DEVELOPMENT OF INTELLIGENT DECISION SUPPORT MEANS FOR EFFECTIVE MICROTUNNELING CONSTRUCTION PLANNING

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The construction technology of microtunneling has been widely adopted for laying utility pipe in well developed cities featuring congested road surfaces and complicated underground spaces. This paper summarizes our recent efforts of research and applications of artificial intelligence and simulation modelling, aimed at developing effective decision support means for practicing engineers to predict production rates and enhance job performances on microtunneling projects. In particular, the paper addresses the issue that how practicing engineers can apply artificial neural networks (ANN) and simulation for microtunneling construction planning. In order to make sound and timely decisions, practitioners can benefit from the integration of the two different modelling methods: a macroscopic view on the production rate is obtained from the ANN model, in contrast with a microscopic view on detailed site operations from simulation. The short term productivity prediction from ANN assists in decision making for material delivery, while efficiency improvement of the surface logistics management through simulation increases resource utilization and removes any unneeded idling or waiting time in operations.

Keywords: Artificial Intelligence, Operations Simulation, Process Modelling, Trenchless Technology.

INTRODUCTION

The construction technology of microtunneling has been widely adopted for laying utility pipe in well developed cities featuring congested road surfaces and complicated underground spaces. Uncertain underground conditions and problems due to various production systems (including the slurry system, the tunnel boring machine system, the laser-based alignment control system, the electrical and mechanical system and the surface logistics system,) all make microtunneling production rates broadly fluctuate and render conventional quantitative methods for construction planning to be inadequate and less effective, for example, Critical Path Method (CPM) or mathematical programming techniques. Nido et al. (1999) stated operations simulation is instrumental in analyzing and improving the performances of a microtunneling project, leading to productivity increase on the micro-tunnel boring machine's (MTBM) operation and improvement on utilization rates of labour resources. Chapman et al. (2007) expressed the research needs in trenchless

technology in terms of studying machine-ground interaction by identification and measurement of soil conditions and exploration of accurate case history data.
This paper summarizes our recent efforts of research and applications of artificial intelligence and simulation modelling, aimed at developing effective decision support means for practicing engineers to predict production rates and enhance job performances on microtunneling projects. In the present research, the use of an Artificial Neural Network (ANN) model is proposed to characterize MTBM's production rate subject to different influential factors including ground conditions and various supporting systems. By continuously training the ANN model with the most recent data from the jobsite, prediction of the tunnelling production rate and hence the overall project duration can be updated with much improved accuracy.

A simplified discrete event simulation approach (SDESA) model is established according to the simulation methods proposed in Lu (2003) and Lu et al (2007) in attempt to simulate different workflows on a typical microtunneling project. Technological constraints and resource interdependencies are encoded in the simulation model to mimic the actual project situation. The simulation model allows an engineer to conduct virtual experiments for practical scenarios on a computer, with the goal of improving performances of the surface logistics system. Experiments can be done to shed light on any consequences from altering the quantities of resources and the site layout design. As such, the surface logistics management can be synchronized with the underground microtunneling operations, producing more productive resource configurations, more efficient site layout design and just-in-time logistical flows of pipe sections.

Twin tunnels across a river were constructed by microtunneling in Hong Kong during the period from March to July 2009. This microtunneling project is used as a practical case to demonstrate applications of ANN model and SDESA model for predicting production rates, streamlining site operations and boosting resource utilization.
With the help of these intelligent decision support methods, effective microtunneling construction planning can be achieved through accurate production rate prediction and effective surface logistics management.

CURRENT PRACTICES FOR PLANNING MICROTUNNELING CONSTRUCTION

Not differing from other construction technologies, a tentative construction plan for microtunneling is prepared with references made to historical data and geological data on similar previous cases. A Gantt chart is usually employed to show the schedule at different stages with logical sequence linkages. During the construction stage, the Gantt chart is implemented as a guideline for executing the activities contained in the project plan. Actual production cycle times were collected from site operations and used for calculating the average production rate and forecasting remaining production cycle times and overall project duration. The construction schedule in the Gantt chart is then updated in certain time intervals by factoring in the actual production rate under current site situations. When the whole project is finished, the project is archived in the company's management system as a historical case for future references. A flow chart is shown in Fig. 1.

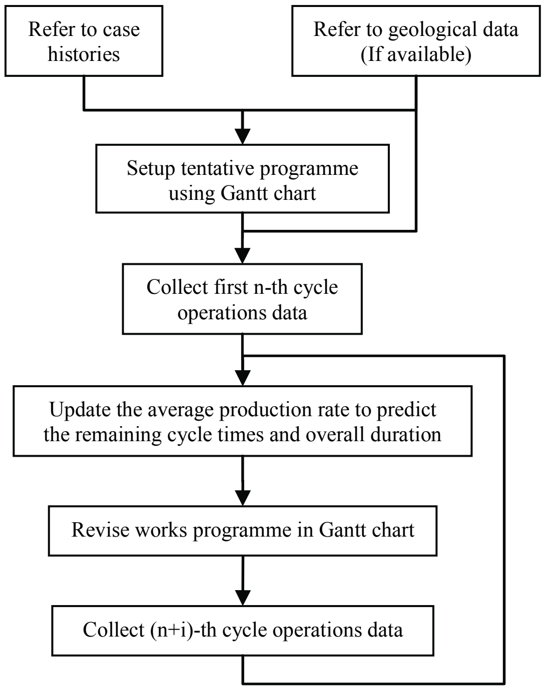

Fig. 1 –Flowchart for Current Operations Management

BRIDGING THE GAP FROM RESEARCH TO PRACTICE

Applications of artificial intelligence and simulation technology have been proposed to address the challenges in construction planning. Lau et al. (2007) identified various uncertain factors that influence project progress and job performance in trenchless construction operations. Portas and AbouRizk (1997) stated that the complex implicit relationship between impacts of work conditions on productivity makes ANN an excellent method for analyzing the impact of work conditions on construction productivity. ANNs are domain independent tools which can generalize functional relationships from historical data sets regardless of the irregularity of parameters. Practitioners are only required to define the target output, identify relevant influential factors and gather data to calibrate ANNs.

Surface logistics management is critical to streamlining the production of microtunneling. With the help of simulation tools, the site logistics system can be configured using computer-based simulation experiments. The simulation model is prepared in our research with its input structured into hierarchical levels so as to suit users with different levels of modeling expertise. The simplest way is to directly apply the template of microtunneling operations simulation and specify the corresponding parameters for each work flow, the site layout definition, activity durations and resources. Domain experts can also refine the model structure to suit specific site conditions and tailored construction technology.
How to apply ANN and simulation for microtunneling construction planning are illustrated in Fig. 2 and discussed in detail as follows. The ANN model and simulation model are established during the planning stage. The site operations data is collected to (1) train the ANN model to forecast the production rate on the next cycle and (2) update the production rates for the remaining cycles of the simulation model so to predict overall project duration. With more operations data available, the actual

production rate is checked against the ANN prediction for error analysis and the production rate on the remaining cycles is accordingly updated in the simulation model for reassessing the overall project duration. The latest data set is then used to expand the ANN training data and retrain the ANN.

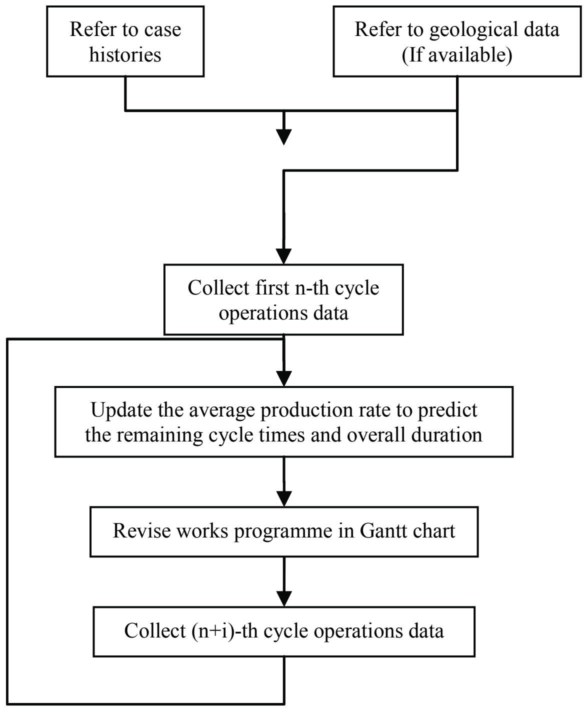

Fig. 2 –Flowchart for Applications of ANN and Simulation Modelling

In order to make sound and timely decisions, practitioners can benefit from the integration of the two different modelling approaches: a macroscopic view on the production rate is obtained from the ANN model, in contrast with a microscopic view on detailed site operations from simulation. The short term productivity prediction from ANN assists in decision making for material delivery, while efficiency improvement of the surface logistics management through simulation increases resource utilization and removes any unneeded idling or waiting time in operations. The two approaches complement each other in rendering management decision support.

Artificial Neural Network (ANN) Modelling

Based on the real case, an ANN model was established during the planning stage for characterization of the production rate subject to different influential factors, including ground conditions and various operations supporting systems (the slurry system, the tunnelling operations system, the laser system, the electrical and mechanical system and the surface management system.) During the construction stage, the ANN model was trained with the site operations data sourced from site records and non-critical factors were dropped by factor analysis. The Radial Basis Function Neural Network (RBFNN) was adopted in our research because of simple model structure and rapid calibration process. The optimum modelling parameters such as the number of clusters can be determined by trial and error, resulting in an ANN model calibrated within an acceptable error threshold. The continuous learning and updating of the ANN model can be achieved as the most updated site data become available.

Operations Simulation Modelling

A SDESA model is established for planning typical microtunneling construction. Practitioners can customize the model template in accordance with specific site conditions, for instance, adjusting the numbers of cycles or repetitions for each work flow and changing the quantities of resources available. The simulation model then becomes ready for performing simulation experiments on a computer. Domain experts could make use of the high flexibility of the model structure to modify logical sequences (e.g. the installation of inter-jacks or spacers), impose rules on pipe section deliveries and modify the site layout based on actual operations. Further simulation updating is necessary to assisting the construction planner in continuously revising the tentative completion date based on site information gathered. Once the model inputs are updated, the simulation experiments are conducted again to determine the remaining project duration and allocate the resources to synchronize system components and realize just-in-time material deliveries.

INTERFACES BETWEEN ACADEMIC MODELS AND PRACTICAL APPLICATIONS

In order to transfer the research into the practice, model inputs are mostly sourced from those data already collected in existing management systems and model applications are structured into different control levels. Practitioners are only required to setup the ANN and simulation models from tailoring the templates. As ANN is not domain dependent, no revision is required to model structure. Instead, selection of the input parameters and the number of clusters (hidden nodes) is vital to making a good model for prediction of the production rate. For simulation models, the microtunneling simulation template can be adopted and fed with model inputs based on project planning details. Simulation experiments can be performed to optimize the resources and time management on site. With minimal learning effort, domain experts can refine and fully control the models to cater for their project needs by including more operations details. The logical sequences between various workflows can be amended by addition or omission of some, which is not limited to installation of inter-jacks or spacers.

The day-to-day operations data are routinely logged in daily site records. The prediction of overall project duration is usually inaccurate without the consideration of various influential factors. In general, it is difficult to forecast the production rate accurately during the construction stage given the complex and ever-changing site conditions. With the decision support provided by ANN and simulation models, activity duration and production rates can be updated with the latest data logged in the daily site records. The predicted result would be more scientific and accurate than the traditional estimation by “guessing”. The trenchless work schedule is broken down into day shifts for productivity analysis with productive periods separated from complementary non-productive periods. Further improvement can be achieved from productivity analysis, aimed to minimize non-productive periods and equipment breakdown time.

The user interface would focus on the applications of the ANN and simulation models and the associated analysis and optimization of operations. Emphasis would be placed on the statistical outputs on key performance factors such as the MTBM's production rate, activities' durations and the utilization of major resources. The cumulative distribution function for the operation cycle time and the utilization rate of the labourers are shown in Fig. 8, the user can further adjust the resource allocation based on the simulation results. On the other hand, given the updated training data set as the project proceeds, the ANN model can assist in prediction of pipe installation cycle time and MTBM's production rate.

Fig. 3 – Site overview of case study microtunneling project

APPLICATION ON HONG KONG'S MICROTUNNELING PROJECT

The application framework was tested on a local project in Hong Kong. As illustrated in Fig. 3, the microtunneling project consisted of the installation of 220 metres long twin tunnels of 1200mm diameter precast concrete sleeve pipe for hosting a power utility cable duct and a domestic gas pipe. The tunnels were aligned to cross a nullah (rain storm canal) and laid 5 metres below the river bed. The twin tunnels would facilitate the installation and future maintenance of the cables and gas mains, and the microtunneling construction method would not involve any open excavation across the river. Slurry shield tunnel boring machine was adopted for constructing both tunnels. A total of 74 concrete segments, each being 3 metres long, were installed to form the micro tunnels. It is noteworthy that the twin tunnels provide a case that applies the same technology under similar job conditions. This has created a suitable environment to validate the ANN and simulation models, which were calibrated with data from one tunnel and used to forecast the system performances on the other.
An ANN model was established to characterize the production rate in consideration of different influential factors including ground conditions, various operations supporting systems and delay factors. The ANN model structure is shown in Fig. 4. Due to the continuity of geology within short length, the soil condition and other operations factors including the jacking time, main jacking force, jacking speed, cutter

torque and face pressure of previously immediate cycle were identified as input variables to predict the coming cycle's production rate. MTBM's misalignment may hinder the advance rate when the operator needs correct the tunnel alignment back to as planned. The pitching, rolling, horizontal and vertical alignments of the TBM's head were thus included in the model input. Various delay effects resulting from hiccups in slurry,

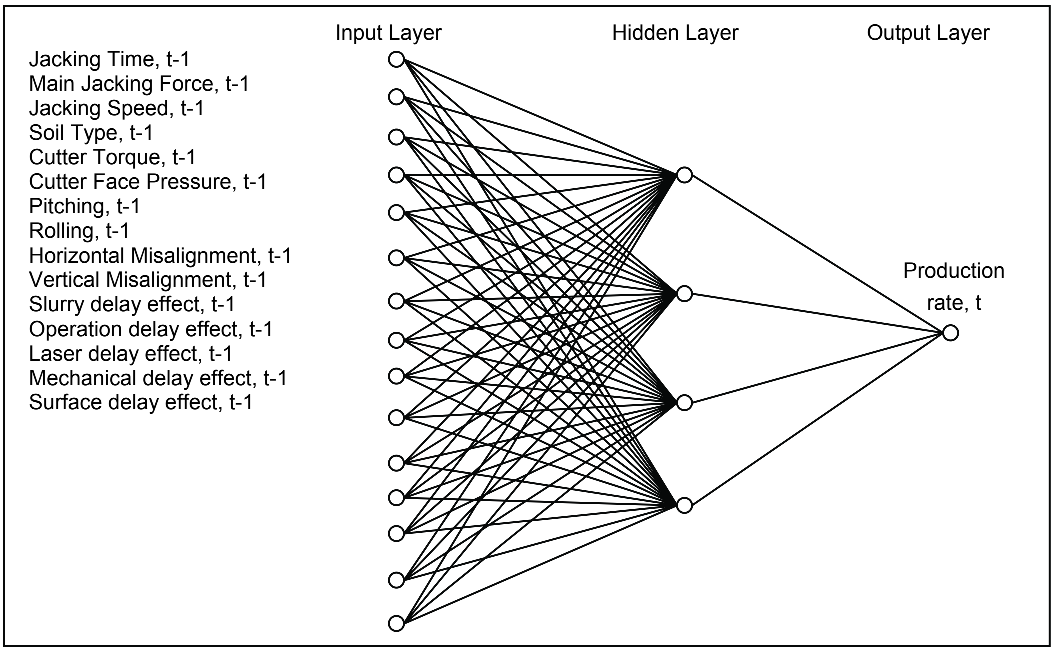

Fig. 4 –Neural Network Model of Microtunneling Construction

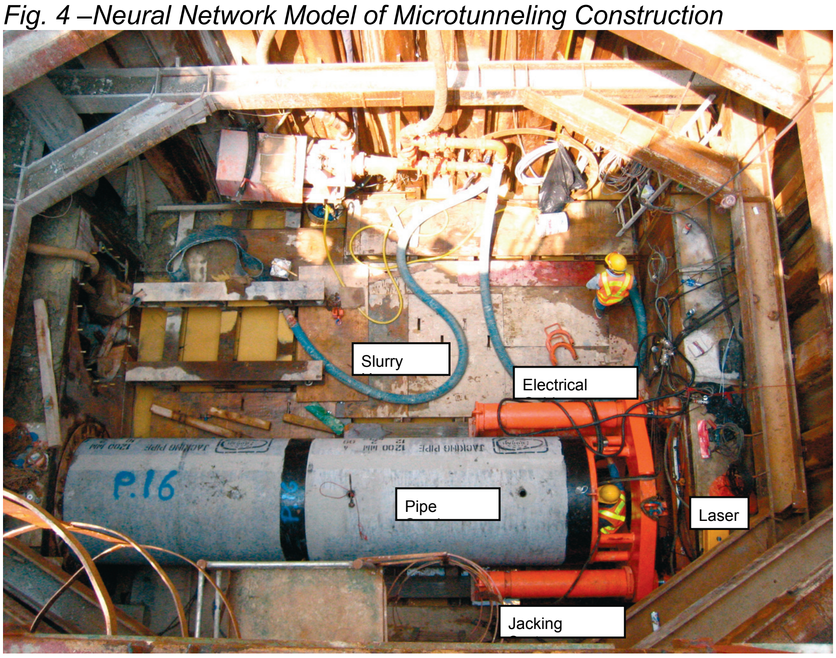

Fig. 5 – Jacking pit layout of microtunneling construction

operation, laser, mechanical and surface were also incorporated in the model. All the above data were sourced from the daily site records on a pipe-section basis.

Fig. 5 and 6 shows the jacking pit layout and equipment for microtunneling construction. A simulation model was established according to SDESA as shown in Fig. 7. The site operations model consisted of logical sequences, activity durations and resource allocation and was defined during the site planning stage. The "Jack" workflow was the major workflow in the model and facilitated by other supporting work flows such as "Mix Lubrication" and "Empty Spoil Tank", and "Pipe delivery" and "Crane (lifting)". The activity durations for site operations were estimated from historical data by the planning engineer.

Fig. 6 – Sedimentation tanks (top left), operations system (top right), total station (bottom left), target board (bottom middle), Crane (bottom right)

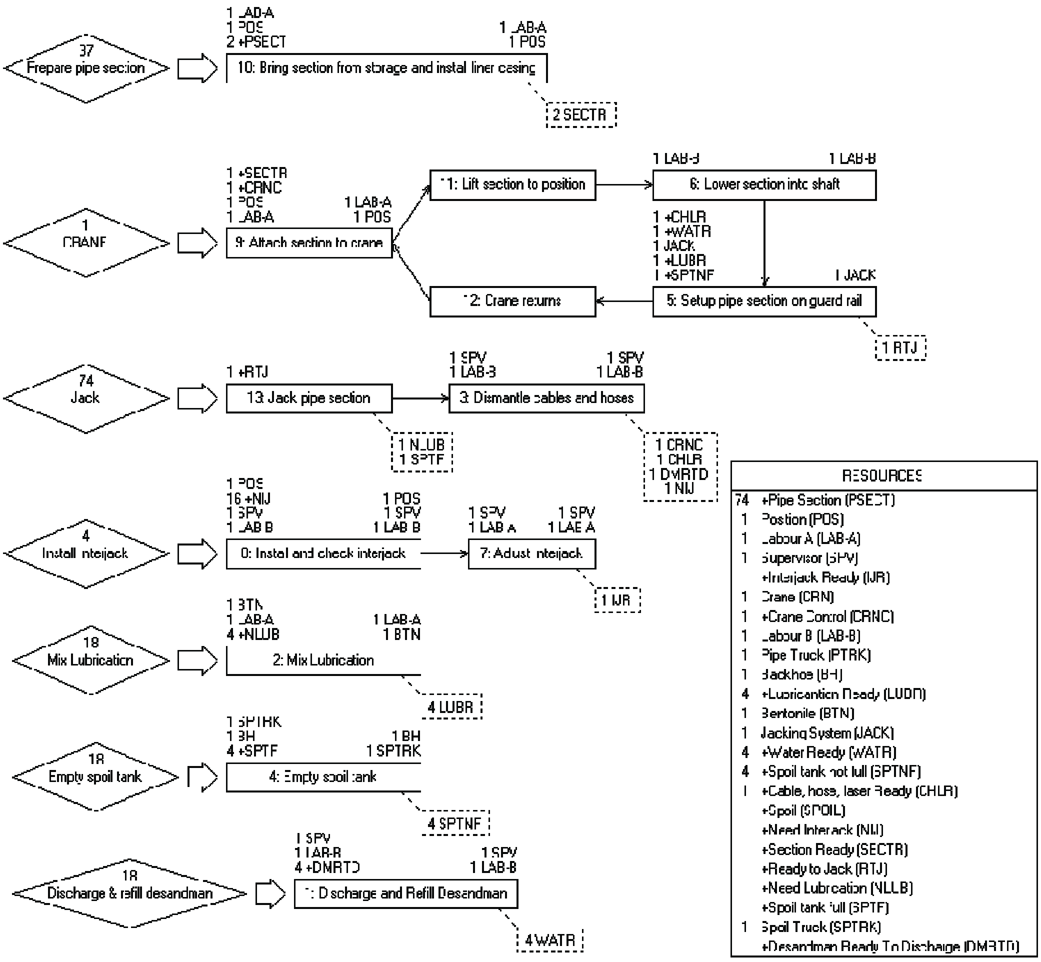

Fig. 7 – Simulation Model for microtunneling construction

At the planning stage, the simulation tool was used to investigate the effects of various combinations of resource allocations, pipe section delivery cycle times and site layout

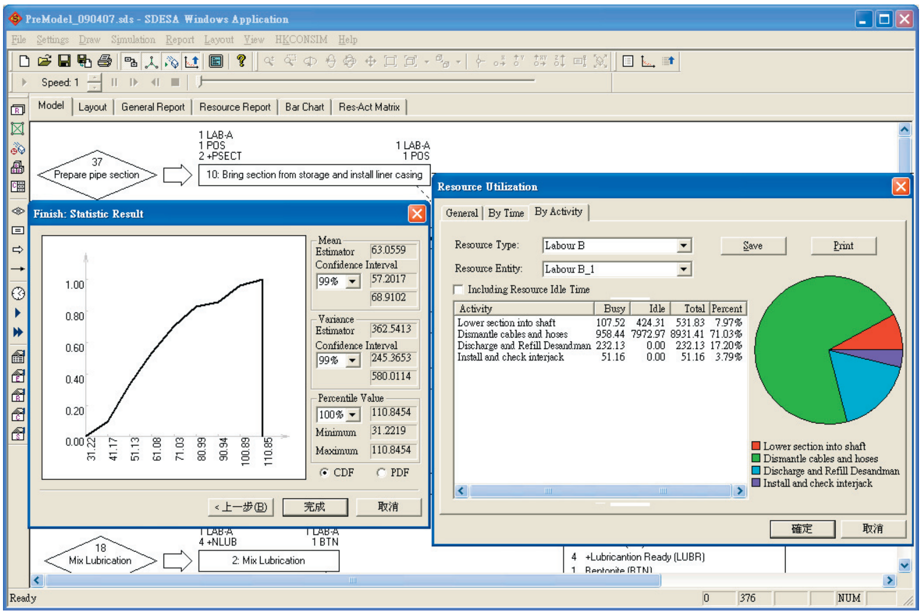

Fig. 8 – Screenshot of SDESA model outputs on activity duration and resource utilization statistics

designs. The statistical distribution of the pipe-section installation cycle time can inform detailed jobsite planning. During the construction stage, the operations information was collected for refining the accuracy of production rate prediction and project duration estimate. Distributions of the production time and non-production time were observed from simulation experiments for further site management. Activity durations and utilization rates of various resources were produced as statistical outputs from the simulation model as shown in Fig.8. With the assistance by simulation tools, the surface logistics management system can be optimized and the production line of the jacking operations can be streamlined. Additional production analysis of microtunneling construction can be performed to determine the overall efficiency of site operations.

CONCLUSIONS

This paper discusses the research, applications and possible technology transfer of artificial intelligence and simulation modelling to support practitioners' decision making in microtunneling construction practice, particularly, predicting the tunnel boring machine's production rate and configuring the surface logistics system. The use of an artificial neural network (ANN) model (called the Radial Basis Function Neural Network) is proposed to characterize the production rate subject to a collection of influential factors including ground conditions and various construction supporting systems. By continuously updating the ANN model with current data as the project proceeds, the accuracies of the production rate prediction and hence the project duration estimate can be improved. In addition, a simplified construction operations simulation model was established to simulate different workflows defining the surface logistics system on a typical microtunneling project. A local microtunneling project with twin-tunnels constructed across the river was used as a practical case to demonstrate the applications of ANN and simulation models. By hiding the computing algorithms, those models can be tailored as intelligent decision support means to assist construction engineers in confronting the complexities and uncertainties in microtunneling, streamlining site operations and site layout design, and boosting the utilization rates of site resources. In conclusion, these intelligent modelling methods as proposed hold the potential to be at the disposal of construction engineers to improve the current practices for microtunneling construction planning.

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