions of work, or
- rearrangement of work groups (as is often the case in conventional advances), or
- constantly changing conditions

affect not only construction itself but also the training effect. If the familiarisation period has not ended yet, it may be extended, and if familiarisation is already complete, another familiarisation period may result. The resulting increased or repeated training effect is the result of the impairment and cannot be attributed to the sphere of the contractor if the impairment could not be predicted or if the impairment lies within the client's sphere [11]

If the chain of impairment plus extension of time results in additional costs, these must be refunded pursuant to standard contract terms used in Austria and many other countries [12]. Among other things, these costs include additional costs resulting from increased training effects. The methods described above for analysing familiarisation make it possible to calculate the costs accured and then also the additional costs caused by the training effect.

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