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TBM Tunneling Construction Time with Respect to Learning Phase Period and Normal Phase Period

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Abstract

In every tunnel boring machine (TBM) tunneling project, there is an initial low production phase so-called the Learning Phase Period (LPP), in which low utilization is experienced and the operational parameters are adjusted to match the working conditions. LPP can be crucial in scheduling and evaluating the final project time and cost, especially for short tunnels for which it may constitute a major percentage of the total project completion time. The contractors are required to have a better understanding of the initial phase of a project to provide better estimates in the bidding documents. While evaluating and shortening of this phase of low production is important for increasing the productivity and daily advance rate of the machine, there has been limited a direct study and assessment of this period. In this work, we discuss the parameters impacting LPP, and introduce a new methodology for its evaluation. In this regard, an algorithm is introduced for estimation of the approximate extent of LPP based on some TBM tunneling case histories. On the basis of many statistical analyses conducted on the actual data and application of two different shapes of linear and polynomial for the description of LPP, a linear function is proposed for estimation of the learning phase parameters. The major parameters of this function are the learning conditions' rating and the proportion of LPP to tunnel diameter (X1/D). Analysis of the correlation between these two parameters show a very good coefficient of determination ($R^2 = 92\%$). This function can be used for the evaluation of TBM advance rates in LPP and for adjusting the TBM utilization factor in the initial stages of a TBM tunneling project. The learning phase can affect the overall utilization rate and completion time of the tunnels, especially when their lengths are around a couple of kilometers. A true understanding of the LPP characteristics can help the contractors to come up with a more accurate bidding time and cost evaluation, and may also benefit the clients to arrange a better schedule for the final project delivery to the public.

1. Introduction

Identification of the tunnel boring machine (TBM) performance parameters and their influential factors has been the primary focus of several research works in the recent years. For example, the works presented by [1-11] are among the major efforts performed to predict the TBM penetration rate. The studies conducted by [14-17] are among the few efforts to evaluate the TBM advance rates. In this regard, improvement of the available prediction tools or introduction of the new models for the estimation of the TBM advance rates in various ground conditions have been the primary goals of these studies. The daily advance rate (AR) of TBM is defined as the length of the tunnel excavated during each working day, and is expressed in m/day. AR is the key component of the estimation of a tunnel project schedule and cost, and it is a function of the TBM penetration rate (PR) as well as the machine utilization. Obviously, while the rock conditions could be the same throughout the tunnel, the daily AR is typically lower at the earlier stages of the operation due to

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the lower utilization. Generally, the daily AR of a TBM starts at a low value and increases gradually to reach a steady state normal rate as the operators learn about the machine and its capabilities as well as the machine-ground interaction. During this early stage, the tunnel crew fine-tune the auxiliary operations to achieve a consistent level of the production as they streamline the activities and gradually increase the machine productivity. Figure 1 shows a diagram of AR versus elapsed time or Cumulative Advance Rate (CAR) versus elapsed time. The LPP diagram is generally curved, while the Normal Phase Period (NPP) portion of the diagram is a straight line (Figure 1)

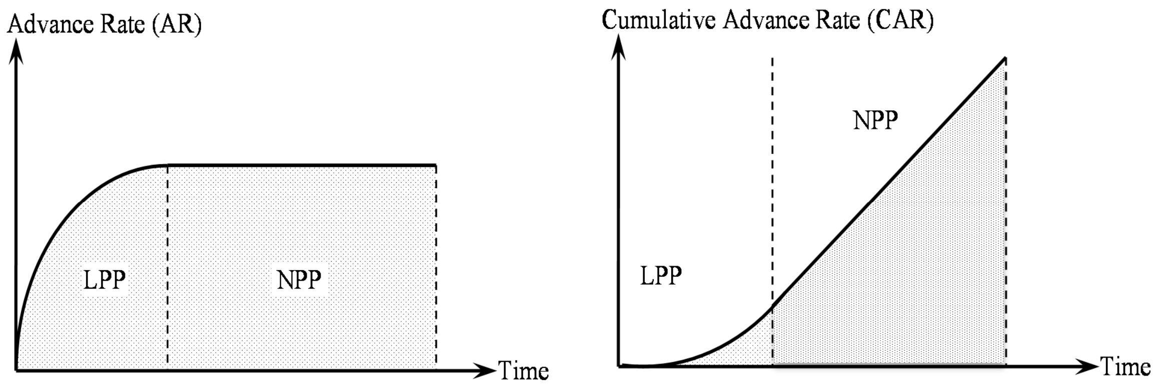

Figure 1. A schematic sketch of LPP and NPP for two common TBM progress diagrams.

As noted by [18-24], the major factors influencing the learning phase (or start-up) can be divided into the following four groups:

- **Man/Personnel**
  - Qualification and motivation
  - Construction site organization
  - Communication on the construction site
  - Access to skilled labor
  - Crew absenteeism and/or unrest
- **Machine and support system**
  - Machine type (e.g. gripper TBM or shielded TBM)
  - Support requirements
  - Condition of TBM (i.e. whether it is new or used)
  - Condition of the back-up system (i.e. whether it is new or used)
  - Ground support type (e.g. segmental lining)
- **Geology**
  - Rock mass condition
  - Presence of extreme mining areas and their types, as explained by [25]
  - Water inflow quantity
  - Alternation of the soft and hard layers
- **General conditions**
  - Degree of difficulty (e.g. available space for the tunnel portal, etc.)
  - Intensity of work preparation
  - Populated or unpopulated areas
  - Local conditions (e.g. cold weather, etc.)

Some researchers such as Brockway [26], and Wais and Wachter [23] have presented some examples of the effect of learning on the ring erection time and the cycle time for some EPB shield TBMs (Figures. 2 and 3). A simple observation is that as the number of installed ring (horizontal axis) increases, the required time for the ring installation (vertical axis) decreases. According to Brockway [26], in the operation of M-30 road tunnel in Madrid, the time of ring installation is reduced from over 400 minutes (in the beginning of the tunnel excavation) to less than 100 minutes (after installation of 1000 rings or 2 km of tunnel excavation). This means that as the tunnel excavation continues, the efficiency of the crew in performing their related tasks improves, and in overall, one can conclude (and it is evident) that the utilization increases. Meanwhile, the question is how fast an operation can reach a consistent production and how to account for this phase in the calculation of the TBM production, advance rate, and overall tunnel completion time, especially for shorter tunnels, where the learning phase could be a substantial part of the entire tunnel excavation time.

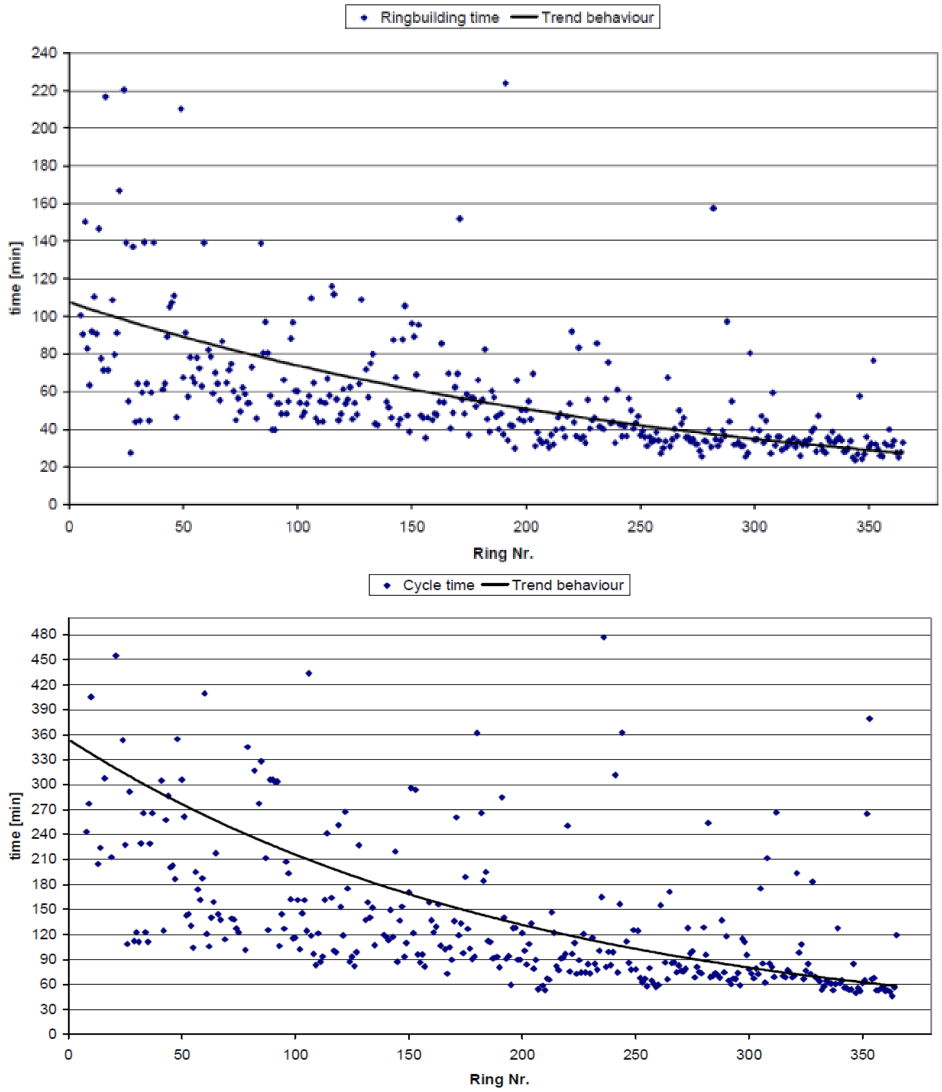

Figure 2. Ring building and cycle times according to the Herrenknecht control system for a tunnel diameter of 5 m excavated by an EPB TBM [23].

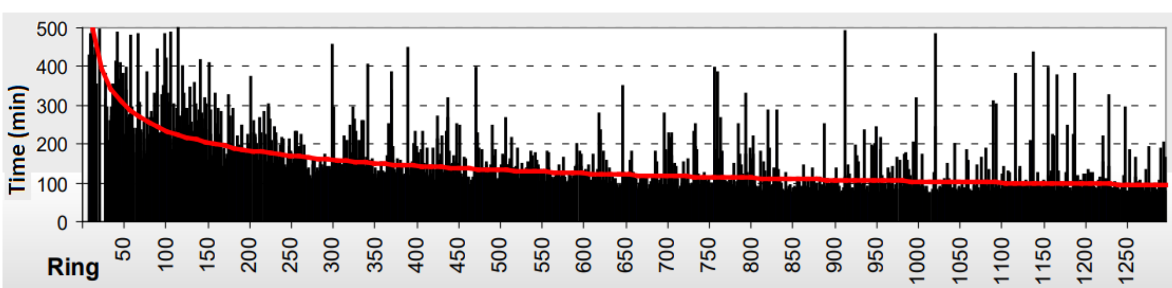

Figure 3. Ring building and cycle times according to Brockway [26] for M-30 road tunnel of 15.2 m diameter, excavated by an EPB TBM.

2. Modeling the LPP Effect

A rule of thumb in the TBM tunneling industry for the evaluation of LPP is to consider the first month period as LPP and the remaining as NPP. Laughton [17] has shown an analysis of the 48 TBM datasets using this method by showing the "start-up efficiency", which is the percentage of the first month AR to the Average Advance Rate (AAR) of the remaining months (Figure 4). This method is a rough estimate and cannot reflect the effects of different conditions on LPP. As reported by Wais (2002), and Wais and Wachter [23], among the different functions, the exponential function is one of the common formulas used for the estimation of the effect of LPP (Gehring and Wachter methods, Equations. 1 and 2 for methods 1 and 2). This is similar in other industries for the production rate evaluation, as explained by [27-31]. In the method proposed by Gehring and Wachter, a familiarization factor is calculated, which reflects the speed of adaptation of the procedures for different tunneling activities to achieve the highest possible (normal) production rate.

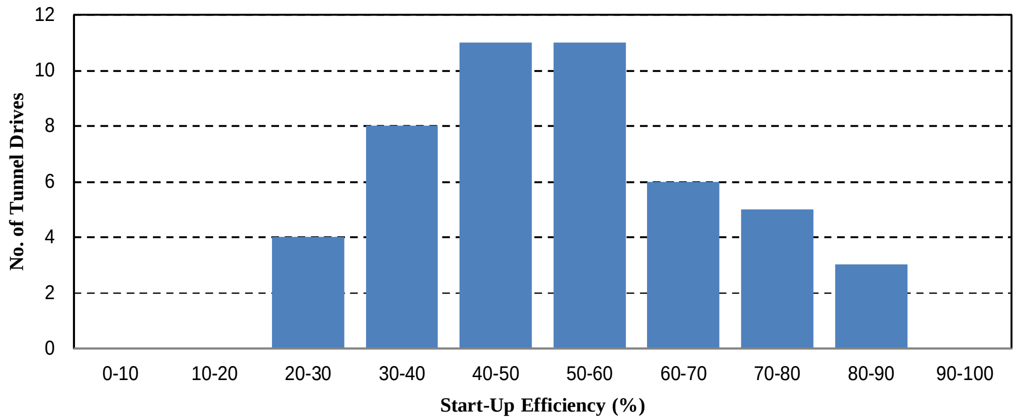

Figure 4. Histogram of start-up efficiency for gripper TBMs according to Laughton [17].

$$f_{famil} = 1 - e^{-0.65d} \quad \text{(Method 1)} \qquad (1)$$

where f_{famil} = percentage of the maximum rate of advance (familiarization factor)

d = duration of tunneling (in months)

$$L(t) = a \cdot (1 - e^{-ct}) \cdot f_1 \quad (f_1 = \frac{I_N}{I_B}) \quad \text{(Method 2)} \qquad (2)$$

where t = duration of tunneling in working days [wd]
L(t) = daily advance rate of day 't'[m/wd]
c = learning curve parameter obtained from Table 1 considering the total rating of LRH, which is the summation of the proposed ratings for human, machine, surrounding, and rock sub-factors in different work conditions of good, standard, and poor (Figure 5).

$\mathbf{f_1}$ = parameter of the filter function for the penetration rate, which is IN/IB.

IN = net penetration rate [m/h] for a specific zone along the tunnel.

IB = reference net penetration rate [m/h] (based on the presented examples by Waise and Wachter [1], IB is the average penetration rate over the entire tunnel length).

a = learning curve parameter selected from IB ((based on the presented examples by Waise and Wachter [23], 'a' is the average advance rate over the entire tunnel length) [m/wd].

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In these methods, the formulas are used for the entire tunnel excavation period from the beginning to the end. The difference between the equations for LPP and NPP is that the familiarization function values in NPP are very close to 1. The component $(1 - e^{-ct})$ in Equation 2 (here called f_f) is similar to f_{famil} in Equation 1. f_{famil} and f_f are the percentages of the NPP advance rate determined at various times during the learning period. According to Waise [32] in Gehring methodology, $f_f = 95\%$ can represent the end of LPP. In the next sections, using the actual data from various tunneling projects around the world, a data analysis is conducted to discuss about the range of specific parameters of the Waise and Wachter's formulas through back-analysis. The next section is an introduction to the database compiled and used for this purpose

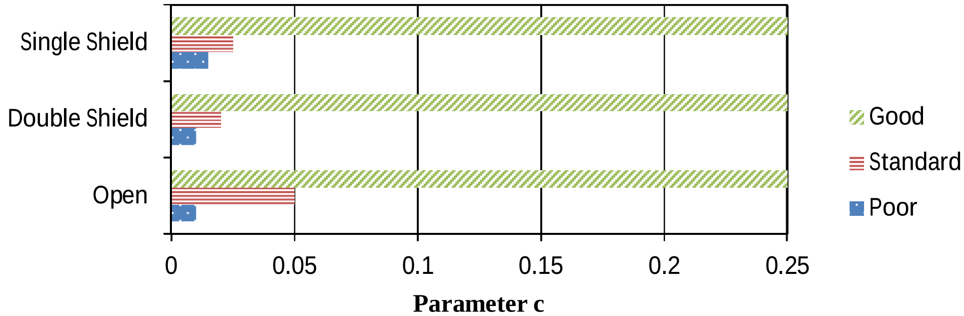

Figure 5. Learning curve parameter c for different TBM types [23].

Table 1. Learning conditions rating according to Waise and Wachter [23].

Group	Factors	Standard	Good	Poor	Points
Human	Personal	Permanent staff 40-50%, familiar with tunneling, enough auxiliary staff avail. flexible working hours, small fluctuation	100% permanent staff, very flexible working hours, following an earlier site (from former sites)	Low amount of permanent staff, labors from the third world countries, high fluctuation rigid working hours rules	
	Organization	Clear allocation of function and responsibility, to experienced staff	Organization already in practice (from former sites)	Unclear functions and responsibility	
	Communication	Good ability to communicate in one common language for the key positions	Communication already in practice (from former sites)	No or only minor ability to communicate in one language	
Machine	Diameter	Working space and power of the machine match with diameter	Lower planned diameter (performance reserve)	Diameter does not match with machine and trailer concept (too big, too small)	
	TBM type and trailer system	tested and familiarized to the key personal, suitable for soil conditions, suitable trailer, good logistics	System already in practice (from former sites)	System and its components do not fit together	
	Condition	TBM and trailer in a good refurbished condition, standard prone to break down	New system, low prone to break down	TBM and trailer used, high prone to break down	
	Support	Tested and familiarized to the key personal, suitable for TBM type	System already in practice (from former sites)	unaccustomed, unpractical support system	
Surrounding	Infrastructure	Good accessibility, sufficient area, electric power and water	Good accessibility, sufficient area, electric power and water. Already developed site from former construction	poor accessible, poor conditions of area insufficient water and electric power	
	Supply	Competitive suppliers, enough area for storage, suitable spare stock	Already known suppliers from former sites, no time pressure	New or unsuitable suppliers, lack of storage area, insufficient spare stock	
	Starting situation	Filling of key positions already known minor obstacles by temporary measures low weathered soil and water at the start, secured start position (Abutment Frame, Starting trestle, Start Ring)	Complete personal available, no obstacles temporary measures, no weathered soil and no water at the starting position secured start position (Abutment Frame, Starting trestle, Start Ring)	Insufficient staff available, many obstacles by temporary measures, insufficient start position, completely weathered soil with water during start, high time pressure	
Rock	Formation	No gas, loose rocks, drilling possible low water inflow	No gas, stable, good to very good drillable (not too hard), no water inflow	Gas, unstable soil, Water inflow, many changes in soil conditions	
			LRH:		

*** Ratings: 1 for poor; 3 for standard; 5 for good. LRH is the total sum of all of the ratings. LRH ranges for poor, standard, and good conditions are 11-22, 23-43, and 44-55, respectively.**
**** It should be noted that Waise and Wachter [23] did not provide any relationships between LRH and ‘c’.**

3. Database description

For the purpose of the following data analysis, a detailed information of tunnel weekly advance rates of 31 tunnels from around the world is compiled in a database. It should be noted that this data is part of the comprehensive TBM performance prediction database explained by Farrokh et al. [2, 3 33] and compiled from the contractor’s reports and the literature. Table 2 shows the range of the major parameters of this database. Figures. 6 and 7 show the boxplots and histograms of the major parameters of the database.

Table 2. Descriptive information of the database.

TBM type	Number of projects	Length (m)	Diameter (m)	UCS (MPa)	PR (m/h)	AR (m/day)
Open	17	1576-13400	3.4-11.8	30-176	1.2-8	9.9-49
Single-shield	6	2073-5620	3.4-12.4	14-263	1.9-2.6	6.4-17.28
Double-shield	8	5223-21300	3.6-8.1	30-190	2-3.5	6.55-29

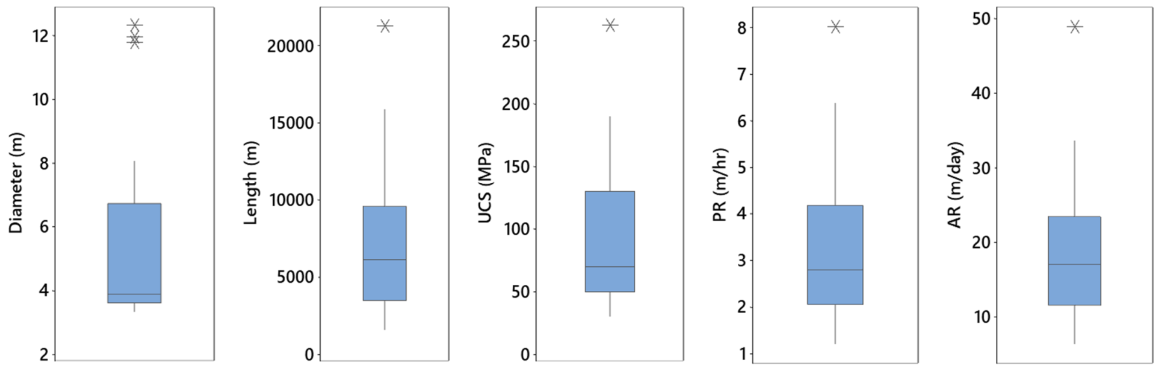

Figure 6. Boxplots of the major parameters of the database.

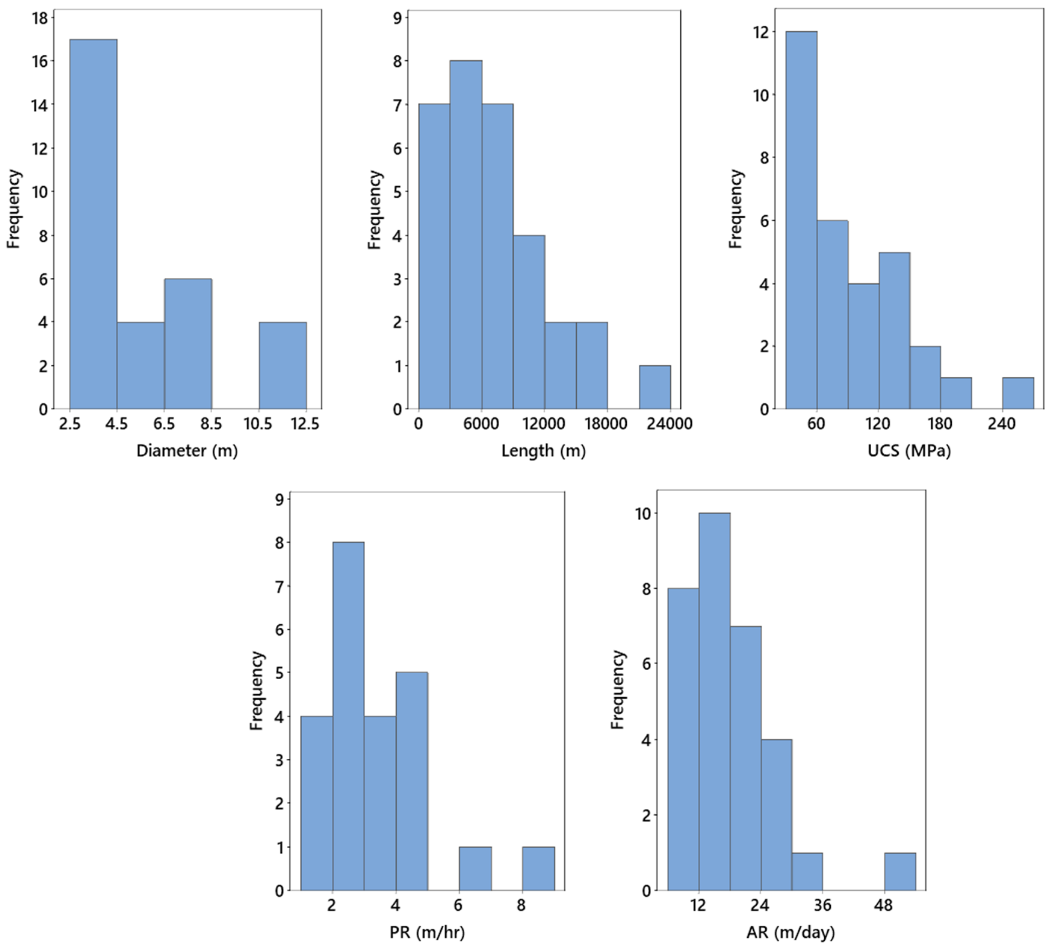

Figure 7. Histograms of the major parameters of the database.

As seen in Table 2, and Figures 6 and 7, the wide range of these parameters indicate that the data cover various tunneling conditions that are required for the subsequent analyses.

4. Back-analysis

In this section, on the basis of the advance rate data from the database explained in the previous section, the range of specific parameters of the Waise and Wachter's formulas are back-calculated. Table 3 shows the back-calculated corresponding time for $f_f = 95\%$ for various types of TBMs under standard conditions using the average value of c for three categories of learning condition.

Table 3. Corresponding f_f values in standard condition.

TBM Type	Values of constant "c" in standard conditions	Corresponding time of $f_f = 95\%$ (days)	Corresponding time of $f_f = 95\%$ (months)
Double-Shield TBM	0.02	210	7
Open TBM	0.05	60	2
Single-Shield TBM	0.025	120	4

According to Waise and Wachter [23], the corresponding LPP times for double-shield and single-shield TBM are rather high, while in common cases, they are around two months for these types of machines. Table 4 provides the two basic parameters of Equation 2 (‘a’ and ‘c’) through back-analysis on 31 tunnel weekly advance rate information assuming $f_1 = 1$.

It should be noted that ‘a’ and ‘c’ were explained previously after Equation 2. Having values of 'a' from the real weekly data, it was possible to back-calculate parameter 'c' using Equation 2. The condition in Table 4 refers to the categories of parameter ‘c’ shown in Figure 5. The last column represents the corresponding time of L(t) function (Equation 2) at which 95% of 'a' is obtained.

Table 4. Back-analysis results of Equation 2 parameters for 31 tunnel cases.

Excavated diameter (m)	Excavated length (m)	a	c	Condition	Corresponding time of $f_f = 95\%$ (weeks)
3.52	6130.3	158.9	0.1813	Good	3
3.35	9520	176.6	0.055	Good	8
3.56	6954	191.95	0.0155	Standard	27
3.56	7350	151.81	0.0176	Standard	24
4.8	5200	110.83	0.0295	Standard	15
4.5	21300	145.56	0.0153	Standard	28
4.5	15686	133.92	0.0139	Standard	30
11.81	1576	104.29	0.0035	Standard	>24
6.73	5223	113.56	0.0344	Good	13
3.84	5613.5	142.5	0.028	Standard	15
7	7654	55.79	0.1154	Good	4
7	9559	60.42	0.1525	Good	3
3.6576	2540.2	109.55	0.0192	Standard	22
3.4	13400	278.67	0.0944	Good	5
3.43	2073	84.34	0.0994	Good	4
3.5	10120	237.23	0.0748	Good	6
4.88	13060	140.72	0.0854	Good	5
8.07	7201.65	148.07	0.0346	Good	12
3.7	15880	160.53	0.0562	Good	8
11.8	3480	68.75	0.0244	Standard	17
11.98	4326	109.12	0.0209	Standard	20
12.35	5620	125.91	0.0161	Standard	26
3.9	2960	117.65	0.0237	Standard	18
6.5	10314.5	83.16	0.0227	Standard	19
3.9	2890	80.86	0.0524	Good	0.5
3.9	6558.5	118.33	0.5	Good	0.5
3.62	2820.4	97.82	0.5	Good	0.5
3.63	5930	146.51	0.072	Good	6
3.9	4412	131.21	0.5	Good	0.5
3.9	1919	163.55	0.051	Good	8
6.5	6914	95.2	0.5	Good	0.5

As it can be seen, the corresponding time of $f_f = 95\%$ (that is the end of LPP) for the standard condition is between 15 and 30 weeks (or between 4 and 7 months), which seems relatively high. The following list shows some of the reasons that might cause overestimation of the learning phase period, which can result in underestimation of the overall utilization and advance rate of the operation.

- Using one fit formula for both LPP and NPP may cause overestimation of LPP: the learning curve parameters can be affected by the TBM advance rate fluctuations of NPP, as shown in the Figure 8 example.
- The best Fit function may not represent all shapes of learning phase: as shown in the Figure 9 example, the fit function does not represent the true shape of LPP.
- Since there is one fitting function for the learning and normal phases, the transition point is unclear due to having a continuous line and, in some cases, the learning parameters can push the beginning point of normal phase fitted line out of a long period of time.

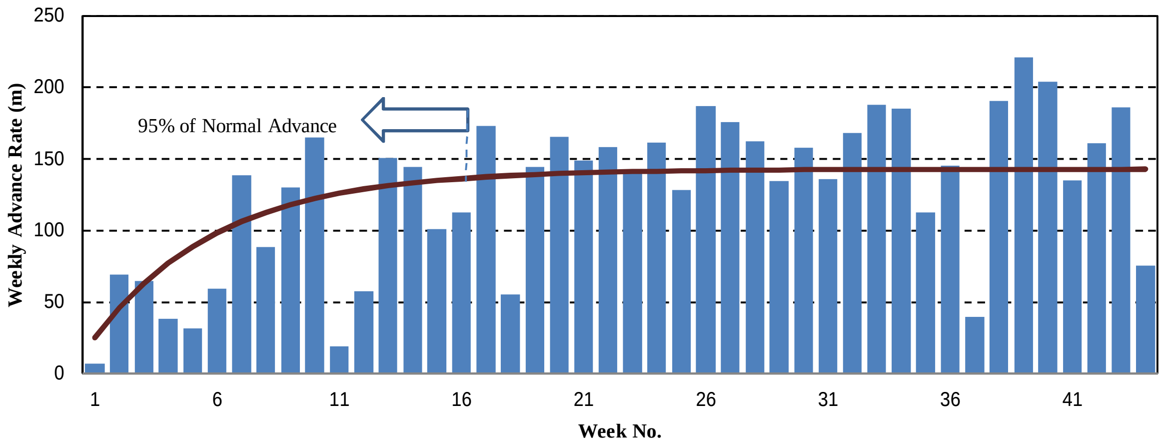

Figure 8. Learning phase overestimation because of TBM advance rate fluctuations of normal weeks (using the Waise and Wachter fitting function).

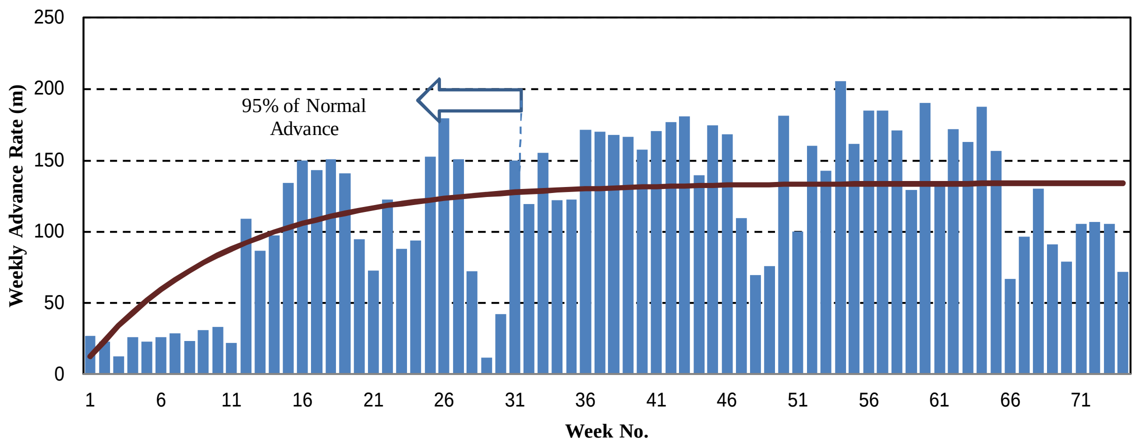

Figure 9. Learning phase overestimation because of unreal shape of learning curve function (using the Waise and Wachter fitting function).

This paper is an attempt to provide a new methodology for assessing the LPP based on the previous case histories of field performance of several TBMs. The difference between this and the previously noted methods accounts for two separate functions for two portions of LPP and NPP. In the following sections, we discuss this methodology in more detail.

5. New Methodology

The practical application of this analysis and the proposed models is in the performance prediction of a TBM for a new project. In such applications, one normally develops an estimate of the penetration rate (PR) based on the available models (e.g. CSM [34-36] and NTNU [37, 38] models), with more details on the machine and ground conditions. Then an estimated Utilization rate (U) is used to calculate an AR. Alternatively, other models (e.g. Q_{TBM} [39] and RME [40-44] can be used to directly estimate AR from a certain set of input parameters. Nonetheless, in both cases, the estimated daily advance rate is based on what is called the normal operating conditions in a given reach or stretch of a tunnel, and does not reflect the learning period. As such, given that the estimated AR reflects NPP, if a model could estimate the LPP and a function could show the progression of the estimated AR or U through this period, a more accurate estimate of both parameters could be achieved.

The proposed method involves breaking the graph of AR of a specific time increment (i.e. week) into the two portions of Learning Phase Period (LPP) and Normal Production Period (NPP). For LPP, a linear function (Equation 3) was selected to represent the gradual increase in AR (or alternatively utilization). For NPP, a horizontal line (Equation 4) is selected to represent the average advance rate of normal phase (Y1) based on the common performance prediction models. It should be noted that for LPP, other functions such as polynomial function might be more realistic since they can describe the shape of LPP curve better when it has a convex or concave shape. Figure 10 shows an example of using polynomial function to fit LPP AR. One issue for a non-linear equation is how to obtain the coefficients without incurring huge errors. The analyses for polynomial function coefficients turned out to be very susceptible to the variation in the other information (e.g. tunnel diameter) that was collected for several tunnel projects in a database. Hence, at the end, the simpler form of linear function was chosen for the LPP analyses.

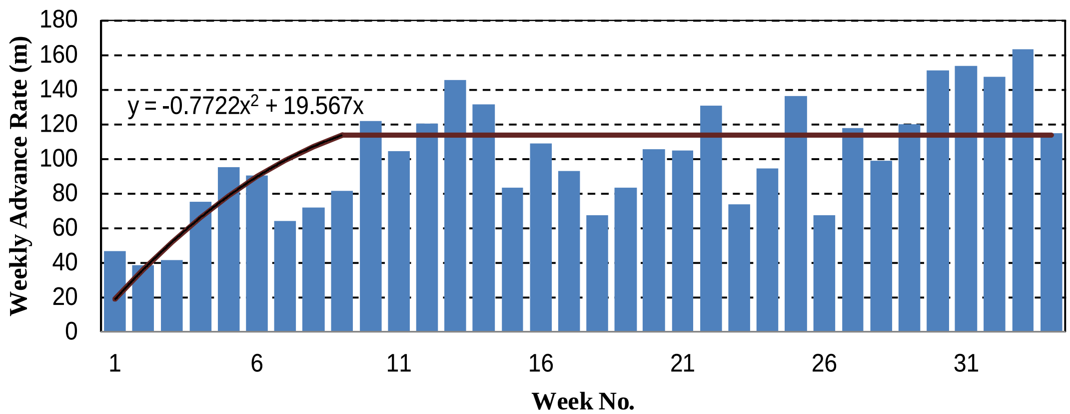

Figure 10. LPP fit function using a polynomial function

$$Y = a \cdot X \text{ (for } 0 < X < X1\text{, where } 0 < Y < Y1) \quad (3)$$

$$Y = Y1 \quad (4)$$

Figure 11 shows the elements of LPP function in the newmethod. X1 and Xn represent the ending time of LPP and the ending time of NPP, respectively.

In order to find the unknown parameters of the LPP and NPP functions from the real advance rates, the steps of the following flowchart (Figure 12) are followed and applied to the data of 44 TBM tunneling projects.

The main procedure in this flowchart is to make the area under the LPP fitting function (A1 in Figure 13) equal to or as close as possible to the corresponding CAR of X1. Figure 14 shows two examples of the obtained fitted functions for the periods of LPP and NPP.

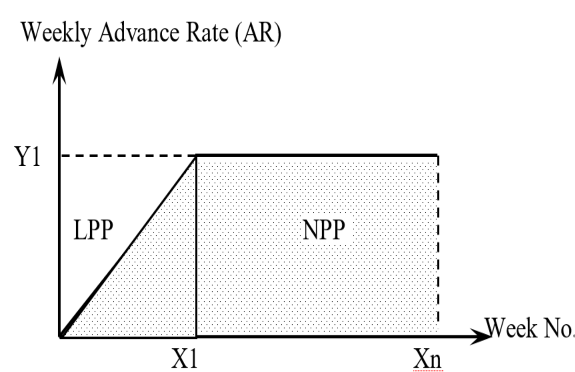

Figure 11. A schematic representation of fitting functions' elements.

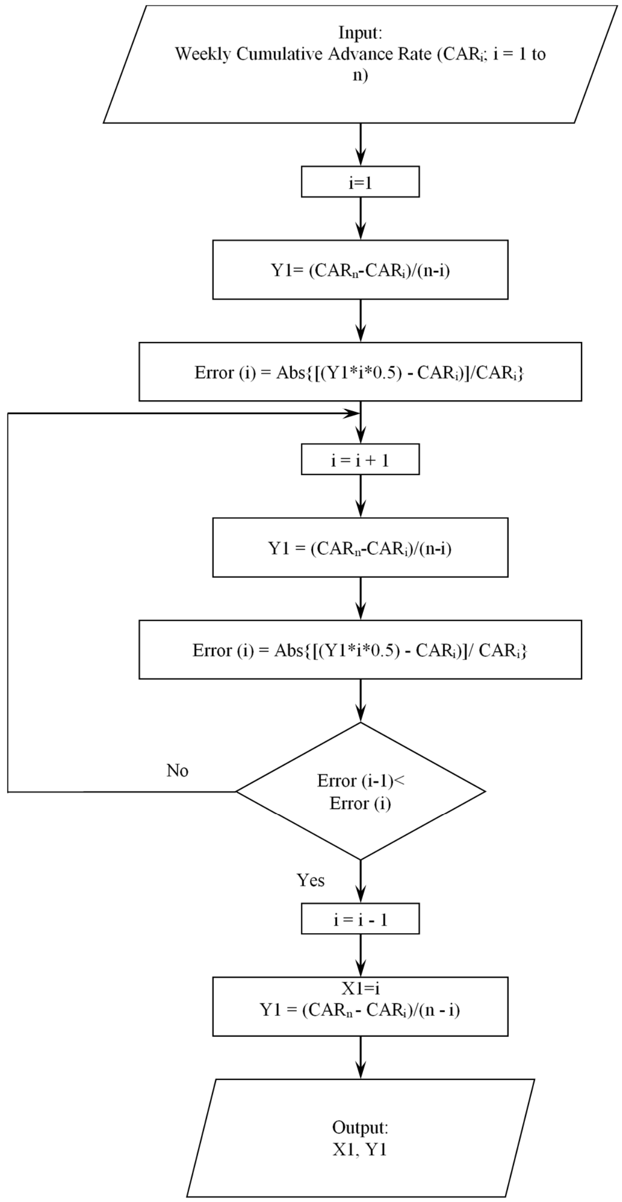

Figure 12. Flowchart of finding the parameters of fitting functions.

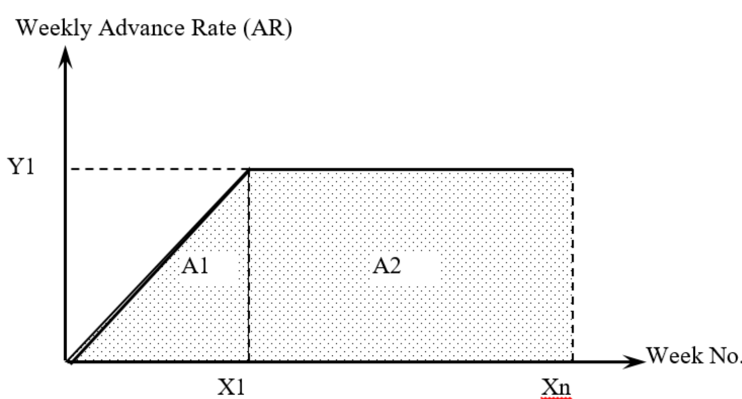

Figure 13. Areas under fitting functions.

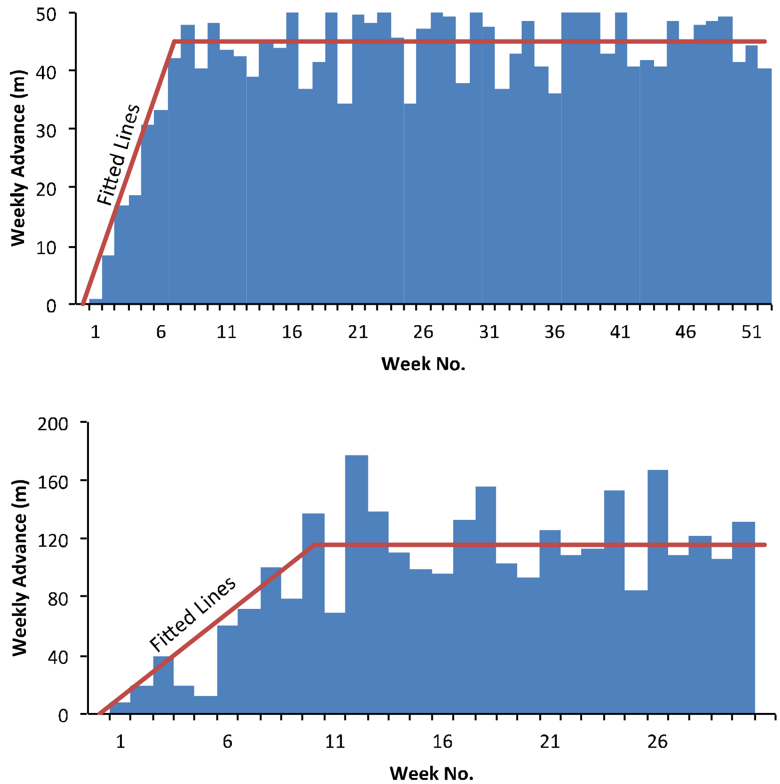

Figure 14. Examples of obtained fitting functions.

This procedure can be applied for different periodic times such as daily, weekly, and monthly periods. In highly variable rock mass conditions, it is possible to use the utilization factor instead of AR to compensate for the differences in the penetration rates (PR) within different geological zones. It should be noted that in this case, the utilization factor should represent LPP, meaning in calculating the utilization factor, the total time should be working time, which includes weekend maintenance. One problem with using the utilization factor instead of AR might be the unreal high values of utilization factors during LPP due to slow cautious penetration of TBM that can lead to an inaccurate outcome for the LPP parameters.

Another point is that the best fitting functions are susceptible to the NPP parameters, meaning that having unproductive or low productive weeks can change the results of the calculations of the total area under the functions, and this causes a shift towards finding inaccurate values. Unproductive or low production weeks, especially in "Adverse Ground Conditions", has nothing to do with learning period and training of the staff or adjusting the TBM equipment to the job site. Therefore, if a period of time is certainly not related to LPP or NPP, it should be eliminated from the calculations.

6. Evaluation of Proposed LPP Function' Parameters

As noted earlier, one important parameter that is necessary for LPP is the duration of LPP (X1). The Waise and Wachter's methodology [23] has considered various parameters for evaluation of the learning time and the TBM AR. One issue with this methodology is that AR for both LPP and NPP is obtained from one formula, and there is no explicit definition for the end of LPP. Furthermore, the reduction effects of the learning phase is considered for the whole period of tunneling or a long portion of it (refer to Table 3). As discussed earlier, in the proposed methodology, two separate fitting functions are introduced to represent the common trends better. Furthermore, the common practice in AR prediction is to add AR of LPP separately to AR of NPP (e.g. see Abd Al-Jalil [14], Laughton [17]). Figure 15 shows the difference between the new fitting functions and the exponential function of Waise and Wachter.

A series of analyses was conducted on the information of 44 tunneling projects (compiled by Farrokh et al. [2, 3, 33]) to estimate the parameters of the new LPP model (refer to the flowchart in Figure 12). Based on these analyses, the X1/D ratio (called the learning phase ratio) has turned out to be one of the best parameters for LPP evaluation for different tunnel diameter sizes (D). In this ratio, X1 is week number and D is tunnel diameter in m. Figure 16 shows the histogram of the distribution of this ratio for these tunnels.

As it can be seen in Figure 16, the distribution of the learning phase ratio is highly skewed, and therefore, the average value is not an appropriate parameter for this data. The median simply shows the most appropriate central value for this data. It means that if we do not consider other factors, on average, we need to consider 1 week/m of diameter for LPP. If we want to follow the most commonly practiced LPP, this ratio is 0.5 week/m of diameter. Overall, in lack of information, especially crew experience, which is very hard to judge, the ratio of 0.5-1 is recommended for LPP calculations.

Further analyses were performed to include other factors, and to have a better understanding of the learning phase ratio. The results of the final analysis are shown in Figure 17. In this graph, LR is the learning conditions rating, which can be roughly obtained from Table 5. This table is similar to what Waise and Watcher presented for obtaining the learning condition rating (Table 1). In this table, RMR is the rock mass rating and LRH is the learning condition rating according to Waise and Wachter.

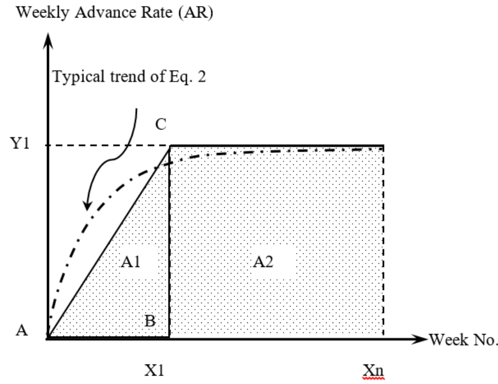

Figure 15. Comparison between the linear and exponential functions for LPP.

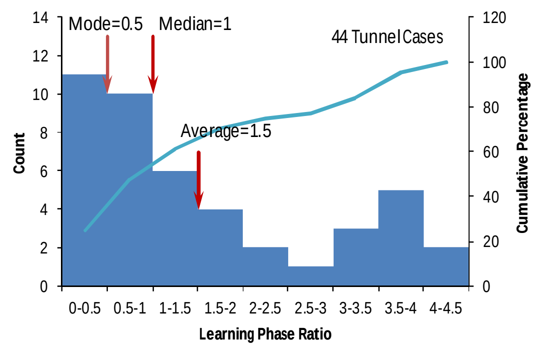

Figure 16. Histogram of distribution of the learning phase ratio for 44 tunnels.

Table 5. LR rating in different learning conditions.

Good (LRH = 44 - 55)	Standard (LRH = 23 - 43)	Poor (LRH = 11 - 22)
-High experienced crew - TBM and BU low prone to break down - Good logistics LR = 100 + RMR	- Experienced crew - TBM and BU standard prone to break down - Regular logistics LR = 50 + RMR	-No/low experience - TBM and BU high prone to break down - Bad logistics LR = RMR

RMR: Rock Mass rating

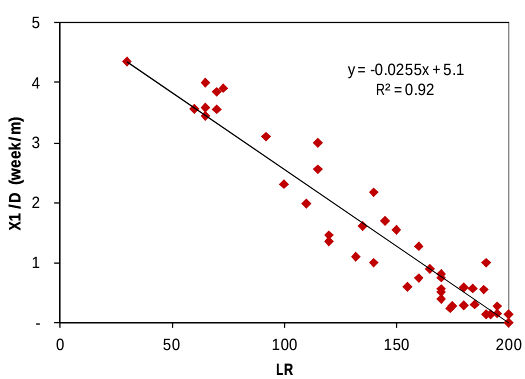

Figure 17. Analysis results for obtaining X1/D.

Once the X1/D ratio is obtained, X1 and A1, which are the excavated lengths of tunnel during LPP, can be easily calculated. Having A1 and X1, it is possible to calculate the Xn (total tunneling time), as shown in Equation 5.

$$Xn = X1 + (A - A1)/Y1 \tag{5}$$

In this calculation, 'A', the area under the curve, is, in fact, the total length of the tunnel and 'A1' is the length of the tunnel excavated in the learning period. Having X1, Xn, and Y1, it is possible to obtain the tunnel advance for the learning phase. The following example shows different steps of obtaining the LPP parameters using the proposed methodology.

7. Example

In this section, an example of line fitting using the formulas introduced in the previous section is shown. The actual advance rate data is obtained from [45] for the Konjancham tunnel. This tunnel is located in the Ilam Province in Iran and is under construction with a 5.56 m diameter double-shield TBM. The data analysis in this section is focused on the first 4.8 km length of this tunnel, which is excavated in 28 weeks. According to the actual data, the NPP advance rate is 191 m. The average RMR value of the rock mass is 45 (varying from 42 to 47), and the learning condition is good. Hence, the learning conditions rating (LR) is calculated from Table 5 to be 145. Table 6 shows a summary of the required input parameters and the required formulas for the calculation of LPP and NPP advance rates. Figure 18 shows the LPP and NPP advance rate for this project. As it can be seen, the fitted lines for LPP and NPP match very well with the general trend of the actual data. X1 in this project is around 8, which means the first 8 weeks is in LPP. The percentage of X1 with respect to Xn is around 30%, indicating the importance of LPP even for a tunnel length of 5 km, which is relatively a long tunnel. This example in its own shows the major importance of the correct evaluation of LPP for the prediction of the project time, especially in the early phase of a project (e.g. in the phase of bidding) when the project schedule plays a major role for cost planning.

Table 6. Summary of the formulas and the calculation results.

Parameter	Formula/Description	Value	Unit
A	Tunnel length/Area under fitting functions	4800	m
LR	Learning conditions' rating	145	
D	Tunnel diameter	5.56	m
Y1	Average AR for NPP	191	m/week
X1/D	-0.0255LR+5.1	1.4	Week/m
X1	(-0.0255LR+5.1)*D	8	Week
A1	X1*Y1 *0.5	745	m
a (slope value)	Y1/X1	24.5	
Xn	X1+(A-A1)/Y1	29	week
Average AR for the entire tunnel	A/Xn	165	m/week

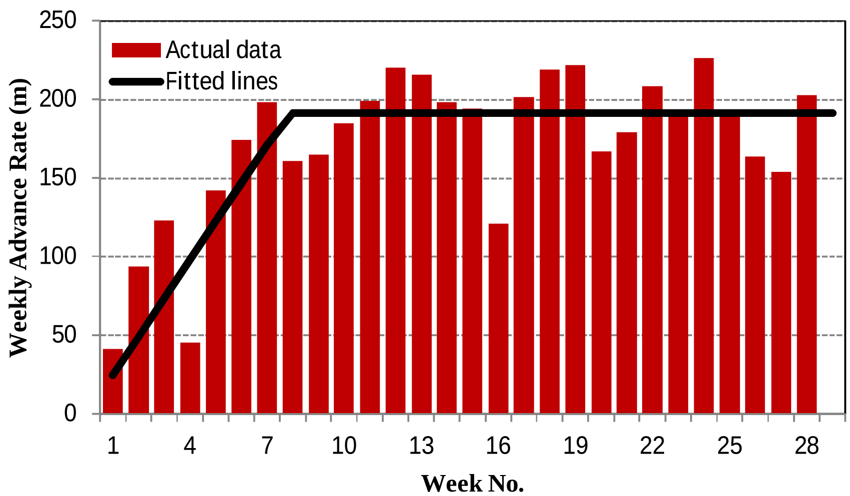

Figure 18. LPP and NPP for the example case.

8. Conclusions

Learning Phase Period (LPP) in the TBM excavation process is a low production phase, which can be distinguished easily from the Normal Phase Period (NPP) in almost all the TBM tunneling projects. LPP can play an important role in scheduling the tunnel excavation and assessing the tunnel project cost. This is especially true for shorter tunnels in hard rocks. There are a few approaches in the prediction of the learning curve time and its impact on the overall tunneling period. The prediction of LPP depends on several factors, and it is still a difficult and uncertain task.

In this paper, a new methodology for the estimation of LPP was introduced, which included:

- Breaking the graph of advance rate of a specific time increment (i.e. week) into two explicit portions of LPP and NPP. The benefit of this method is that the end of LPP is clearly defined, and the effect of LPP is not continued for the whole length of the tunnel.

- LPP is characterized with an inclined line starting from zero and ending with the normal advance rate obtained from the common performance prediction models.
- NPP is characterized with a horizontal line representing the average advance rate of the normal phase.
- A series of analyses on the information of 44 tunneling projects showed that the X1/D ratio (called as the learning phase ratio) ranged between 0 and 4.5 with an average value of 1.5 and a median of 1.
- Learning conditions' rating (LR) (that is obtained from the crew experience, machines' breakdown frequency, and RMR value) is found to be highly correlated with X1/D. The obtained formula from this correlation can be used to predict the slope value of the LPP line.
- When the LPP function' parameters are defined, it is possible to calculate the completion time of the project with both the LPP and NPP fitting functions drawn in a single graph.

The benefits of the proposed method become more prudent during the bidding phase of a project when the accuracy in the evaluation of both construction time and cost (which are related) becomes so important.

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ارزیابی زمان اجرای تونل سازی با ماشین حفاری TBM با توجه به دوره زمانی یادگیری

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چکیده:

در هر پروژه تونل سازی با ماشین تونل زنی (TBM)، یک مرحله اولیه با نرخ پیشروی کم وجود دارد که اصطلاحاً به آن دوره زمانی یادگیری (LPP) اطلاق می شود. در این دوره، پارامترهای عملیاتی ماشین برای مطابقت با شرایط کار تنظیم می‌شوند. اهمیت این دوره زمانی در برنامه‌ریزی و ارزیابی زمان و هزینه نهایی پروژه، به ویژه برای تونل‌های کوتاه که ممکن است درصد عمده‌ای از کل زمان اتمام پروژه را زمان یادگیری تشکیل دهد، بیشتر است. در حالی که ارزیابی و کوتاه شدن این مرحله برای افزایش بهره‌وری و سرعت پیشروی روزانه ماشین حفاری بسیار اهمیت دارد، مطالعات بسیار کمی در این زمینه انجام شده است .در این مطالعه ، در مورد پارامترهای مؤثر بر LPP بحث شده است و یک روش جدید برای ارزیابی آن ارائه شده است. در این راستا از یک الگوریتم برای تخمین زمان تقریبی LPP بر اساس اطلاعات واقعی تعداد زیادی تونل‌های حفر شده با TBM استفاده شده است. بر اساس تجزیه و تحلیل آماری انجام شده بر روی داده‌های واقعی و استفاده از دو شکل مختلف خطی و چند جمله ای برای توصیف تابع LPP ، یک تابع خطی برای تخمین پارامترهای آن ارائه شده است. مهمترین پارامترهای تاثیرگذار در این زمینه شامل امتیاز شرایط یادگیری و نسبت زمان LPP به قطر تونل (X1 / D) است. تحلیل همبستگی بین این دو پارامتر، ضریب تعیین خوبی را نشان می‌دهد. دوره زمانی یادگیری می‌تواند بر میزان بهره‌وری کلی و زمان اتمام تونل‌ها تأثیر بگذارد، خصوصا زمانی که طول آنها کمتر از دو کیلومتر باشد. درک صحیح از خصوصیات LPP می‌تواند به پیمانکاران کمک کند تا ارزیابی مناسبی از زمان و هزینه‌های پروژه داشته باشند، همچنین امکان برنامه‌ریزی برای تحویل نهایی پروژه را نیز فراهم می‌کند.

کلمات کلیدی: ماشین تونل زنی، نرخ پیشروی، دوره زمانی یادگیری، ارزیابی زمان.