2023 European Conference on Computing in Construction
40th International CIB W78 Conference
Heraklion, Crete, Greece
July 10-12, 2023

EVALUATION OF DETERMINISTIC MODELS FOR THE EXCAVATOR'S THEORETICAL PRODUCTIVITY ESTIMATION IN THE DIGGING AND TRENCHING OPERATIONS

Amirmasoud Molaei[1,2], Marcus Geimer[1], and Antti Kolu[2]

[1]Institute of Mobile Machines, Karlsruhe Institute of Technology, Karlsruhe, Germany
[2]Radical Innovation Research Group, Novatron Ltd., Pirkkala, Finland

Abstract

This paper investigates the automatic theoretical productivity estimation of an excavator in digging and trenching operations. The actual productivity cannot solely reveal the machine's performance since there are various operating conditions that can significantly influence the excavator's actual productivity. The theoretical productivity estimation is certainly required because it is the highest feasible productivity level and provides a reference to evaluate the actual productivity. In this paper, two of the most pertinent deterministic models to calculate the excavator's theoretical productivity are introduced. Then, the impacts of operating conditions are investigated. Finally, estimated theoretical cycle times are evaluated by comparison with the actual cycle times.

Introduction

Heavy-duty mobile machines (HDMMs) play significant roles in the world and are a major source in many industries, including the mining, forestry, and construction sectors. The industries face tough challenges such as the shortage of skilled human operators, harsh environments, lack of safety, and particularly low productivity (Geimer (2020)). According to studies, the productivity of the construction industry has only improved by 1% over the past 20 years. Additionally, it has been found that the costs of the equipment used in a construction project could account for 5% to 10% of the direct costs, and it can account for up to 40% of direct costs in a highway construction project (Kassem et al. (2021)). Therefore, improving the productivity of HDMMs can be a promising solution.

To enhance the productivity of HDMMs, it is important to remember the common quote "If you cannot measure it, you cannot improve it" (Lingard et al. (2013)). In traditional productivity monitoring, manual observing is exceedingly time-consuming, costly, and error-prone. The inability to precisely estimate the productivity of HDMMs in earth-moving operations is a significant barrier to efficiently managing ongoing projects as well as accurately costing and budgeting for future projects. An automatic method is required to measure the productivity of HDMMs under diverse operating conditions. In addition to reducing operating time, fuel consumption, and costs, monitoring the productivity of HDMMs can also help to optimize planning and working parameters, identify potential project issues, and improve management and economic conditions. Furthermore, human operators can enhance their skills by utilizing the feedback provided by machines' productivity (Machado et al. (2021)).

In the construction industry, the hydraulic excavator is one of the most crucial pieces of equipment. Excavators are multi-functional machines that can perform a variety of activities, including digging, loading, trenching, cutting, and grading soil. Figure 1 depicts a typical hydraulic excavator. This human-operated machine is mainly driven by using a hydraulic system. The traveling body, swing body, and front digging manipulator are the excavator's three main components. The machine's manipulator is made up of the boom, arm, and bucket. Also, the excavator has three revolute joints between the swing body, boom, arm, and bucket (Molaei et al. (2022)).

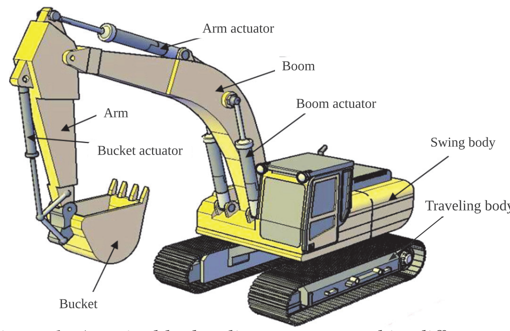

Figure 1: A typical hydraulic excavator and its different parts (Molaei et al. (2022)).

Estimating the productivity of HDMMs in earth-moving tasks is a major challenge. In all construction projects, the expected output per unit of time is referred to the productivity, which specifies the costs and duration of projects. Generally, the quantity of material and the operation cycle time are the determining parameters for the productivity of most cyclical types of machinery. The quantity of transferred material per unit of time (or per cycle) is the easiest way to define the excavator's productivity. The quantity can be expressed as the weight or volume of the material. Cycle time represents the amount of time it takes a machine to perform a repetitive task of a process. The cycle time of an excavator in the digging and trenching operations consists of the required time for (1) filling the bucket, (2) swinging loaded, (3) dumping materials, and (4) swinging empty (Chen et al. (2022)). There are various variables and conditions that can significantly influence the excavator's productivity:

1. Excavator
   - Size of the excavator
   - Bucket capacity
   - Repairs and maintenance
2. Relative position between excavator and material
   - Digging depth
3. Relative position between excavator and dumping po-

sition
    - Swing angle
    - Relative height
    - Dumping condition
4. Site conditions
    - Type of material
    - Site congestion
5. Skill of human operator
6. Weather conditions

Digging depth and type of material are essential factors in the scooping sub-task. It is obvious that when the location of the material gets deeper or the material gets harder, it takes longer to perform the scooping sub-task. The swing angle is another variable that can increase or decrease the time of swinging loaded/empty and subsequently the overall cycle time (Langroodi et al. (2021)). Also, the swinging time highly depends on the machine's size because small machines can cycle faster than large machines. In addition, the cycle time can be influenced by dumping conditions. Furthermore, the excavator's productivity highly depends on the skills of the human operator. Moreover, filling the bucket substantially depends on the type of material and environmental conditions during the operation. The filling extent or bucket fill factor can be higher for homogeneous and fine-grained materials and lower for high-boulder content materials. Another parameter that can alter the quantity of material in the bucket is the material's water content. Actually, when the quantity of water is greater, the actual amount of material is lower since part of the bucket is filled with water. On the one hand, the moisture increases the stickiness, which results in a longer dumping time, but on the other hand, the moisture in coherent materials can increase the bucket fill factor (Kujundžić et al. (2021)).

As previously described, a variety of factors can influence the excavator's productivity. The excavator's real or actual productivity cannot lonely represent the machine's performance. To assess the actual productivity, the excavator's theoretical productivity or the highest feasible productivity level must be automatically determined based on the operating conditions. The production performance ratio is obtained by comparing the actual productivity against the theoretical productivity to indicate the level of productivity:

$$PPR = \frac{Q_{actual}}{Q_{theoretical}}, \tag{1}$$

where PPR indicates the production performance ratio, Q_{actual} is the actual productivity, and $Q_{theoretical}$ shows the theoretical productivity. The closer the index PPR is to one, the higher the machine's performance. In selecting a construction machine for a project, it is incredibly important to consider the machine's capability. The index PPR can easily help worksite managers to compare the machine's productivity with its capability, ensure the machine works at full capacity, meets the needs of the project, and provides a high return on investment.

Among different tasks of excavators, digging and trenching are two of the most critical tasks that could be automated. Despite this, there is no automatic method to calculate the theoretical productivity of an excavator based on the operating conditions, such as swing angle and digging depth when the machine is performing the task. In this paper, two deterministic methodologies, Komatsu® (Komatsu (2013)) and BML (Bau (1983)) models are introduced to automatically estimate the theoretical productivity of an excavator in the digging operation. The methods are highly regarded because of their capacity to accurately capture the physical features of the problem. The input variables of the models, including swing angle and digging depth, are automatically estimated using the proposed methods in (Molaei et al. (2022)). Then, the methods are extended for the trenching operation. The introduced methods can be automatically utilized in different excavators to calculate the index PPR and analyze the productivity of the operation. Additionally, the effects of operating conditions such as swing angle and digging depth on theoretical productivity are studied. Finally, the obtained theoretical cycle times are evaluated using the actual cycle times measured by a medium-rated excavator operated by inexperienced and experienced operators in a private worksite.

The structure of this paper is as follows: Firstly, the literature review is presented. Secondly, the deterministic methods to estimate the theoretical productivity of an excavator in the digging operation are presented. Then, the presented models are extended to estimate the theoretical productivity of an excavator in the trenching operation. In the next section, the outcomes of the introduced models are shown and compared with the gathered data. The conclusion section brings the paper to a close.

Literature Review

Although the productivity of a fleet made up of several excavators and dump trucks has been exceedingly investigated, the productivity of each individual excavator has been overlooked.

Several studies propose data-oriented approaches to estimate the productivity of earthwork machines, including excavators. These methods train and test their models using historical data, manufacturers' handbook data, or computer-simulated data. Edwards and Holt (2000) presented a multiple regression (MR) model to predict the excavator's cycle time as a measure of productivity. In the regression model, the inputs or predictor variables consist of the machine's weight, swing angle, and digging depth. The utilized dataset was obtained from companies' performance handbooks and was extremely limited. Edwards and Griffiths (2000) proposed a feed-forward artificial neural network (ANN) with back-propagation training to predict the hydraulic cycle time of excavators using the same dataset of Edwards and Holt (2000). The proposed ANN has a higher performance than the proposed MR model. Also, Tam et al. (2002) used this dataset to train an ANN. The results showed that the performance of the ANN is superior to the MR model. Yang et al. (2003) proposed a computational intelligent fuzzy model to predict the excavator's cycle time using the same dataset of Edwards and Holt (2000). In (Ok and Sinha (2006)), linear regression and neural network methods are compared with each other to estimate the daily productivity of dozers. The neural network was able to generate more accurate results than the regression analysis models. Schabowicz and Hola (2007) presented an ANN combined with queuing theory based on the generated dataset from computer simulations. In (Holt and Edwards (2015)), the operator competence is modeled, and the impact of this variable on productivity is analyzed. Kassem et al. (2021) proposed a deep neural network approach for productivity estimation that is trained using data obtained from telematics systems installed on equipment in the field.

When historical data from earth-moving operations are not accessible, process-oriented techniques should be utilized. To predict the productivity of an excavator in the digging operation, a deterministic mathematical model is proposed in an industry guideline (Bau (1983)). The BML guideline is provided by a common committee of the Central Association of the German Construction Companies (Zentralverband des Deutschen Baugewerbes) and the Federation of the German Construction Industry (Hauptverband der Deutschen Bauindustrie). Also, two models are presented in construction equipment manufacturers' handbooks, Komatsu® (Komatsu (2013)) and Caterpillar® (Caterpillar (2018)). Schaufelberger and Migliaccio (2019) presented a method that is inspired by the model of Caterpillar®. The provided model by Caterpillar® cannot be utilized automatically since it is a descriptive model and requires human intervention. Moreover, several simple models are introduced in construction operations planning textbooks (Peurifoy et al. (2018); Nunally (2014)) that do not consider the operating conditions in an acceptable level of detail. In the methods, the effects of operating conditions are modeled by using several correction factors. Productivity is affected by two types of factors, controllable and uncontrollable factors. The operating conditions, such as digging depth, swing angle, and bucket capacity represent controllable factors, and other parameters, such as weather conditions and the operator's skills are uncontrollable factors. In (Panas and Pantouvakis (2010a,b)), it has been analyzed that the productivity of an excavator is highly affected by the swing angle and digging depth during the operation. In (Litvin and Litvin (2020)), the effects of the dumping condition and swing angle on the excavator's cycle time are analyzed. Kujundžić et al. (2021) analyzed the impacts of material specifications on the excavator's productivity. At this moment, no method is available to automatically estimate the theoretical productivity of an excavator during performing the digging and loading operations, and there is no agreement among academic and industrial sources on the models and elements that should be taken into account in the theoretical productivity estimation (Ng et al. (2016)).

Methodology

In this section, two prominent process-oriented methods to estimate the excavator's productivity in the digging and trenching operations are presented. In the methods, the ideal productivity is modified by several correction factors corresponding to the operating conditions. Although different methodologies propose different correction factors, their main characters are similar.

Bank or unexcavated, loose, and compacted volumes are three different forms of soil volumes in earth-moving operations. Bank volume is the measurement of the amount of soil that is already in the ground. Loose volume is the volume of material that is piled in stockpiles or the back of dump trucks in a loose condition without having been disturbed during excavation and removal (Peurifoy et al. (2018)). The definition of productivity in the digging and trenching operations are in loose and bank conditions, respectively.

BML Model

The productivity of a hydraulic excavator in the digging operation based on the BML model (Bau (1983)) is formalized by equation (2):

$$Q_{BML} = \frac{V_{CECE} \times f_{fill}}{t_{th,BML}} \times f_{swing} \times f_{depth} \tag{2}$$

where Q_{BML} is the excavator's productivity in a loose condition $[m^3/sec]$, V_{CECE} is the heaped bucket capacity according to the CECE (Committee for European Construction Equipment) standard $[m^3]$, f_{fill} is the bucket fill factor $[-]$, $t_{th,BML}$ is the theoretical cycle time $[sec]$, f_{swing} is the swing angle factor $[-]$, and f_{depth} is the digging depth factor $[-]$.

The definition of heaped bucket capacity is highly significant since it can remarkably influence the volume of material in the bucket and subsequently the excavators' productivity. There are two standards for heaped bucket capacity, the Society of Automotive Engineers (SAE) standard and the Committee for European Construction Equipment (CECE) standard. The schematics of SAE and CECE standards are shown in Fig. 2. The angles of repose for material above the strike-off plane in SAE and CECE standards are $1:1$ (45°) and $1:2$ $(\sim 27^\circ)$, respectively. It has been seen that $V_{SAE} \approx [1.10 - 1.20] \times V_{CECE}$. It is obvious that the bucket capacity is expressed in a loose condition (Kujundžić et al. (2021)).

The fill factor f_{fill} is a correction coefficient that improves the estimation of bucket capacity. Actually, the heaped

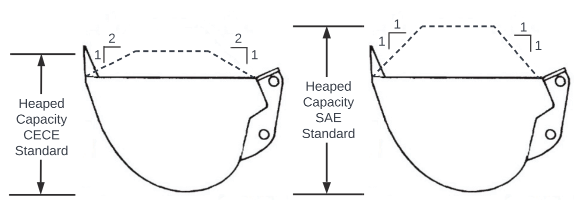

Figure 2: Heaping according to the SAE and CECE standards.

Table 1: Soil categories and bucket fill factors in the BML model.

Category	Material	Fill factor
High excavability	Loose to firm sand, sand and gravel, rubble	1.13
Medium excavability	Mixed-grain soils, lake clay, loam	1.20
Low excavability	Hard compacted clay, silt and clay, boulders	1.15
Very low excavability	Blasted rock or similar soil types	0.95

bucket capacity does not consider the type of material being excavated. The fill factor adjusts the heaped bucket capacity according to the type of material to represent the bucket's actual payload. The soil excavability categories and fill factors in the BML model are shown in Table 1.

In the BML model, the theoretical cycle time is calculated based on the heaped bucket capacity ($V_{CECE} \geq 0.3\,m^3$) and soil excavability categories. The theoretical cycle time for materials with high excavability (e.g. sand and gravel) is formalized by equation (3):

$$t_{th,BML} = -0.50 \times V_{CECE}^2 + 4.19 \times V_{CECE} + 13.13, \quad (3)$$

and for materials with medium and low excavability (e.g. hard compacted clay) is calculated by equation (4):

$$t_{th,BML} = -0.07 \times V_{CECE}^2 + 3.30 \times V_{CECE} + 15.52. \quad (4)$$

There is no estimation for the theoretical cycle time of the very low excavability category in the BML model (Panas and Pantouvakis (2010a)).

The swing angle is a horizontal angle between the scooping and dumping positions. The swinging time is one of the main parts of the cycle time. In the BML method, the swing angle coefficient is approximately calculated using equation (5):

$$f_{swing} \approx 1.754 \times \theta^{-0.1258}; \theta \in [45^\circ, 180^\circ]. \quad (5)$$

Variations of swing angle within the range of $[45^\circ, 180^\circ]$ influences $\pm 10\%$ variations in productivity.

In the BML method, the digging depth coefficient f_{depth} for low and very low excavability materials is approximately calculated using equation (6):

$$f_{depth} \approx h_d^{-0.1039}; \;\; h_d \geq 1\,m, \quad (6)$$

and for high and medium excavability soil types is approximately calculated by equation (7):

$$f_{depth} \approx h_d^{-0.1164}; \;\; h_d \geq 1\,m. \quad (7)$$

For $h_d < 1\,m$, the digging depth factor can be considered equal to one. When the digging place gets deeper, it has only a negative impact on productivity which can reach up to 20% in extreme cases (i.e. for $h_d > 8\,m$).

The calculation of the swing angle and digging depth factors requires automatic estimations of the swing angle and digging depth during the operation. Molaei et al. (2022) proposed two methods for the estimation of the swing angle and digging depth. These methods use cabin encoder measurements and bucket position estimation. The bucket position is calculated using inertial measurement units (IMUs) and the forward kinematics of an excavator.

Komatsu Model

In this section, the Komatsu model (Komatsu (2013)) to calculate the excavator's theoretical productivity in the digging operation is presented. According to the Komatsu model, the excavator's productivity is obtained by using equation (8):

$$Q_{KOM} = \frac{V_{SAE} \times f_{fill}}{t_{th,KOM} \times f_{con}} \quad (8)$$

where Q_{KOM} is the excavator's productivity in a loose condition $[m^3/sec]$, V_{SAE} is the heaped bucket capacity according to the SAE standard $[m^3]$, $t_{th,KOM}$ is the theoretical cycle time $[sec]$, and f_{con} is the conversion factor $[-]$.

In the Komatsu model, bucket fill factors are defined within the range of $[0.70, 1.20]$ based on the soil types. Bucket fill factors for different materials are shown in Table 2.

Table 2: Bucket fill factors in the Komatsu model.

Material	Fill factor
Excavating natural ground of clayey soil, clay, or soft soil	1.1-1.2
Excavating natural ground of soil such as sandy soil and dry soil	1.0-1.1
Excavating natural ground of sandy soil with gravel	0.8-0.9
Loading blasted rock	0.7-0.8

In the Komatsu model, the theoretical cycle time $t_{th,KOM}$ is calculated based on the swing angle and the machine's model. The excavator's model is the representative of machine's weight and capability. The theoretical cycle times for different Komatsu® excavators and different swing angles are shown in Table 3. In fact, the theoretical cycle time for each model of the excavator is approximated by using an increasing piece-wise linear function of the swing angle.

In the Komatsu model, the digging depth and dumping conditions are included in a correction factor that is called the conversion factor f_{con}. The theoretical cycle time $t_{th,KOM}$ is adjusted by using the conversion factor that is introduced in Table 4. The conversion factor can vary from 0.70 to 1.80 based on the digging depth and dumping conditions. The digging depth condition is the ratio of the digging depth to the machine's maximum digging depth capability. The maximum digging depth capability refers

Table 3: *Theoretical cycle times in the Komatsu model.*

Model	Swing angle	
	45° ~ 90°	90° ~ 180°
PC78	10 ~ 13	13 ~ 16
PW148	11 ~ 14	14 ~ 17
PC130, PC138US	11 ~ 14	14 ~ 17
PC160	13 ~ 16	16 ~ 19
PW160, PW180	13 ~ 16	16 ~ 19
PC190	13 ~ 16	16 ~ 19
PC200, PC210, PC228US	13 ~ 16	16 ~ 19
PW200, 220	14 ~ 17	17 ~ 20
PC220, PC230, PC240	14 ~ 17	17 ~ 20
PC270, PC290	15 ~ 18	18 ~ 21
PC300, PC350	15 ~ 18	18 ~ 21
PC400, PC450	16 ~ 19	19 ~ 22
PC600, PC700	17 ~ 20	20 ~ 23
PC750, PC800, PC850	18 ~ 21	21 ~ 24
PC1250	22 ~ 25	25 ~ 28
PC2000	24 ~ 27	27 ~ 30

Table 4: *Conversion factors in the Komatsu model.*

Digging depth condition	Dumping condition			
	Easy	Normal	Rather difficult	Difficult
Below 40%	0.7	0.9	1.1	1.4
40% - 75%	0.8	1.0	1.3	1.6
Over 75%	0.9	1.1	1.5	1.8

to the maximum vertical distance the bucket can reach below the horizontal line of the wheels. The schematic of the maximum digging depth is shown in Fig. 3. There are three intervals for the digging depth condition:

- Below 40%,
- 40% - 75%,
- Over 75%.

Also, there are four different dumping conditions including:

- **Easy**: dump onto spoil pile,
- **Normal**: large dump target,
- **Rather difficult**: small dump target,
- **Difficult**: small dump target requiring maximum dumping reach.

Trenching Operation

The trenching operation is one of the most frequent and essential tasks in various construction projects. An automatic method for the excavator's theoretical productivity estimation in the trenching operation can be a fundamental step toward autonomous excavators. The productivity definition in the digging operation cannot be utilized in the

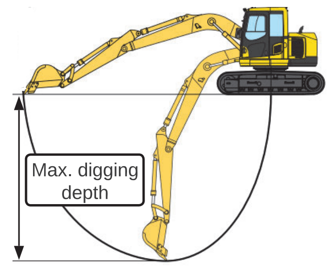

Figure 3: *The schematic of the maximum digging depth (Komatsu (2013)).*

trenching operation and must be modified. In the trenching operation, contractors typically estimate the productivity of an excavator in terms of the linear length of the trench per unit of time. The productivity of the excavator in the trenching operation is obtained by equation (9):

$$Q_{Tr} = \frac{Q_{Dig}}{A_{Tr}} \times \frac{1}{f_{swell}} \tag{9}$$

where Q_{Tr} is the excavator's theoretical productivity in the trenching operation $[m/sec]$, $Q_{Dig} \in \{Q_{BML}, Q_{KOM}\}$ is the excavator's theoretical productivity in the digging operation $[m^3/sec]$ which is calculated according to the BML or Komatsu models described in the previous section, A_{Tr} is the cross-sectional area of trench $[m^2]$, and f_{swell} is the swell factor $[-]$.

The cross-sectional area of a trench is a determining factor in the productivity of the trenching operation. The trench specifications, particularly the cross-sectional area, can be easily obtained using building information modeling (BIM) and localization data. BIM technology creates and maintains digital representations of construction projects across their lifetime. BIM is supported by a wide range of tools and technologies and can be effectively utilized for productivity estimation in earth-moving tasks (Kassem et al. (2021)).

The term "swell factor" refers to an increase in volume that happens when a block of rock breaks up to form rubble or when a mass of soil is excavated. Actually, when the material is excavated, the density of the material decreases or the volume increases. It has been studied that the swell factor is influenced by the granulometric composition of the respective material, and there is a significant correlation between the bucket fill factors and corresponding swell factors. The definition of the theoretical productiv-

Table 5: *Swell factors (Komatsu (2013)).*

Material	Swell factor
Excavating natural ground of clayey soil, clay, or soft soil	1.22-1.43
Excavating natural ground of soil such as sandy soil and dry soil	1.25-1.46
Excavating natural ground of sandy soil with gravel	1.18-1.41
Loading blasted rock	1.49-1.80

ity in the digging operation is expressed in a loose condition, whereas the definition of the theoretical productivity in the trenching operation is in a bank condition. The swell factor is utilized to convert the productivity definition from the loose condition to the bank condition. Table 5 presents the swell factors for different materials (Kujundžić et al. (2021)).

Results

In this section, the effects of swing angle and digging depth conditions on the theoretical cycle times are analyzed, and then theoretical cycle times obtained from the introduced models are evaluated using the actual cycle times measured from an excavator.

In the sensitivity analysis, it has been assumed the model of the excavator is Komatsu® PC138US, the heaped bucket capacity based on the SAE standard is 0.37 m^3, the maximum digging depth capability is equal to 5.48 m, the material is sand & gravel, and the dumping condition is the large dump target. Based on these assumptions, the impacts of the swing angle and digging depth on the theoretical cycle times are analyzed. Firstly, it has been assumed the pile of material is on the ground surface (the digging depth is equal to zero), and the swing angle varies from 45° to 180°. Figure 4 shows the variations of theoretical cycle times based on the swing angle. As shown, the absolute difference is less than 3.5 *sec*, and when the swing angle increases, the difference between the models decreases. The Komatsu model is highly sensitive to swing angle variations. When the swing angle increases within the range of $[45°, 180°]$, the theoretical cycle times in the Komatsu and BML models increase approximately 55% and 19%, respectively. Secondly, it has been assumed the swing angle is equal to 90°, and the digging depth varies from zero to the maximum digging depth capability of the excavator. Figure 5 illustrates the variations of theoretical cycle times based on the digging depth. Also, in this scenario, the absolute difference is less than 3.5 *sec*. When the digging depth increases, the theoretical cycle times in the Komatsu and BML models increase by approximately

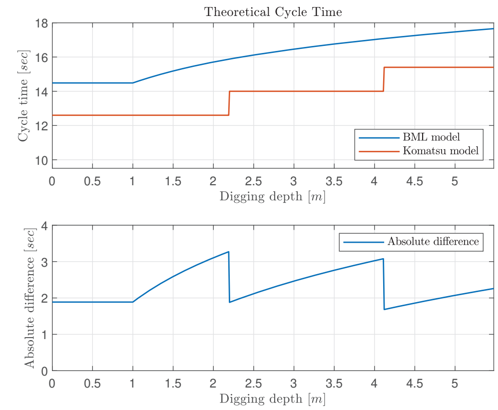

Figure 5: Theoretical cycle times based on the digging depth.

22%. On average, in both scenarios, the theoretical cycle times obtained from the BML model are approximately 15% greater than the Komatsu model.

In the next step, the theoretical cycle times are compared with the actual cycle times. Four experiments have been done by experienced and inexperienced operators using a medium-rated excavator (Komatsu® PC138US) in a private worksite with no ongoing construction project. The first and second operations are performed by an experienced operator, and the swing angles are approximately equal to 60° and 120°, respectively. The third and fourth operations are performed by an inexperienced operator, and the swing angles are approximately equal to 60° and 120°, respectively. To automatically estimate the theoretical cycle time, the swing angle and digging depth estimations are required. The swing angle and digging depth are estimated using the proposed methods by Molaei et al. (2022). The swing angle estimations for all experiments are presented in Fig. 6. For the sake of brevity, the visualization of digging depth estimations is not needed. In all experiments, the digging depth estimations are almost zero because the pile of material is on the ground surface.

Firstly, the actual cycle times in the first and third experi-

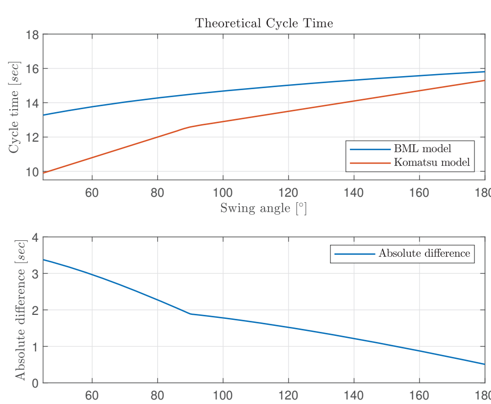

Figure 4: Theoretical cycle times based on the swing angle.

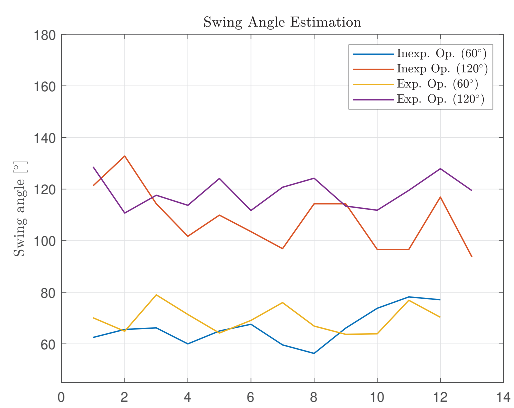

Figure 6: Swing angle estimations in different experiments.

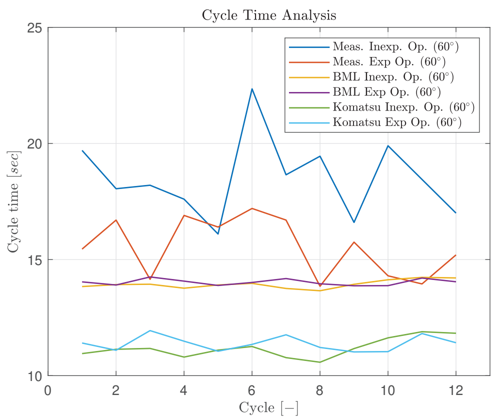

Figure 7: Comparison of the actual and theoretical cycle times in the first and third experiments.

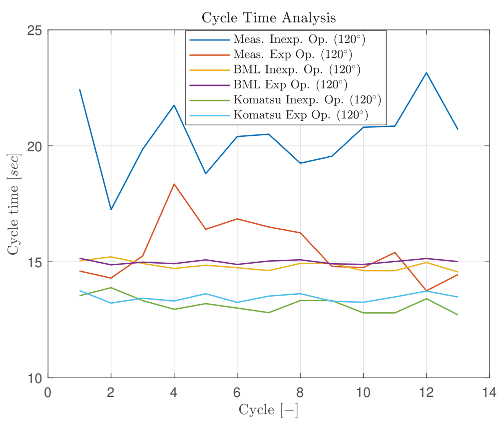

Figure 8: Comparison of the actual and theoretical cycle times in the second and fourth experiments.

ments (60° swing angle) are compared with the theoretical cycle times obtained by the BML and Komatsu models. Figure 7 demonstrates the measured and theoretical cycle times. As shown, the actual cycle time in the first experiment, which has been done by an experienced operator, is lower than the third experiment, operated by an inexperienced operator. On average, the actual cycle time in the first experiment is approximately 10% and 35% greater than the BML and Komatsu models, respectively. However, the actual cycle time in the third experiment is approximately 32% and 65% greater than the BML and Komatsu models, respectively. The measured and theoretical cycle times in the second and fourth experiments (120° swing angle) are presented in Fig. 8. On average, the actual cycle time in the second experiment is approximately 3% and 15% greater than the BML and Komatsu models, respectively. However, the actual cycle time in the fourth experiment is approximately 37% and 55% greater than the BML and Komatsu models, respectively. In some cycles, the experienced operator can perform the digging operation with equal or lower cycle time compared to the BML model.

Conclusions

In this paper, two models, named BML and Komatsu, for the theoretical productivity estimation of an excavator in the digging operation are introduced. There are various operating conditions, such as swing angle and digging depth, that can significantly influence the excavator's productivity. To analyze the excavator's actual productivity, a method is required to automatically estimate the theoretical productivity based on the operating conditions. In the next step, the models are extended to be able to use in the trenching operation. Finally, the impacts of swing angle and digging depth on the Komatsu and BML models are analyzed. Then, the theoretical cycle times provided by models are compared with the actual cycle times. It has been illustrated that the BML model is more conservative and provides a more realistic theoretical cycle time compared to the Komatsu model. The Komatsu model is more optimistic and indicates stronger sensitivity to particular elements, such as the swing angle. Using the automatic productivity estimation methods, managers and operators can continuously track the excavators' productivity in worksites.

In this paper, it has been assumed the type of material and dumping condition in the operation are known. Classification methods are required to automatically identify the type of material and dumping condition in the operation. Another challenge is that some parts of operating conditions such as swing angle less than 45° or the heaped bucket capacity less than 0.3 m^3 are not modeled in the methods. In addition, the Komatsu model calculates the theoretical productivity based on the excavator's model. The machine's weight and capability should be utilized rather than the excavator's model. Another deficiency is that the BML model cannot calculate the theoretical cycle time for materials in the very low excavability category. In the trenching operation, materials fall back into the trench from trench walls, and the operator needs to spend time cleaning the trench. A fall-in factor is required to model this cleaning time in the theoretical productivity estimation of the trenching operation.

Acknowledgments

This project is part of the MORE-ITN project (MORE (2020)), which has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 858101. The MORE project is an innovative European Industrial Doctorate (EID) research and training programme that tries to answer the challenges of HDMMs. Eight researchers in the MORE-ITN project work on three main work packages: 1) Process, 2) Machine, and 3) Control.
We would like to express our sincere gratitude to Jari Valtonen for his assistance with the data collection phase.

References

Bau, F. E. B. L. (1983). Handbuch BML: Daten für die Berechnung von Baumaschinen-Leistunge, 3rd edition.

Caterpillar (2018). Caterpillar Performance Handbook. Cat® publication by Caterpillar Inc., Peoria, Illinois, USA, 48th edition.

Chen, C., Zhu, Z., and Hammad, A. (2022). Critical review and road map of automated methods for earthmoving equipment productivity monitoring. Journal of Computing in Civil Engineering, 36(3):03122001.

Edwards, D. and Griffiths, I. (2000). Artificial intelligence approach to calculation of hydraulic excavator cycle time and output. Mining Technology, 109(1):23–29.

Edwards, D. J. and Holt, G. D. (2000). Estivate: a model for calculating excavator productivity and output costs. Engineering, Construction and Architectural Management, 7(1):52–62.

Geimer, M. (2020). Mobile Working Machines. SAE International, Warrendale, PA.

Holt, G. D. and Edwards, D. J. (2015). Analysis of interrelationships among excavator productivity modifying factors. International Journal of Productivity and Performance Management, 64(6):853–869.

Kassem, M., Mahamedi, E., Rogage, K., Duffy, K., and Huntingdon, J. (2021). Measuring and benchmarking the productivity of excavators in infrastructure projects: A deep neural network approach. Automation in Construction, 124:103532.

Komatsu (2013). Specification and application handbook. Komatsu, Tokyo, Japan, 31st edition.

Kujundžić, T., Klanfar, M., Korman, T., and Briševac, Z. (2021). Influence of crushed rock properties on the productivity of a hydraulic excavator. Applied Sciences, 11(5):2345.

Langroodi, A. K., Vahdatikhaki, F., and Doree, A. (2021). Activity recognition of construction equipment using fractional random forest. Automation in construction, 122:103465.

Lingard, H., Wakefield, R., and Blismas, N. (2013). If you cannot measure it, you cannot improve it: Measuring health and safety performance in the construction industry. In the 19th Triennial CIB World Building Congress, Queensland University of Technology, Brisbane, Queensland, Australia.

Litvin, O. and Litvin, Y. (2020). Evaluation of effect of the excavator cycle duration on its productivity. In E3S Web of Conferences, volume 174, page 01010. EDP Sciences.

Machado, T., Fassbender, D., Taheri, A., Eriksson, D., Gupta, H., Molaei, A., Forte, P., Rai, P. K., Ghabcheloo, R., Mäkinen, S., et al. (2021). Autonomous heavy-duty mobile machinery: A multidisciplinary collaborative challenge. In 2021 IEEE International Conference on Technology and Entrepreneurship (ICTE), pages 1–8, Kaunas, Lithuania. IEEE.

Molaei, A., Geimer, M., and Kolu, A. (2022). An approach for estimation of swing angle and digging depth during excavation operation. In Proceedings of the 39th International Symposium on Automation and Robotics in Construction, pages 622–629, Bogota, Columbia. International Association for Automation and Robotics in Construction (IAARC).

MORE (2020). MORE-ITN project. `https://www.more-itn.eu/`. [Online; accessed 1-August-2022].

Ng, F., Harding, J. A., and Glass, J. (2016). An eco-approach to optimise efficiency and productivity of a hydraulic excavator. Journal of cleaner production, 112:3966–3976.

Nunally, S. W. (2014). Construction methods and management. Technical report, D-CST/3759 PR-186.

Ok, S. C. and Sinha, S. K. (2006). Construction equipment productivity estimation using artificial neural network model. Construction Management and Economics, 24(10):1029–1044.

Panas, A. and Pantouvakis, J. P. (2010a). Comparative analysis of operational coefficients' impact on excavation operations. Engineering, Construction and Architectural Management, 17(5):461–475.

Panas, A. and Pantouvakis, J. P. (2010b). Evaluating research methodology in construction productivity studies. The Built & Human Environment Review, 3(1):63–85.

Peurifoy, R. L., Schexnayder, C. J., Schmitt, R. L., and Shapira, A. (2018). Construction planning, equipment, and methods. McGraw-Hill Education.

Schabowicz, K. and Hola, B. (2007). Mathematical-neural model for assessing productivity of earthmoving machinery. Journal of Civil Engineering and Management, 13(1):47–54.

Schaufelberger, J. E. and Migliaccio, G. C. (2019). Construction equipment management. Routledge.

Tam, C., Tong, T. K., and Tse, S. L. (2002). Artificial neural networks model for predicting excavator productivity. Engineering Construction and Architectural Management, 9(5-6):446–452.

Yang, J., Edwards, D. J., and Love, P. E. (2003). A computational intelligent fuzzy model approach for excavator cycle time simulation. Automation in construction, 12(6):725–735.