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Sensitivity of TBM's Performance to Structural, Control and Geological Parameters Under Different Prediction Models

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ABSTRACT In general design and analysis of a tunnel boring machine (TBM), many analytical models are proposed to predict the TBM's performance. Various models may result in different performance predictions for the same TBM excavating under the same geological conditions. Therefore, it is essential to perform the quantitative analysis of the impacts from different prediction models and the corresponding key input factors on the TBM's performance. Recently, there is almost no relevant study on such issues for TBM and it is urgent to fill this gap. In this paper, by comparing and analyzing the TBM's performance using different prediction models, three types of total thrust prediction models (the rapid-growth type, the intermediate type, and the slow-growth type) and two types of total torque prediction models (the rapid-growth type and the slow-growth type) are classified and defined for the first time in the TBM-related fields. Then, a global sensitivity analysis (SA) of TBM's performance using the Sobol' method is developed regarding key input factors, including control, structural, and geological parameters. It is found that the relative impacts of the input factors to TBM's performance vary appreciably with the selection of prediction models. Specifically, a global SA on the minimized construction period of a tunneling project with respect to structure parameters is performed. The results show that the structure parameters have similar impacts on the minimized construction period irrespective of the selection of prediction models. The impacts of different prediction models on the minimized construction period of a tunneling project using Genetic Algorithm (GA) are investigated by finding the optimal control and structure parameters. The results interestingly show that the selection of the TBM's performance prediction models has a marginal impact on the minimized construction period but yields partly different key parameters.

INDEX TERMS Tunnel boring machine, global sensitivity analysis, performance prediction, minimized construction period.

I. INTRODUCTION

As a complex electromechanical system, the Tunnel Boring Machine (TBM) is widely used because of its high security, high efficiency and environment friendly [1]. Figure 1 shows a typical scheme of a hard rock TBM, which contains a number of sub-systems, e.g., the cutterhead driving system, the thrust system, the cutterhead system, etc. To ensure a high-performance, every sub-system should work synergistically and efficiently to maintain a high efficiency in hard rock breaking and a low tool wear rate. The high efficiency in hard rock breaking requires a sufficient thrust from the thrust system and a high torque from the cutterhead driving system. The low tool wear rate makes demands on a reasonable structure of the cutterhead system. Based on the above analysis, in this paper three performance metrics, including the total normal thrust, the total torque of the cutterhead, and the cutter life, are selected for evaluating the TBM's performance in tunneling projects, which are detailedly described as follows:

- Total normal thrust: Thrust is the power source of TBM's normal forward excavation, so the stability and reliability of the thrust directly affect the construction period of the whole tunneling operation. TBM usually works under the ground where many unexpected conditions may happen, such as the hydrops and the hard rocks. The thrust should overcome the resistance coming from these

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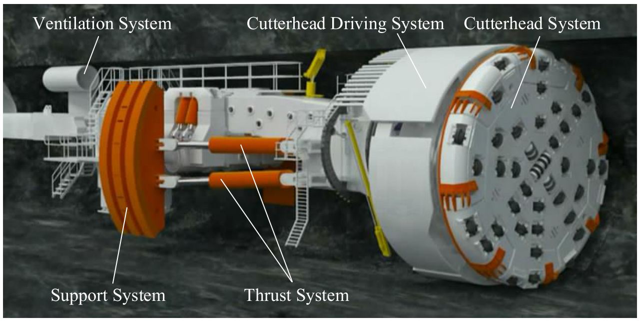

FIGURE 1. **A typical diagram of the hard rock TBM [1].**

extreme conditions to move the machine forward. The thrust is mainly affected by factors such as the fording depth and rock properties.

- Total torque of the cutterhead: The torque provided by the cutterhead driving system powers the cutterhead to overcome the tangential rock resistance for excavating. Under the complex underground geological conditions, the locked rotor may happen due to some emergencies, e.g., unexpected hard rock and overlarge penetration, which can lead to unwanted maintenance shutdown with great economical loss. Therefore, enough torque is desired to drive the cutterhead to avoid such stoppage and complete the tunneling projects within the scheduled construction period and cost restriction.
- Cutter life: During the tunneling operation, cutter changing is generally complex and time consuming. Such a complex process can greatly delay the construction and largely increase the project cost. Thus, it is greatly significant to accurately predict the cutter lifetime during the tunneling engineering of the TBM to avoid expected cutter failure.

Due to the complexity of TBM's electromechanical system, the above three performance metrics are generally challenging to predict, especially combined with complex geological conditions. In the literature, a number of models have been developed for predicting TBM's total thrust, total torque, and cutter life, such as the Evans model [2], the Colorado School of Mines (CSM) model [3], and the Wijk model [4]. Among the prediction models, some are established depending on relevant tests (e.g., rock squeeze), while others are proposed based on the practical experience. All the prediction models have totally different formular expressions, so it is essential to explore the differences between various prediction models of the total thrust, the total torque, and the cutter life. Besides, the accuracy of TBM's performance preditcion greatly relies on the accuracy, flexibility, and reliability of the prediction models. Each prediction model has its specific characteristics and input factors, which may present different effects on the prediction accuracy. Thus, it is important to explore the sensitivity of the TBM's performance to the control, structural, and geological parameters. Sensitivity analysis (SA) is the study of how the variation in the output of a model can be apportioned qualitatively or quantitatively, to different sources of variation, and of how the given model depends upon the information fed into it [5]. By the process of SA, the relevant engineers studying on the TBM and tunneling engineering can have a deeper understanding on the performance prediction and undertake a reasonable selection from different prediction models. Sensitivity analysis could help (i) determine the most influential parameter(s) to promote informed application, (ii) select a suitable prediction model under complicated geological conditions, and (ii) further advance the improvement of prediction models.

A. PERFORMANCE ANALYSIS FOR TBM

Currently, many existing literatures focus on the TBM's performance. For example, Armaghani *et al.* [6] proposed a new model based on the gene expression programming (GEP) to estimate TBM's performance by means of the penetration and results showed that the developed GEP model provides higher capability in estimating TBM's penetration compared with some other methods. Liao *et al.* [7] proposed an adaptive robust control (ARC) law based torque allocation technique scheme for hard rock TBM, finding that the proposed method can ensure better motion synchronization of the driving motors and driving torque allocation. Sun *et al.* [1], [8] developed a multidisciplinary design optimization (MDO) model for the design of TBM and proposed new excavation strategies by considering both the control and structure parameters, results showed the proposed excavation strategy with adaptive structure and control parameters could significantly shorten the construction period and reduce the cost and energy consumption. Ghasemi *et al.* [9] developed a fuzzy logic model to predict the penetration based on the collected data from a hard rock TBM tunnel using rock properties such as uniaxial compressive strength, rock brittleness, distance between planes of weakness and the orientation of discontinuities in the rock mass. Entacher *et al.* [10] designed a new scaled rock cutting test rig and found that the scaled rock cutting tests are superior input parameters for TBM performance prediction compared to commonly used geotechnical standard tests.

B. SA USED IN THE TUNNELING ENGINEERING

SA has been widely used in different tunneling engineering. For example, Ebrahimy *et al.* [11] performed SA to explore the impact of chosen variables on the duration of a tunneling project and found that the total storage capacity had the largest impact on tunneling duration. Kwon *et al.* [12] carried out SA to investigate the influence of the Excavation Damaged Zone (EDZ) on the mechanical stability of an underground research tunnel, finding that the in situ stress ratio, Young's modules, and EDZ size are the three main parameters. Mahdevari and Torabi [13] used Relative Strength of Effects (RES) in their modeling to perform an SA and found that all input parameters have meaningful effects on the output, which can be used to reasonably predict and manage tunnel convergence. Yazdani-Chamzini *et al.* [14] employed

TABLE 1. Thrust prediction models and inputs.

Model	Formula	Control	Structure				Geology			
		h	r	α	δ	N	UCS	τ	σ_t	σ_{is}
Evans	$F_v = \frac{4}{3}\sigma_c h\sqrt{r^2-(r-h)^2}\tan\frac{\alpha}{2}N$	√	√	√		√	√			
Roxborough	$F_v = 4\sigma_c h\sqrt{2rh-h^2}N$	√	√			√	√			
CSM	$F_v = 2.12\delta r\phi^3\sqrt{\frac{\sigma_c^2\sigma_t s}{\phi\sqrt{r\delta}}}\cos\frac{\phi}{2}N$	√	√		√	√	√		√	
Wijk	$F_v = 3\sigma_c\sqrt{hd}(\delta+h\tan\frac{\alpha}{2})N$	√	√	√	√	√	√			
Ozdemir	$F_v = d^{0.5}h^{1.5}[\frac{4}{3}\sigma_c+2\tau(\frac{s}{h}-2\tan\frac{\alpha}{2})]\tan\frac{\alpha}{2}N$	√	√	√		√	√	√		
Akiyama	$F_v = \sigma_c r^2(\tan\alpha\sin\phi-\cos^2\phi\tan\alpha\ln(\frac{1+\sin\phi}{\cos\phi}))N$	√	√	√		√	√			
Frenzel	$F_v = \frac{3}{25}\sqrt{2rsh\sigma_{is}}\tan\alpha N$	√	√	√		√				√

the cosine amplitude method (CAM) to identify the most sensitive factors affecting road header performance that is a crucial in tunneling projects, and found the most significant parameters are the UCS and specific energy (SE), and the least effective parameter is the rock quality designation (RQD). Zhao *et al.* [15] conducted an SA to numerical simulations of a shield supported mechanized tunnel excavation in soft soil, finding that the global SA is more reliable than the local SA for non-linear models, and the friction angle plays the most significant role in plastic deformation and soil's elastic deformation that is highly dependent on the stiffness and friction angle. Touran and Asai [16] developed several simulation models to investigate the impact of a number of variables on the tunnel advance rate of TBM by SA, including the number of trains, travel time, TBM penetration rate, and various rock types. Beiki *et al.* [17] performed two approaches of sensitivity analyses, based on "statistical analysis of RSE values" and "SA about the mean" and found that the variables of UCS, geological strength index (GSI), and RQD play more prominent roles in predicting modulus of the rock mass in tunneling projects. Yang *et al.* [18] presented a no-tension elastic-plastic model and an optimized back-analysis technique for stability analysis of underground tunnels, during which they conducted an SA of the genetic algorithm optimization procedure to identify suitable geo-material properties. The results showed that the tunnel displacement significantly depends on the elastic modulus and internal friction angle, and less depends on the cohesion strength.

Though the performance of TBM has been well studied in literatures, most of the current work only focuses on a specific aspect or single model rather than the analysis and comparison between different models. A better understanding of the relationship between different performance prediction models would be helpful to design and analyze the TBM for special tunneling projects under complicated geological conditions. To this end, the TBM's performance, including the total normal thrust, the total torque of the cutterhead, and the cutter life, estimated using different prediction models is compared and analyzed. Besides, global sensitivity analyses are performed to explore the impacts of input factors on the different prediction models and the minimized construction period of the tunneling engineering, trying to provide reasonable basis for suitable models selection.

The reminder of the paper is organized as follows. Section II discusses different prediction models of the TBM, based on which the TBM's performance, including the total thrust, the total torque, and the cutter life, estimated using different prediction models is compared and analyzed. In Section III, a global SA of TBM's performance to control, structure, and geology parameters using the Sobol' method are explored. A global SA on minimized construction period of the tunneling engineering to structural parameters is performed in Section IV. Section V presents a optimization to explore the impacts of different prediction models of TBM on the minimized construction period of a tunneling project. Section VI provides the concluding remarks.

II. PERFORMANCE PREDICTION MODELS

A. TOTAL NORMAL THRUST

A number of thrust prediction models are available in the literature. Among these models, seven are adopted in this work as listed in Table 1, including the Evans model, the Roxborough model [19], the CSM model, the Wijk model, the Ozdemir model [20], the Akiyama model [21], and the Frenzel model [22]. Many of these models have been improved, e.g., the CSM being updated by Rostami [23], [24] and modified by Yagiz [25] and Saffet [26]. Table 1 also lists input parameters in each thrust prediction model, where σ_c (MPa) is the compressive strength of the rock, h (m) is the penetration, r (m) is the radius of the cutter, α (°, degree) is the blade angle of the cutter, N is the number of the cutters, ϕ (°, degree) is the cutter contact angle, σ_τ (MPa) is the brazilian tensile strength, s (m) is the cutter spacing, δ (m) is the cutter wear flat, d (m) is the cutter diameter, τ (MPa) is the shear strength without sideward-wall, and σ_{is} (Mpa) is the point load index for the rock parallel to the excavating surface. It is seen that the inputs to all the thrust models can be categorized into three groups, i.e., control parameters, structure parameters, and geology parameters. But each model may utilize different number of parameters from each category, e.g., the Evans model takes the structure parameters r and α as the inputs, while the CSM model uses r, δ, and N. Note that in practical tunneling projects, some

TABLE 2. Torque prediction models and inputs.

Model	Formula	Control	Structure				Geology			
		h	r	α	δ	N	UCS	τ	σ_t	σ_{is}
Roxborough	$T = 4\sigma_c h^2 \tan\alpha N \frac{D(N+1)}{4N}$	√		√		√	√			
CSM	$T = 2.12\delta r \phi^3 \sqrt{\frac{\sigma_c^2 \sigma_t s}{\phi\sqrt{r\delta}}} N \frac{D(N+1)}{4N}$		√		√	√	√		√	
Wijk	$T = \frac{\sqrt{\frac{h}{2r}\{\delta + \frac{2h\tan\frac{\alpha}{2}}{3}\}}}{\delta + h\tan\alpha} f_v N \frac{D(N+1)}{4N}$	√	√	√	√	√	√		√	
Ozdemir	$T = [\sigma_c h^2 + \frac{4\tau\phi h^2(s - 2h\tan\frac{\alpha}{2})}{2r(\phi - \sin\phi\cos\phi)}]\tan\frac{\alpha}{2} N \frac{D(N+1)}{4N}$	√	√	√		√	√	√		

TABLE 3. Cutter life prediction models and inputs.

Model	Formula	Control	Structure				Geology					
		h	r	α	δ	N	UCS	σ_{PLT}	CAI	φ	SJ	AVS
Wijk	$l_f = \frac{\varphi d \delta^3 \cot\frac{\alpha}{2}}{3\sigma_c\sqrt{hd}(\delta + h\tan\alpha)\sqrt{\sigma_c\sigma_{PLT}}(CAI)^2}$	√	√	√	√		√	√	√	√		
Frenzel	$l_f = \frac{2057}{CAI}\frac{r}{216}$		√				√					
NTNU	$CLI = 13.84(\frac{SJ}{AVS})^{0.3847}$										√	√
Gehring	$V_s = 0.74CAI^{1.93}$								√			

special cutters differing from general ones are installed on the edge and center of a cutterhead. To simplify the analysis in this paper, it is assumed that only general cutters are used and the cutters layout is uniformly distributed. Thus the cutter spacing is described as

$$s = \frac{D}{2N} \tag{1}$$

And the total thrust is obtained by

$$F_v = f_v N \tag{2}$$

B. TOTAL TORQUE OF THE CUTTERHEAD

For the torque output from the cutterhead driving system, many models have also been proposed up to now. Table 2 lists four torque prediction models that are widely used in practical tunneling engineering. In Table 2, D (m) is the cutterhead diameter and f_v (kN) is the normal thrust acting on a single cutter. The rest parameters have been explained in Section II-A. The same as the thrust models, the inputs to these torque models also include three types of parameters, i.e., the control parameters, structure parameters, and geology parameters. As described in the Section II-A, it is assumed that all cutters are general shape and uniformly distributed, then the torque can be obtained by

$$T_t = f_t N \frac{D(N+1)}{4N} \tag{3}$$

where f_t (kN) is the tangential thrust acting on a single cutter.

C. CUTTER LIFE

The lifetime of a single cutter can be defined in many ways: (i) the total volume of the rock breaking before the cutter's failure; (ii) the continuous excavating distance before the cutter's failure; (iii) the normal excavating time before the cutter's failure, etc. A significant amount of research has been done in the literature to study the cutter life, which is briefly summarized in Table 3. φ (Pa^2/m) is the wear coefficient of the cutter, σ_{PLT} (MPa) is the point load test index for tensile rock strength, *CAI* is the Cerchar Abrasivity Index of the rock, *SJ* (dmm) is the Sievers' J-value, and *AVS* (mg) is the Abrasion Value Steel. Among the four prediction models, the Wijk model [4] and the Frenzel model [27] utilize the cutter rolling length to define the cutter life; the NTNU model [28] quantifies the cutter life using boring hours for cutter disc rings of steel; and the Gehring model [29] defines the cutter life as the ring weight loss due to rock breaking before the cutter's failure. Due to such different defining standards, it is meaningless to directly compared the cutter life between different prediction models, so the TBM performance analysis performed in Section II-D does not cover the aspect of the cutter life. From Table 3, the Wijk model utilizes all the three types of parameters, including control parameters, structure parameters, and geology parameters, to determine the cutter life; the Frenzel model uses the structure and geology parameters except the control parameters; for the NTNU model and the Gehring model, only the geology parameters are selected. This is because some of the cutter life models are established depending on relevant tests, while others are proposed based on the practical experience, as mentioned in Section I.

D. ANALYSIS OF TBM'S PERFORMANCE PREDICTION MODELS

1) NUMERICAL SETTINGS

In the analysis of this section, the rock type excavated by the TBM is assumed to the limestone and its actual properties can be found in [30]. In this paper, the diameter of the excavated tunnel D is assumed to be 10 m. Besides, it is also

TABLE 4. Constant parameters of TBM.

Parameter	r (mm)	α (°)	δ (mm)	N	D (m)
Value	200	45	8	50	10

assumed that there are 50 disc cutters uniformly laid on the cutterhead with the cutter radius r and the cutter edge angle α being 200 mm and 45° respectively. In order to achieve the comparison and analysis between different prediction models, the cutter wear flat δ is set to be 8 mm uniformly. Overall, the related constant parameters of the TBM are listed in Table 4.

2) THRUST MODELS ANALYSIS

Figure 2 shows the variation of the total thrust with increasing penetration with respect to different prediction models. In the practical engineering, the penetration is usually set to be within the range less than 15 mm/r based on the general rock hardness. But in order to figure out the difference between various prediction models, the range of the penetration is enlarged to be 0 to 30 mm/r. Among the seven prediction models, the Wijk model estimates the largest thrust, while the Evans Model predicts the smallest thrust. It is seen that the tendencies of these seven models varying with the penetration can be classified into three types: (i) the rapid-growth type, including the Roxborough Model and the Wijk Model; (ii) the intermediate type, including the Ozdemir Model and the Akiyama Model; and (iii) the slow-growth type, including the Evans Model, the CSM Model, and the Frenzel Model. For the rapid-growth type, the thrust predicted by the Wijk Model is continuously larger than that predicted by the Roxborough Model in the entire region of penetration h. For the intermediate type, when the penetration h is less than 26 mm/r, the Ozdemir model predicts larger thrust than the Akiyama model does; when the penetration h is over 26 mm/r, the Ozdemir model predicts smaller thrust than the Akiyama model does. The slow-growth type shows a more complicated situation. With the penetration h increasing, the Frenzel model always predicts the largest thrust within the slow-growth type. When the penetration h is less than 20 mm/r, the predicted thrust by the three slow-growth models ranks from large to small is: the Frenzel model, the CSM model, and the Evans model. When the penetration h is over 20 mm/r, the ranking changes to: the Frenzel model, the Evans model, and the CSM model. From the overall viewpoint, the ranking will be more complicated if all the seven models are compared together. Take the range 7 mm/r $\leq h \leq$ 9 mm/r as an example, the predicted thrust obtained from the seven models ranks from large to small is: the Wijk model, the Roxborough model, the Ozdemir model, the Frenzel Model, the CSM Model, the Akiyama model, and the Evans model. This ranking will fully change within a different penetration region. It is concluded from Fig. 2 that the main reason causing such different appearance of the three models

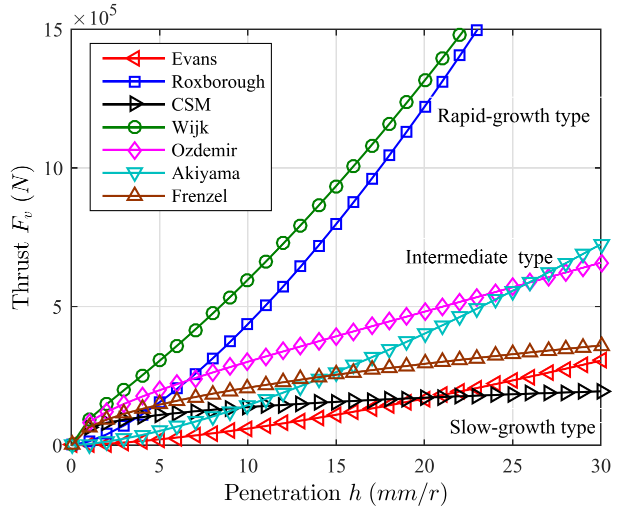

FIGURE 2. Variation of thrust with penetration.

is the different establishing ways for the thrust prediction models, including relevant tests and practical experience.

3) TORQUE MODEL ANALYSIS

For the same purpose by enlarging the range of the penetration h for the thrust model, the range of penetration of the torque prediction models is also enlarged to be 0 to 20 mm/r. Figure 3 shows the variation of the torque with increasing penetration. It is seen that the tendencies of these four models can be classified into two types. One is the rapid-growth type, including the Roxborough model and the Wijk model, the other is the slow-growth type, including the CSM model and the Ozdemir model. For the slow-growth type models, the Roxborough model estimates a larger torque than the Evans model does. While for the rapid-growth type models, the Wijk model predicts a larger torque when the penetration h is less than 12 mm/r, and the Roxborough model predicts a

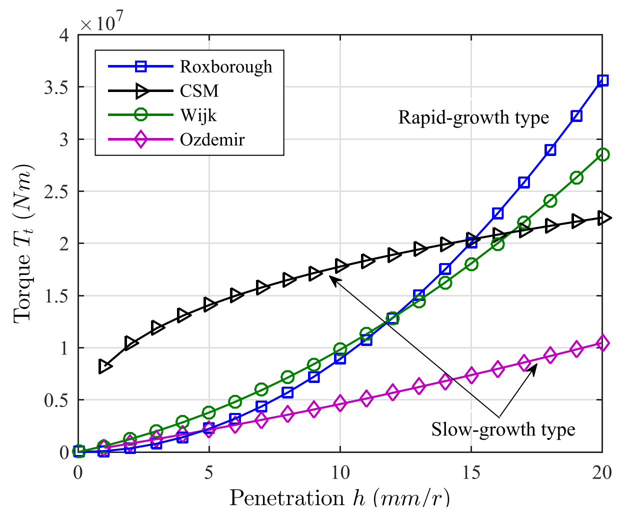

FIGURE 3. Variation of torque with penetration.

larger torque when the penetration h is larger than 12 mm/r. With the changing penetration, the ranking of the torque obtained from the four models is greatly different. It can be also concluded that the different establishing ways for the torque prediction models is again the main reason causing the different appearances of the two models.

III. SA OF TBM'S PERFORMANCE

The SA focuses on the influences of the input changes on the outputs of the system or the model, and also the influences on the system or model itself, by giving quantitative sensitivity results. It can find out which parameters have greater influences on the system performance, significantly analyze the stability of optimal performance, and clearly direct the next step of optimization process, especially when the raw data to some degree is inaccurate or inconstant. Given the great significance to the optimization methods and evaluations, the SA has come to be one research hotpot and many SA methods have been proposed. Currently, the Sobol' method [31] and the Fourier amplitude sensitivity test (FAST) [32] are two popular methods of the SA. In this paper, the Sobol' method is adopted to perform the SA. An overview of the Sobol' method is provided in Section III-A.

A. SOBOL' METHOD

The Sobol' SA method is a variance-based Monte Carlo method. It was first proposed by Sobol [31] and has been widely used in many fields, such as economics, environmental science, sociology, and machinery. For a function with k input variables,

$$y = f(x) = f(x_1, x_2, x_3, \cdots, x_k) \tag{4}$$

where $0 \le x_i \le 1$, the main idea behind Sobol' method for the computation of sensitivity indices is to decompose $f(x)$ into summands of increasing dimensionality as follows.

$$f(x_1, \cdots, x_k) = f_0 + \sum_{i=1}^{k} f_i(x_i) + \sum_{1 \le i < i \le k} f_{ij}(x_i, x_j) + f_{1,2,\cdots,k}(x_1, \cdots, x_k) \tag{5}$$

Based on the multiple integration method, f_0 is a constant and the integrations of every summand over any of its own variables must be zero:

$$\int_0^1 f_{i_1,i_2,\cdots,i_k}(x_{i_1}, \cdots, x_{i_k}) dx_{i_1} \cdots dx_{i_s} = 0 \quad (1 \le k \le s) \tag{6}$$

Sobol [33] also certified that the decomposition of (5) is unique and all the summands can be obtained using the multiple integration method. Thus, the total variance of $f(x)$ can be described as:

$$V = \int_{\Omega^k} f^2(x)dx - f_0^2 \tag{7}$$

where $\Omega^k = \{x | 0 \le x_i \le 1\} (i = 1, 2, \cdots, k)$. The partial variances can be obtained from (5), given by,

$$V_{i_1,i_2,\cdots,i_s} = \int_0^1 \cdots \int_0^1 f^2_{i_1,i_2,\cdots,i_s}(x_{i_1}, \cdots, x_{i_k}) dx_{i_1} \cdots x_{i_k} \tag{8}$$

where $1 \le i_1 < \cdots < i_s \le k$ and $s = 1, 2, \cdots, k$. By squaring and integrating (5) over the entire Ω^k, it is obtained that

$$V = \sum_{i=1}^{k} V_i + \sum_{1 \le i < j \le k} + \cdots + V_{1,2,\cdots,k} \tag{9}$$

So the sensitivity $S_{i_1,i_2,\cdots,i_s}$ can be described as

$$S_{i_1,i_2,\cdots,i_s} = \frac{S_{i_1,i_2,\cdots,i_s}}{V} \quad 1 \le i_1 < \cdots < i_s \le k \tag{10}$$

S_i is the first-order sensitivity index of x_i that represents the main impact on the output y; S_{ij} $(i \ne j)$ is the second-order sensitivity index that represents the cross impact of x_i and x_j on the output y. The total sensitivity index of x_i is the sum of all order sensitivity indices [34], given by

$$S_{Ti} = S_i + \sum_{j \ne i} + \cdots \tag{11}$$

The sensitivity indices of all the input variables must satisfy the following condition:

$$\sum_{i=1}^{k} S_i + \sum_{1 \le i < j \le k} S_{ij} + \cdots + S_{1,2,\cdots,k} = 1 \tag{12}$$

So the total sensitivity index of x_i can be calculated using the variance $V_{\sim i}$ that is the sum of variances of all input variables other than x_i [35].

$$S_{Ti} = 1 - \frac{V_{\sim i}}{V} \tag{13}$$

B. UPPER AND LOWER BOUNDS OF INPUT PARAMETERS

Defining reasonable bounds of studied parameters is important for performing an efficient and accurate SA [36]. As described in Sections II-A ~ II-C, one control parameter, four structural parameters, and four geological parameters should be investigated for thrust prediction models and torque prediction models; two control parameters, four structural parameters, and six geological parameters should be investigated for the cutter life prediction models. Based on the practical engineering, the ranges of all the three types of parameters are defined in Table 5.

C. SA RESULTS

1) SA OF THE TOTAL NORMAL THRUST

By setting the sample size of each input parameter being 1000, Fig. 4 presents the sensitivity of 7 thrust prediction models to the 9 input parameters listed in Table 1. It is seen that the relative impacts of the input parameters varies a lot among different prediction models. For the Evans model and the Roxborough model, the penetration h is the major factor

TABLE 5. Upper and lower bounds of input parameters.

Bound	Control	Structure				Geology								
	h (mm)	r (mm)	α (°)	δ (mm)	N	UCS (MPa)	σ_{PLT} (MPa)	CAI	φ (Mpa)	SJ (dmm)	AVS (mg)	τ (Mpa)	σ_t (Mpa)	σ_{is} (Mpa)
Lower	0	50	30	2	20	100	5	1	15×10^{24}	1	0.5	30	5	5
Upper	20	250	120	20	120	300	15	5	20×10^{24}	100	50	100	15	15

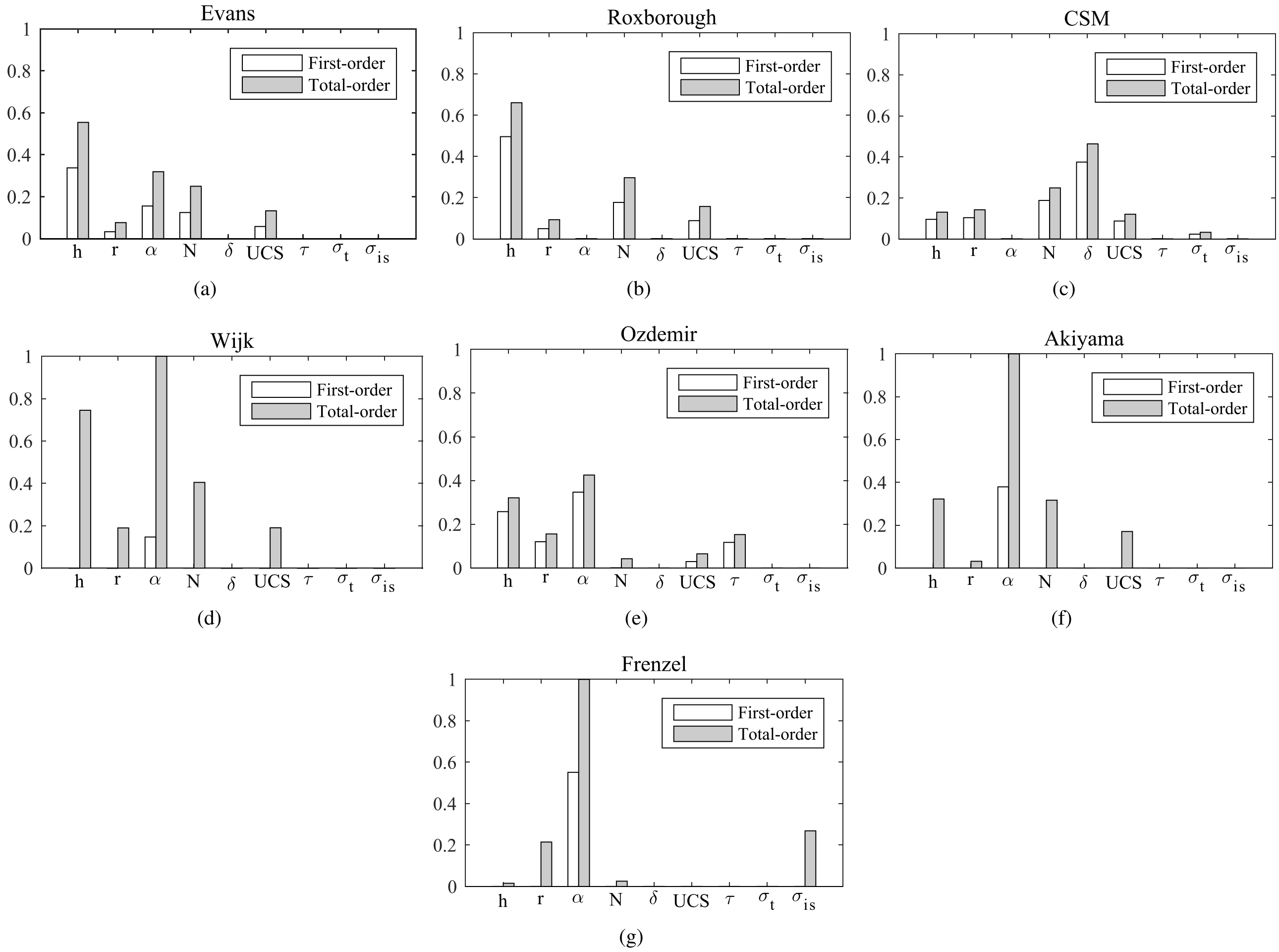

FIGURE 4. Sensitivity of the seven thrust prediction models to 9 input parameters: (a) Evans model; (b) Roxborough model; (c) CSM model; (d) Wijk model; (e) Ozdemir model; (f) Akiyama model; (g) Frenzel model.

that affects the total thrust. While under the Wijk model, the Ozdemir model, the Akiyama model, and the Frenzel model, the blade angle α is the decisive factor. It is also found that the most sensitive factor impacting the CSM model is the cutter tip width δ. From the analysis above, one specific parameter may be the decisive factor in one thrust model, however, it will have no impact in another prediction model, e.g., the cutter tip width δ. The reason of this phenomenon is the different establishing ways for the thrust prediction models, either relevant tests or vast practical experience. For example, when establishing the Evans prediction model, more attentions should be paid to the control and structural parameters rather than various geological parameters. Nevertheless, more attentions should be paid to the various geological parameters when building the CSM model for the total thrust.

From Figs. 4(a) $\sim$ 4(g), it can be observed that all of the total-order sensitivity indexes of the nine input parameters are higher than the corresponding first-order indexes, which reflects that the control parameters, the structural parameters, and the geological parameters used in the prediction models are strongly coupled with each other to influence the total thrust. For the Wijk model, the Akiyama model, and the Frenzel model, only the blade angle α presents a first-order sensitivity index, while other input parameters only present the total-order sensitivity indices. From this, it illustrates that only the blade angle α impacts directly the output of total thrust under these three prediction models, but in contrast other parameters impact the output entirely through the coupling interactions. So when conducting the design and optimization for TBM, the interaction between different types of input parameters should be fully taken into account.

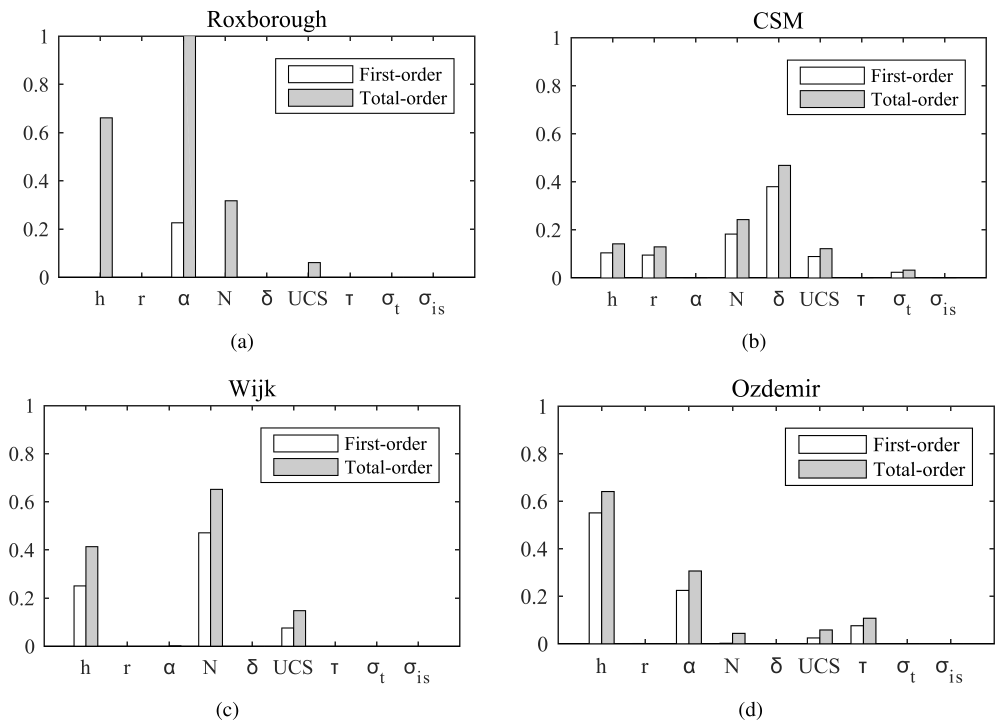

FIGURE 5. Sensitivity analysis of the four torque prediction models to 9 input parameters. (a) Roxborough model; (b) CSM model; (c) Wijk model; (d) Ozdemir model.

2) SA OF THE TOTAL TORQUE OF THE CUTTERHEAD

Figure 5 illustrates the sensitivity of four torque prediction models to the 9 input parameters. It is observed that the torques predicted by the four different models are affected by different parameters. For the Roxborough model, the most decisive factor is the blade angle α; for the CSM model, the most decisive factor is the cutter tip width δ; for the Wijk model, the most decisive factor is the disc cutter number N; and for the Ozdemir model, the most decisive factor is the penetration h. Again, some parameters, e.g., the cutter tip width δ and the blade angle α, play a decisive role in one prediction model while a useless role in another model, the reason of which is still the different establishing ways for the prediction models, either relevant tests or vast practical experience, as analyzed in Section III-C.1.

It is also interesting to find that the torque is more sensitive to the control and structural parameters than the geological parameters. It is observed that all of the total-order sensitivity index is higher than the corresponding first-order index, which means that the coupled interaction between different types of input parameters are also important in the torque prediction. Especially for the Roxborough model, only the blade angle α has a direct impact on the output of torque, while other parameters influence the torque through the coupling effects.

3) SA OF THE CUTTER LIFE

As described in Section II-C, the cutter life can be defined in different ways, so the sensitivity of the cutter life to 12 input parameters should be analyzed based on specific defining standards of corresponding prediction models. Besides, different ways to establish the prediction models makes the SA of such various prediction models to corresponding input factors lead to more different and complex situation, as illustrated in Fig. 6. It is found from Figs. 6(b) $\sim$ 6(d) that the control parameters have no impact on the Frenzel model for cutter life prediction, and the control and structural parameters have no impact on the NTNU model and the Gehring model. Overall, it is observed from Figs. 4 $\sim$ 6 that the geological parameters have more dominant impacts on the cutter life than that on the total thrust and the total torque.

Under the Wijk model, it is observed that the first-order sensitivity indices are all close to 0, while the total-order sensitivity indexes are much higher than first-order sensitivity indexes. The differences between the first-order and total-order sensitivity indexes of other three cutter life prediction models are relatively less than that of the Wijk model. This illustrates that the coupling effects between different types of parameters under the Wijk model are much stronger than the other three models. Thus, when using the Wijk model, more attentions should be paid to the interactions among the input parameters.

IV. SA ON MINIMIZED CONSTRUCTION PERIOD

From the point of view of the whole tunneling engineering, a minimum construction period t (month) is usually set as the overall project objective by taking into account both of the cost and the energy consumption. Therefore, it has great

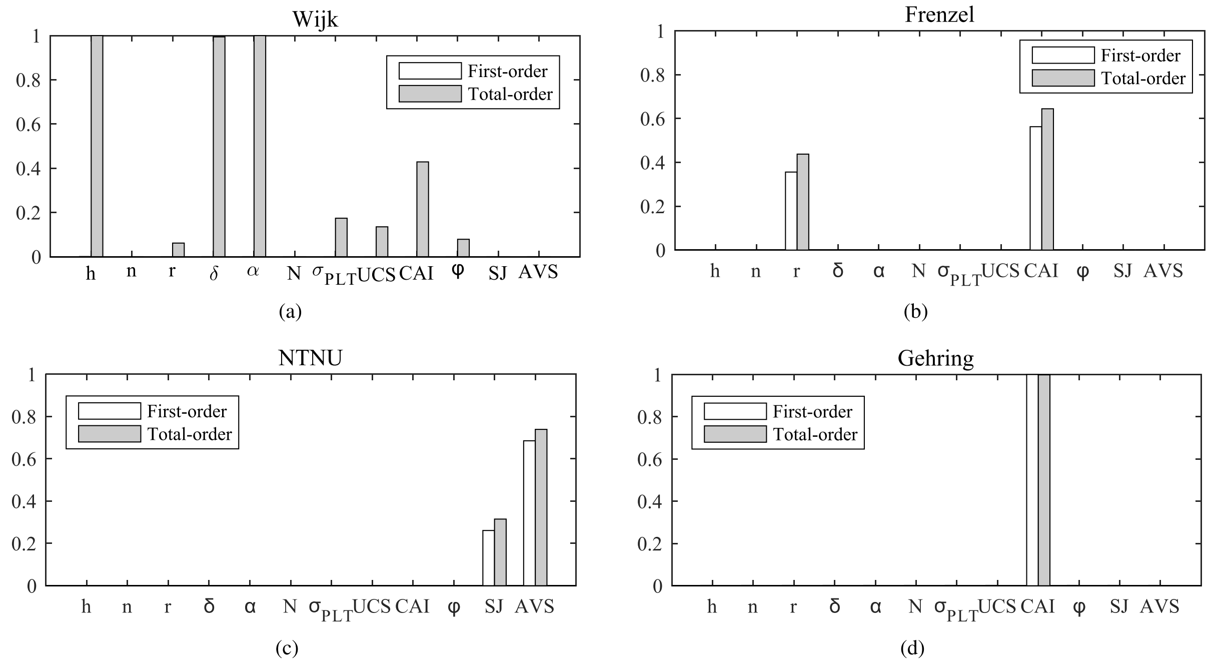

FIGURE 6. **Sensitivity analysis of the four cutter life prediction models to 12 input parameters: (a) Wijk model; (b) Frenzel model; (c) NTNU model; (d) Gehring model.**

practical significance to study the SA on the minimized construction period of a tunneling engineering. Figure 7 shows the differences between the general SA (enclosed by the green dotted line) and the SA on an optimization process (enclosed by the red dotted line). The general SA is performed based on the pure simulation model or pure formula model. But for the SA on optimization process, an optimization model takes role of the simulation model in general SA process. At each iteration of the SA process, a complete optimization process is carried out and the objective function value is served as the analysis target of the SA.

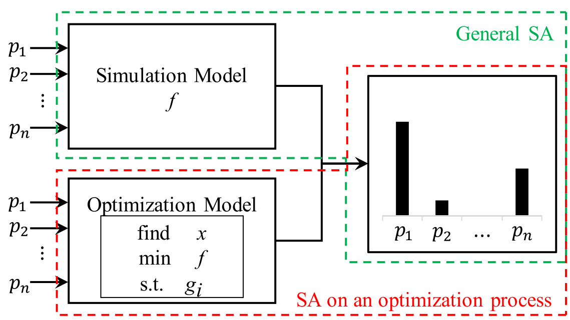

FIGURE 7. **Differences between the general SA and the SA of an optimization process.**

In this section, the sensitivity of the minimized construction period to the structure parameters is analyzed, including the cutter redias r, the blade angle α, and the cutters number N. The working conditions of a TBM are so poor and complex, and the rock type excavated by the TBM is usually predetermined by spot sampling. Then, based on the obtained geological conditions, the structure parameters of the TBM are initially designed in the early stage of the engineering. As seen, the structure parameters greatly influence the construction period within suitable range of the control parameters in the practical tunneling engineering.

Stoppages may happen during TBM's normal excavation due to some irresistible factors, e.g., the cutters change, so the construction period usually consists of two parts: the normal construction time t_n (month) and the auxiliary time t_a (month), as given by Eqs. 14 and 15.

$$t = t_n + t_a \tag{14}$$

$$\begin{cases} t_n = \dfrac{l}{hn} = \dfrac{Nlf_t\bar{R}}{4.1256 \times 10^5 P_t h} \\ t_a = floor(\dfrac{L}{l}) \cdot t_c + \varepsilon t_n \end{cases} \tag{15}$$

where $floor(\cdot)$ is the top integral function and aims to obtain the cutter change times, l (m) is the cutter life, $\bar{R}$ (m) is the average installation radius of cutters, P_t (kW) is the total cutterhead driving power, and L (m) is the length of the tunnel. The expert coefficient (ϵ) is set to be 5, the simple cutter changing time (t_c) is set to be 3 hours based on engineering experience, and the time factor (ε) for maintenance is set to be 0.2. In this paper, a tunnel with a length 10 km is assumed and its diameter D is 10 m. The rock type excavated by TBM is again set to be the limestone.

As mentioned above, the SA in this section is to investigate the impacts of the structure parameters of different prediction models on the minimized construction period within suitable range of the control parameters. So the control parameters are set as the design variables: $X = [P_c] = [h, n]$, and the boundaries are listed in the Table 5. In this Section, three different prediction models, including the Ozdemir model, the Roxborough model, and the Wijk model, are selected to establish the optimization problems. Thus, the optimization models can be shown as follows:

$$\begin{cases} find & X_i = [P_{ci}] = [h_i, n_i] \\ min & f_i = t_i \qquad\qquad i = 1, 2, 3 \\ s.t. & g_i, \end{cases} \tag{16}$$

where i denotes the selected performance prediction models: 1 denotes the Ozdemir model, 2 denotes the Roxborough model, and 3 denotes the Wijk model, respectively.

Based on the performance and structure requirements obtained from the subsystem analysis performed in [1], the constraint g_i can be summarized as (17):

$$g_i = \begin{cases} g_{cutterlife} : l_i \geq 600 \\ g_{thrust} : F_{vi} \leq 15000 \\ g_{shear} : T_{ti} \leq 4 \times 10^6 \\ g_{thrust\ power} : P_{vi} \leq 10 \\ g_{shear\ power} : P_{ti} \leq 5000 \\ g_{structure} : \lambda_i \leq 1.5 \end{cases} \tag{17}$$

where, P_v (kW) is the total hydraulic power and λ_i is the structure parameter of the cutter [4].

Thus the global SA problem can be established. In this section, the Sobol' method is again adopted and the sample size of each input parameter is set to 1000. The ranges of the three structure parameters are listed in Table 5. Figures 8 illustrate the sensitivity of the minimized construction period to the three structure parameters. It is interesting to find that all the three parameters have similar impacts on the minimized construction period irrespective of the selection of prediction models, which is different from the greatly various impacts of the structure parameters on the TBM's performance as described in Section III. It is seen that the blade angle α is the dominant factor influencing the minimized construction period, irrespective of the choice of the prediction models. However, on closer observation, the relative impact of the other two input parameters including the cutter radius r and the cutters number N varies mildly with the choice of the prediction models. From Figs. 8(a) $\sim$ 8(c), it is observed that the cutters number N is the second strongest influencing factor for the Ozdemir model and the Wijk model, while the cutter radius r is the second strongest influencing factor for the Roxborough model. It is also observed from Figs. 8(a) $\sim$ 8(c) that the total-order sensitivity indexes of r, α, and N are all higher than the corresponding first-order indexes, which reflect that these three parameters are strongly coupled with other parameters to influence the maximized construction period, irrespective of the choice of the prediction models. Such coupling effects indirectly indicate that the construction period function is highly nonlinear, so the engineers should carefully take into account the interactions between the input parameters when performing the TBM's design optimization using different prediction models.

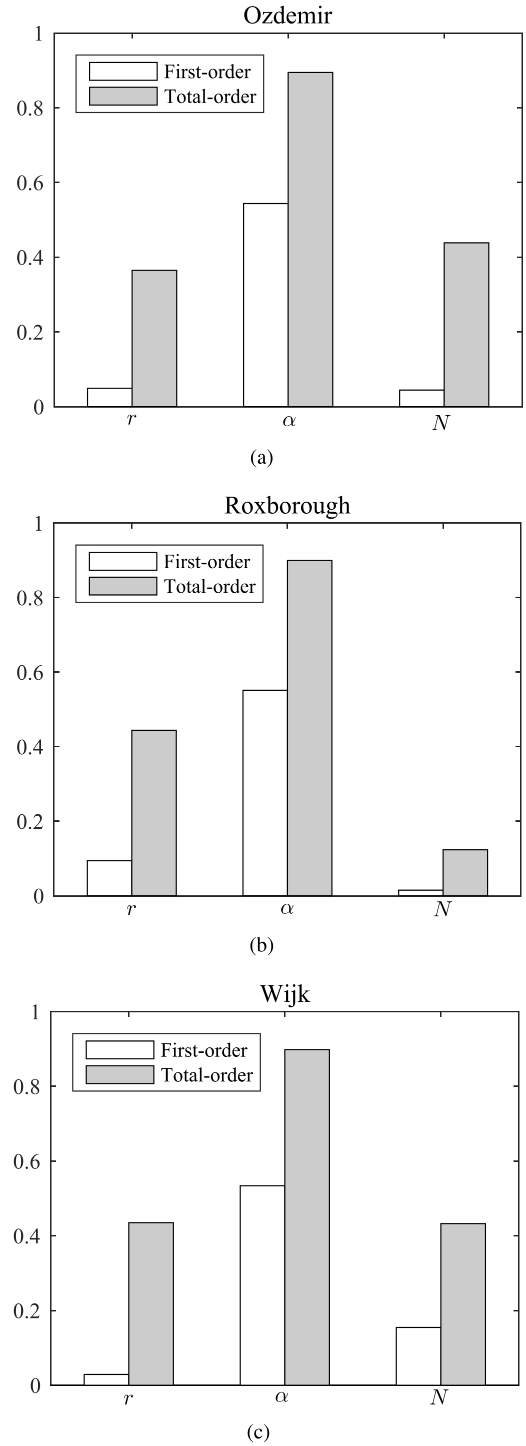

FIGURE 8. Sensitivity analysis on the minimized construction period using different prediction models. (a) Ozdemir model; (b) Roxborough model; and (c) Wijk model.

V. IMPACTS OF DIFFERENT PREDICTION MODELS' SELECTION ON THE MINIMIZED CONSTRUCTION PERIOD

In order to explore the detailed impacts of different prediction models selection on TBM's practical engineering, the minimization of the construction period using three different prediction models are performed, including the Ozdemir model, the Roxborough model, and the Wijk model. From the results of [1], the design strategy with adaptive structure and control parameters could furthest shorten the construction period by reducing the cost and energy consumption. So in this section both the structure and control parameters are taken into account as the design variables: $X = [P_c, P_s] = [(h, n), (r, \alpha, N)]$, and the boundaries are listed in the Table 5. Thus, the optimization models can be shown as follows:

$$\begin{cases} find \quad \boldsymbol{X}_i = [\boldsymbol{P}_{ci}, \boldsymbol{P}_{si}] \\ \qquad\qquad = [(h_i, n_i), (r_i, \alpha_i, N_i)] \\ min \quad f_i = t_i \\ s.t. \quad \boldsymbol{g}_i, \end{cases} i = 1, 2, 3 \tag{18}$$

where i denotes the selected performance prediction models: 1 denotes the Ozdemir model, 2 denotes the Roxborough model, and 3 denotes the Wijk model, respectively.

In order to roundly reflect the effects of the structural and control parameters on the optimization process for the TBM's performance, h and α are selected to depict the feasible regions. Figure 9 illustrates the feasible regions of the corresponding optimization models with respect to different prediction models: (a) the Ozdemir model, (b) the Roxborough model, and (c) the Wijk model. It is observed from Figs. 9(a) and 9(c) that the Ozdemir model and the Wijk model have the similar shape and similar area of the feasible regions, both of which are encircled by the constraints of $L \geq 600$ m, $P_v \leq 10$ kW, and $\lambda \leq 1.5$. From Fig. 9(b), the feasible region of the optimization model using the Roxborough model is rather different compared with the Ozdemir and Wijk models. The shape of the feasible region of the optimization model using the Roxborough model is complex and the corresponding area is much larger than that of the other two models. The corresponding valid constraints include not only $L \geq 600$ m, $P_v \leq 10$ kW, and $\lambda \leq 1.5$, but also $P_t \leq 5000$ kW and $T_t \leq 4 \times 10^6$ Nm. As can be seen, the Roxborough prediction model can lead to a much larger spatial domain for the TBM's design optimization, which will provide more design flexibility than that the Ozdemir and Wijk models can do in the practical engineering.

In this paper, the binary Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [37] is used to solve these three optimizations, and the sample size and the generations are set to be 50 and 200, respectively. After many iterations, all the convergence histories of objective and constraint violation during the three optimizations using different prediction models are obtained as illustrated in Fig. 10. From Fig. 10(a), all the convergence curves of the optimization processes reach the optimal solutions at the different iterations: the 169th iteration for the Ozdemir model, the 175th iteration for the Roxboroug model, and the 145th iteration for the Wijk model. Thus, the corresponding optimization efficiency ranks from high to low is: the Wijk model, the Ozdemir model, and the Wijk model. It is observed that all the optimization processes built by the three different prediction models can converge to

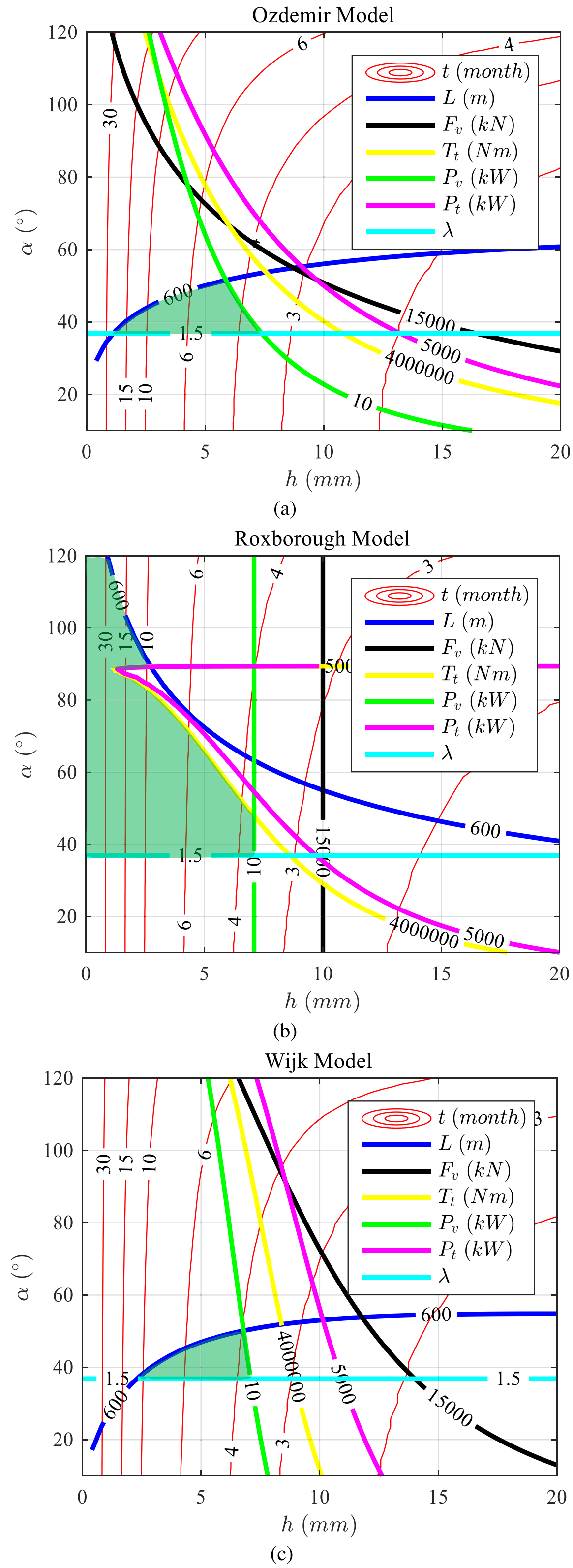

FIGURE 9. **The feasible regions under different prediction models. (a) Ozdemir model; (b) Roxborough model; and (c) Wijk model.**

such similar optimal construction periods: 3.65 month for the Ozdemir model, 3.66 month for the Roxboroug model, and 3.68 month for the Wijk model, among which the Ozdemir model performs the minimum value while the Wijk model

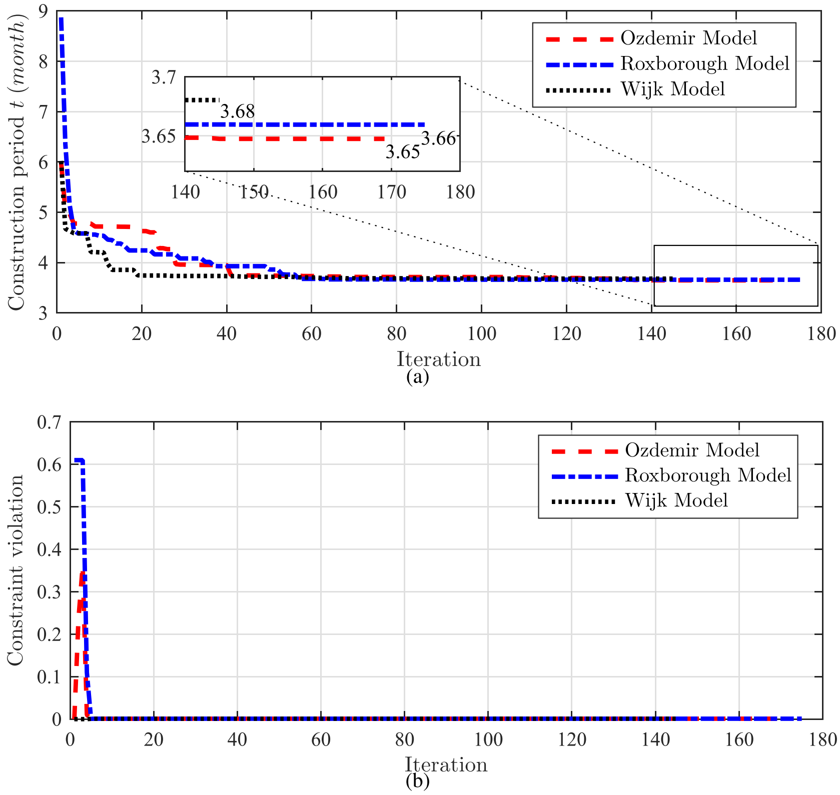

FIGURE 10. **The convergence history of objective and constraint violation during the optimization using different prediction models: (a) the optimization history; (b) the constraint violations history.**

TABLE 6. **The optimization results of the design variables and the objective function.**

Model	Design variable					Objective
	Control		Structure			
	h (mm)	n (r/min)	α (°)	N	r (mm)	t (month)
Ozdemir model	7.06	9.37	36.85	49	216.34	3.65
Roxborough model	7.10	9.39	38.59	46	201.45	3.66
Wijk model	7.10	9.4	36.85	32	239.76	3.68

Note: The gray cell backgrounds donate the histograms based on cell contents.

outputs the maximum value. Figure 10(b) shows that the constraint violations are all zero after the 6th iteration, which shows the credibility of the three optimization processes for the TBM engineering performed in this paper.

The optimization results of the design variables and the objective function are listed in Table 6, where the gray cell backgrounds donate the histograms based on cell contents. It is observed that, although all the three optimization processes using different prediction models output similar construction periods, some of the control and structure parameters are partly different. Detailedly, the penetration h, the blade angle α, and the cutterhead speed n of all the three models have little difference compared with each other, while the difference of the cutter radius r and the cutters number N are relatively big among different models. As seen, the Wijk model uses the largest cutters with the smallest number to complete the same tunneling engineering compared with the other two models. Table 7 lists the optimization results of the TBM's performance/constraints using these three different prediction models. Results show that the performance including F_v, P_v, and λ are almost the same, however, L, T_t, and P_t vary appreciably with the choice of prediction models. Under the same geological conditions, the Wijk model predicts the shortest cutterlife L, while the largest total torque of the cutterhead T_t and the total hydraulic power P_t.

Based on the study of the construction period optimization using different prediction models, it is concluded that: although different prediction models predict different types of tendencies for the TBM's performance (e.g., the thrust and the torque) as described in Section II, but synthetically different prediction models can predict almost the same overall engineering construction period by obtaining partly different structural parameters, control parameters, and constraints (TBM's performance). From the standpoint of performance,

TABLE 7. Optimization results of the constraints using three different prediction models.

Constraints	Model	Range	Optimal result
L (m)	Ozdemir	[600,+∞]	12.50×10^2
	Roxborough		10.55×10^2
	Wijk		9.17×10^2
F_v (kN)	Ozdemir	[0,15000]	9.08×10^3
	Roxborough		9.00×10^3
	Wijk		9.00×10^3
T_t (Nm)	Ozdemir	[0,4×10^6]	2.63×10^6
	Roxborough		2.89×10^6
	Wijk		3.08×10^6
P_v (kW)	Ozdemir	[0,10]	10.00
	Roxborough		10.00
	Wijk		10.00
P_t (kW)	Ozdemir	[0,5000]	2.58×10^2
	Roxborough		2.84×10^2
	Wijk		3.03×10^2
λ	Ozdemir	[0,1.5]	1.50
	Roxborough		1.50
	Wijk		1.50

Note: The gray cell backgrounds donate the histograms based on cell contents.

when the working conditions (e.g., the rock type) are pre-set as this paper, the Wijk model can ensure the tunneling engineering a best performance by outputting a shorter cutterlife L, a larger total torque of the cutterhead T_t, and a larger total hydraulic power P_t. While from the computational efficiency, the Roxborough model performs best. While in actual working conditions which are different from the pre-set conditions in this paper, the priorities of these prediction models will be totally different. In addition, it can be extended that some combined models can also be adopted in the practical engineering based on specific requirements. For example, if more attentions are paid to the energy consumption rather than the cost of the cutters, thus, the Wijk model can be selected to build the power models of the TBM and the Ozdemir model can be selected to build the cutterlife model for the overall TBM's performance prediction.

VI. CONCLUSION

In this paper, the TBM's performance, including the total normal thrust, the total torque of the cutterhead, and the cutter life, estimated using different prediction models is compared and analyzed. Three types of total thrust prediction models (the rapid-growth type, the intermediate type, and the slow-growth type) and two types of torque prediction models (the rapid-growth type and the slow-growth type) are classified and defined for the first time in TBM-related fields. The global sensitivity analyses (SA) of the TBM's performance to control, structure, and geology parameters using the Sobol' method are explored. Results show that the relative impacts of the input parameters on the TBM's performance vary appreciably with the selection of prediction models. From the SA on the minimized construction period of a tunneling engineering, it is found the structure parameters have similar impacts on the minimized construction period irrespective of the selection of prediction models. In order to further explore the impacts of different prediction models on the minimized construction period of a tunneling project, the construction period is optimized using different prediction models, including the Ozdemir model, the Roxborough model, and the Wijk model. It is found that different prediction models can predict similar construction periods by obtaining partly different structure parameters, control parameters.

Different types of prediction models for TBM's performance are usually adopted under specific assumptions, which leads to their limited scope of applications. Thus, such straightforward comparison may not reflect the real applicability of the models from a global perspective. In the future work, a more comprehensive SA can be performed by taking into account the specific application conditions of the prediction models. Besides, different types of uncertainties may present in such a complex system, such as the uncertainty in the manufacturing process and the uncertainty caused during the assembly process. Therefore, an uncertainty analysis of different prediction models could further improve TBM's overall performance, which could be a significant extension for the future work.

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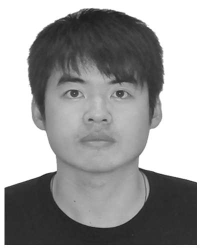

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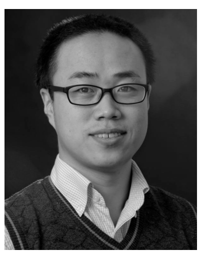

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