Automated Fuzzy Set-Based System for Monitoring the Effects of Productivity Variation on Earthmoving Projects

A. Salah, A. Salem, and O. Moselhi

Abstract—**Productivity monitoring is a crucial process that considerably contributes in the success of earthmoving projects. Over decades, researchers have been focused on identification and assessment of the factors that lead to loss-in-productivity in earthmoving operations. However, considerably less work was focused on the effects of productivity variation on cost and schedule of earthmoving projects. This paper introduces an automated data collection that acquires data from various technological sources. The collected data facilitates the assessment of productivity ratio that assists in continuous monitoring of productivity variation in earthmoving projects. Also, this paper introduces a new fuzzy set-based monitoring system that investigates the effects of productivity variation on cost, schedule and depletion of resources in earthmoving projects based on set of qualitative and quantitative factors. The proposed monitoring system generates an early warning that allows for proactive decision making to avoid delays, overruns, and unnecessary depletion of resources. A case example is used to demonstrate the applicability of proposed method and its features in monitoring and evaluating the effects of productivity variation on cost, schedule and utilization of resources in earthmoving projects. Finally, results are discussed and conclusions are drawn highlighting the features of proposed method and recommendations for future work.**

Index Terms—**Decision making, earthmoving project, fuzzy set theory, monitoring system, productivity variation, resources depletion.**

I. INTRODUCTION

Performance of earthmoving operations contributes considerably to the success or failure of construction projects. Cost of earthmoving operations represent 20% of total cost of construction projects [1] and [2] which explains the importance of monitoring the productivity variation in earthmoving operations. Productivity variation may lead to cost overruns, schedule delays and unnecessary depletion of resources in earth moving operations. Low productivity may generate schedule delay and inefficient use of resources however; high productivity may lead to cost overrun and over depleted resources. Therefore, monitoring the productivity in earthmoving operations is necessary to avoid undesirable consequences that may be harmful for one or more project objectives. The performance level in earthmoving operations is tightly related to productivity rate which is dependent to various operational, environmental, technical and managerial factors. Therefore, assessment of productivity rate is essential for evaluating the performance in earthmoving operations however, productivity assessment solely doesn't provide any indication about possible occurrence of undesirable consequences.

II. BACKGROUND

Monitoring of earthmoving operations receives considerable attention from researchers [1]. However, the majority of existing work focused on the assessment of productivity in earthmoving operations [1], [3] and [4] using traditional methods [1] that require human intervention (i.e. manual or semi-automated) or fully automated methods using various advanced technologies including; RFID [3], GPS [4], video recording [5], [6], GIS [7], or combination of two or more technologies [1] and [7]. Other researchers focused on identifying the factors that lead to low productivity in respect to equipment utilization [8]-[10], Labor productivity [10] and [11], and enhancement of certain process [12] to elevate the productivity and to improve the performance in earthmoving operations [13] and [14]. Regardless of limitations, these methods provide enhancements and corrections for the assessment process of productivity in earthmoving operations. Also, these methods provide various recommendations that can be useful for elevating the productivity in earthmoving operations. However, these methods did not consider the effects of productivity variation on cost, schedule, and efficient use of resources that may lead to failure of earthmoving operations and consequently, failure of construction projects.

This paper aims to introduce an automated fuzzy set-based monitoring system that assists in highlighting the effects of productivity variation on earthmoving operations and in generating an early warning to indicate possible occurrence of undesirable consequences. The proposed monitoring system provides a decision support tool that assists project managers in taking proactive, instead of reactive, decisions to avoid cost overruns, schedule delays and inefficient utilization of resources in earthmoving operations.

The proposed monitoring system includes five modules; automated data collection, productivity assessment, fuzzy set-based monitoring system, productivity analysis, and early warning decision support as shown in Fig. 1.

A. Automated Data Collection Module

This module automates data collection and integrates various data sources (e.g. cameras, smartphones, sensors, etc.…) to acquire the necessary information for assessing accurately the actual productivity in earthmoving operations. Fig. 2 shows the data collection procedure from various sources using a set of advanced technologies.

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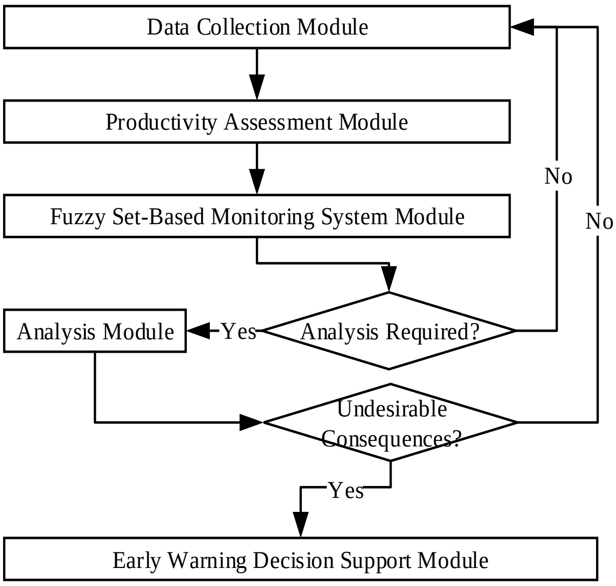

Fig. 1. Framework of proposed monitoring method.

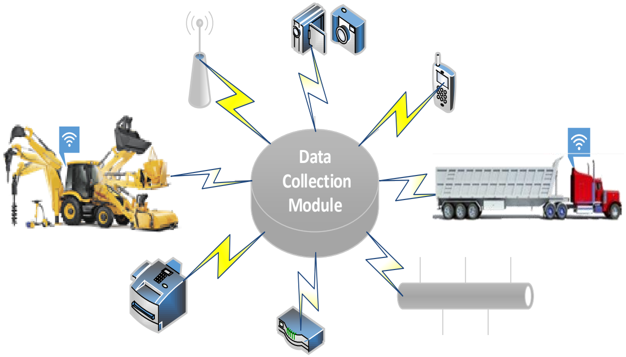

Fig. 2. Overview of proposed automated data collection module.

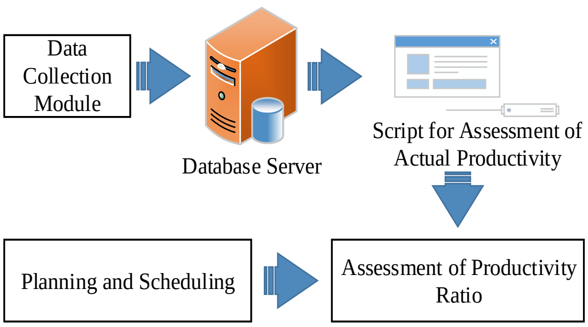

Fig. 3. Productivity assessment module.

B. Productivity Assessment Module

Productivity assessment module utilizes the collected data to evaluate, at each period t, the actual productivity (*AP*) using an assessment script that combines two or more of existing methods [13] and [14] for productivity assessment as shown in Fig. 3. Then, productivity ratio (*PR*) is calculated as the ratio between actual and planned productivities for the same period t using (1).

$$PR(t)=\frac{AP(t)}{PP(t)} \quad (1)$$

where $PR(t)$, $AP(t)$ and $PP(t)$, represent respectively productivity ratio, actual productivity, and planned productivity at time t.

C. Fuzzy Set-Based Monitoring System

The proposed monitoring system introduces a low-optimum-high (LOH) fuzzy set-based monitoring system (see Fig. 4) that identifies the productivity performance based on three states; low, optimum, and high. The upper and lower bounds of each state is organization (project) dependent [16] therefore, each organization has to evaluate lower and upper bound of each fuzzy attribute (e.g. Low) based on their experience in earthmoving operations. The productivity ratio (*PR*) values represents the x-axis of LOH fuzzy system whereas, the membership function (μ) represents the *y*-axis. The ideal value of *PR* equals to 1 whereas actual productivity ratio at period *t*, $PR(t)$, is acquired from the productivity assessment module and illustrated on proposed monitoring system as a vertical indicator as shown in Fig. 4.

It should be noted that no action is required as long as the indicator of actual productivity ratio is located within the optimum area (e.g. between 0.9 and 1.1) as shown in Fig. 4. However, if the indicator, at certain period *t*, moves beyond the optimum area (i.e. Low or High) that means further analysis is needed. In other words, only when there is possibility for occurrence of undesirable events the productivity analysis module is initiated to identify and evaluate the consequences of the event being considered before issuing an early warning that supports the decision making process in earthmoving operation.

L~O and O~H fuzzy areas, shown in Fig. 4, represent the situations where the productivity performance cannot be assessed without further analysis. In this case, the productivity analysis module is initiated to differentiate between low and optimum (optimum and high) states.

D. Productivity Analysis Module

The productivity analysis module generates the fuzzy membership function that represents the L~O (O~H) fuzzy area based on low(high) and optimum fuzzy number using (2). The weights of fuzzy number $\tilde{A}$ and $\tilde{B}$ are calculated respectively as the membership of $\tilde{A}$ and $\tilde{B}$ at actual productivity ratio using (3). It also utilizes the agreement index [16] to differentiate between the low (high) and optimum states.

The agreement index represents the ratio of areas of intersection between the fuzzy membership functions that represent the fuzzy area (e.g. L~O) and each of the states (e.g. L and O) using (4) and (5). Agreement index ratio (AIR) is introduced to differentiate between two different state at a given productivity ratio as presented in (6). Assuming that $\tilde{A}$ represents the low (high) state and $\tilde{B}$ represents the optimum state, if AIR $(\tilde{A},\tilde{B})$ is higher or equal to 1 than the productivity is considered optimum and no further action is required otherwise, it is considered low (high) and that imposes the initiation of early warning decision support module.

$$\tilde{A}\sim\tilde{B} = w_{\tilde{A}}\times\tilde{A} + w_{\tilde{B}}\times\tilde{B} \quad (2)$$

$$w_{\tilde{A}} = \mu_{\tilde{A}}(PR(t)) \quad (3)$$

where $\tilde{A}$ and $\tilde{B}$, represent respectively two fuzzy numbers *A* and *B*. $w_{\tilde{A}}$ and $w_{\tilde{B}}$, represent respectively two fuzzy numbers *A* and *B*.

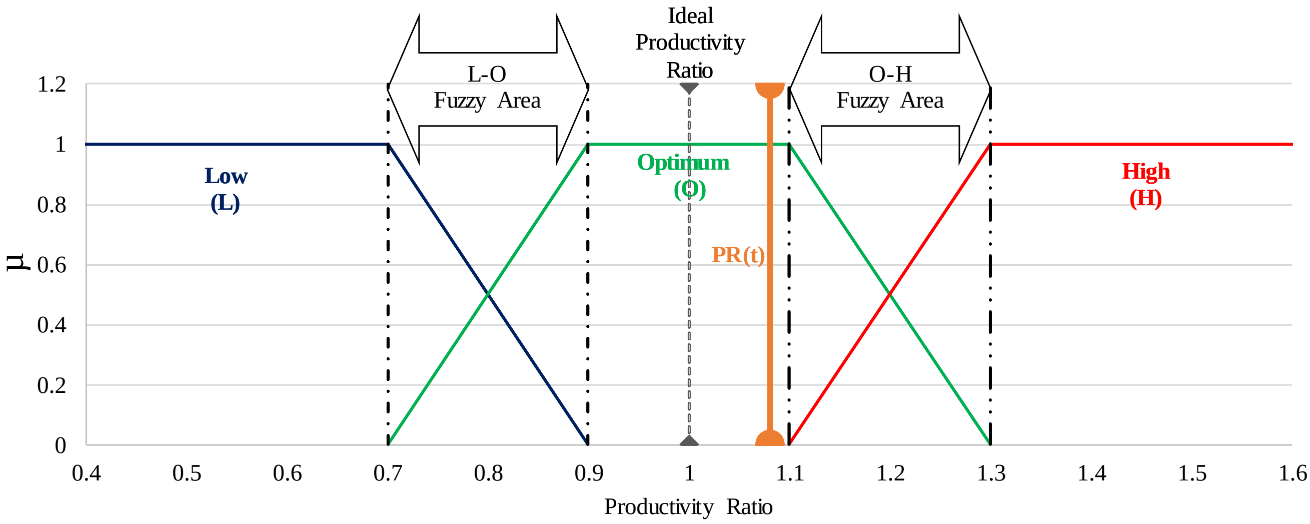

Fig. 4. LOH fuzzy set-based monitoring system.

$\tilde{A} \sim \tilde{B}$ represents the fuzzy number that represents the fuzzy area between A and B, noted also as $\widetilde{A \sim B}$.

$$AI(\tilde{A} \sim \tilde{B}, \tilde{B}) = \frac{\text{Area}(\tilde{A} \sim \tilde{B} \cap \tilde{B})}{\text{Area}(\tilde{A} \sim \tilde{B})} \quad (4)$$

$$AI(\tilde{A} \sim \tilde{B}, \tilde{A}) = \frac{\text{Area}(\tilde{A} \sim \tilde{B} \cap \tilde{A})}{\text{Area}(\tilde{A} \sim \tilde{B})} \quad (5)$$

$$AIR(\tilde{A}, \tilde{B}) = \frac{\text{Area}(\tilde{A} \sim \tilde{B} \cap \tilde{B})}{\text{Area}(\tilde{A} \sim \tilde{B} \cap \tilde{A})} \quad (6)$$

where $AI(\widetilde{A \sim B}, \tilde{B})$ and $AI(\widetilde{A \sim B}, \tilde{A})$ represent the agreement indices between the fuzzy area between $\tilde{A}$ and $\tilde{B}$ and the fuzzy.

$AIR(\tilde{A}, \tilde{B})$ represent the agreement index ratio between the fuzzy number $\tilde{A}$ and $\tilde{B}$.

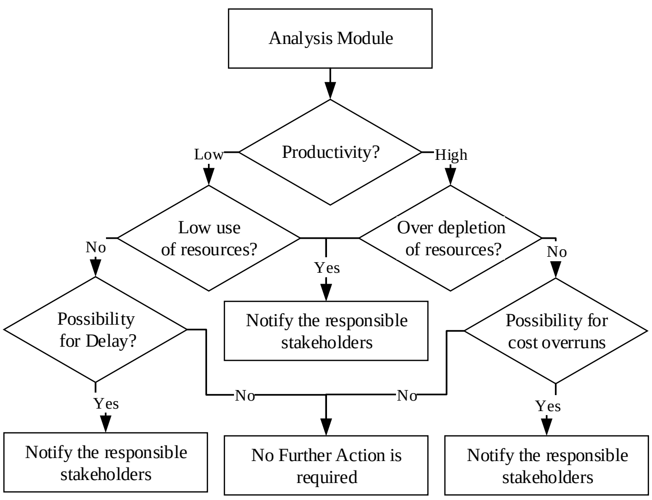

Fig. 5. Early warning decision support module.

E. Early Warning Decision Support Module

Early warning decision support module is initiated based on the identified state (e.g. low) of productivity in earthmoving operations as presented in section D. If, the identified state was low that means there is possibility for occurrence of schedule delay or inefficient use of resources then, the responsible project parties are notified. However, in case where the identified productivity state is high that means there is possibility for occurrence of cost overrun or over depletion of resources (e.g. number of trucks is more than needed) in this case the responsible parties are also notified. The proposed early warning system (shown in Fig. 5) identifies for each consequence the project parties that need to be notified using an embedded notification system. These notifications highlight the need for intervention and allow decision makers to take quick and proactive decisions that may increase the productivity performance and may assist in avoiding schedule delays, cost overruns, and inefficient use of resources.

III. Case Example

This hypothetical example is used to demonstrate the applicability of proposed method and to illustrate its features in monitoring the productivity performance in earthmoving operations. Assuming that the input data are received from various technological sources (see Fig. 6) and used to evaluate the actual productivity (AP) at each period of time t. Assuming that, the actual productivity at period t =50 was evaluated as 106 m^3/day and for the same period of time, the productivity was planned as 125 m^3/day. In this case the productivity ratio for period t=50 is calculate using (1) as 0.85 and that means the LOH fuzzy monitoring system shows the indicator of actual productivity ratio in the $\widetilde{L \sim O}$ fuzzy area as shown in Fig. 6. The weights of each fuzzy state $\tilde{L}$ and $\tilde{O}$ are calculated using (3) as 0.25 and 0.75 respectively. A trapezoidal fuzzy number for $\widetilde{L \sim O}$ fuzzy area is calculated using (2) and (3) and the membership function that represents the $\widetilde{L \sim O}$ fuzzy number is generated as shown in Fig. 6.

$$\widetilde{L \sim O} = 0.25 \times \tilde{L} + 0.75 \times \tilde{O}$$

$$\widetilde{L \sim O} = 0.25 \times [0,0,0.7,0.9] + 0.75 \times [0.7,0.9,1.1,1.3]$$

$$\widetilde{L \sim O} = [0.525,0.675,1.0,1.2]$$

Using the membership functions, the agreement indices of

$\widetilde{L\sim O}$ with $\tilde{L}$ and that of $\widetilde{L\sim O}$ with $\tilde{O}$ are calculated using (4) as follows:

$$AI(\widetilde{L\sim O},\tilde{L})=\frac{Area(\widetilde{L\sim O}\cap\tilde{L})}{Area(\widetilde{L\sim O})}=\frac{0.2}{0.5}=0.4$$

$$AI(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O})}=\frac{0.3}{0.5}=0.6$$

$$AIR(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O}\cap\tilde{L})}=\frac{0.3}{0.2}=1.5$$

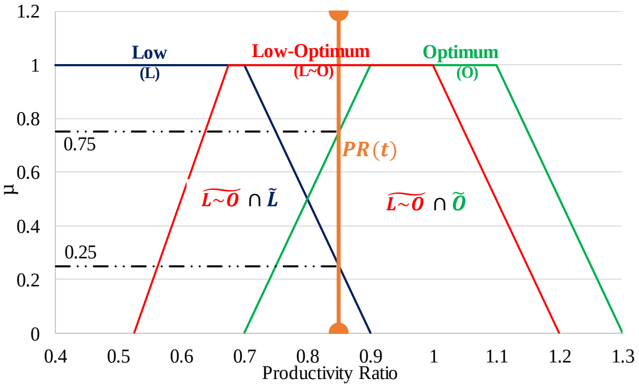

Fig. 6. Agreement index of low optimum with optimum.

In this case, the system identified the productivity as optimum which means no further action is required. However, if the productivity ratio continues to decrease and it reaches a level of 90 m^3/day at period t=60 then, the calculation procedure is modified as follows:

$$PR(60)=0.8$$

$$\mu_{\tilde{L}}(PR(60))=\mu_{\tilde{O}}(PR(60))=0.5$$

$$\widetilde{L\sim O}=0.5\times\tilde{L}+0.5\times\tilde{O}=[0.35,0.45,0.9,1.1]$$

$$AI(\widetilde{L\sim O},\tilde{L})=\frac{Area(\widetilde{L\sim O}\cap\tilde{L})}{Area(\widetilde{L\sim O})}=\frac{0.4}{0.6}=0.67$$

$$AI(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O})}=\frac{0.2}{0.6}=0.332$$

$$AIR(\widetilde{L\sim O},\tilde{O})=\frac{Area(\widetilde{L\sim O}\cap\tilde{O})}{Area(\widetilde{L\sim O}\cap\tilde{L})}=\frac{0.2}{0.4}=0.5<1$$

In this case, the productivity is identified as low which means there is possibility for occurrence of schedule delay or inefficient use of resources. Consequently, the early warning decision support should be initiated and notifications should be sent to decision makers in order to take corrective actions whether to avoid the occurrence of schedule delay or to increase the use of resources if deemed necessary.

IV. Summary and Conclusions

This paper presents a newly developed fuzzy set based monitoring system that automates the tracking of productivity and identifies the effects of productivity variation on schedule, cost and resources allocation in earthmoving operations. The developed system provides a multiple technologies-based framework for automating the data collection about productivity in earthmoving operations. It also introduces a new LOH fuzzy system that identifies the performance level of productivity based on three states low, optimum and high using fuzzy set theory. Also, the developed monitoring system provides a decision support tool with an embedded notification procedure that provides an early warning to highlight the consequences of low or high productivity. The early warning system assists decision makers to take proactive instead of reactive decisions to avoid or reduce the consequences of undesired events. The case example demonstrates the use and applicability of developed method highlighting its features in collecting data using various sources, evaluating of actual vs. planned productivity, monitoring of productivity variation using fuzzy set theory, analysis of results using fuzzy calculation, and providing decision support using an early warning system.

It should be noted that the developed monitoring system assists in monitoring productivity of earthmoving operations and highlights the correct time for intervention. However, this system depends considerably on the accuracy of data collected from various technologies. In this respect, the development of an assessment system that integrates the data collected from various technologies in a manner that elevates the accuracy of productivity assessment is recommended.

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He is the recipient of numerous honors and awards, including the prestigious Walter Shanly Award of CSCE in recognition of outstanding contributions to the development and practice of construction engineering in Canada