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PRODUCTIVITY BASED METHOD FOR FORECASTING COST & TIME OF EARTHMOVING OPERATIONS USING SAMPLING GPS DATA

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SUMMARY: *Accurate estimate of onsite productivity of earthmoving operations is essential for successful delivery of this class of projects. Estimating onsite productivity is a difficult task that requires tracking heavy and costly equipment and requires collecting, managing, and analyzing a considerable amount of data from construction sites on daily bases. Despite the fact that there are many systems available to carry out such process, those systems are expensive and require collection of large volume of data. This paper introduces a newly automated web based system for estimating actual productivity and for forecasting cost and time of earthmoving operations in near real time. The developed system integrates Global Positioning System (GPS) and Geographical Information System (GIS) in addition to four developed algorithms. The proposed system makes use of limited samples of GPS data for tracking and control purpose instead of collecting large volume of data from construction sites. The proposed system considers uncertainties associated with activity durations and cost. The results obtained from the application of the proposed system to two actual projects, indicates that the proposed system can be used as an effective tool for tracking and control of earthmoving operations.*

KEYWORDS*: Cost, Forecasting, GPS, Productivity, Time, Uncertainties*

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1. INTRODUCTION

Estimating onsite actual productivity is a vital function in forecasting cost and time of large earthmoving operations. It is always a main concern of project managers (Alshibani 2011 and 2015). Estimating onsite actual productivity requires tracking and monitoring the construction equipment involved (Eldin and Mayfield 2005, Montaser et al. 2011 and 2012; Alshibani and Moselhi 2007). The tracking process mainly involves the following steps: (1) collection a large volume of data from construction sites; (2) managing, processing, and analyzing the collected data, (3) estimating actual productivity based on the collected data; (4) comparing the estimated actual productivity to that planned(Alshibani 2008); and (5) taking corrective actions, if deviation found. The literature reveals that over the years, many models and systems have been introduced for estimating on-site productivity of earthmoving operations.

Traditionally estimating productivity relies on the use of performance charts provided by equipment manufactory and multiple regressions based models (Edwards and Holt, 2000, Han and Halpin, 2005). The main setback of using performance charts is that they do not reflect actual conditions of project site and they have been found to overestimate the productivity (Han and Halpin, 2005). Other methods were build based on the use of artificial neural networks (ANN) (Tam et al. 2002). ANN is used to estimate equipment productivity of different individual construction equipment such as dozers and excavators (Ok and Sinha , 2006). Tam et al (2002) concluded that both multi-regression and ANN based models could be used to predict excavator productivity although the MLFF is superior to multiple regression models. It is worth it here to note that the application of ANN require the use of a large volume of data to build the model. Using large volume of data can be costly, time consuming, and not accurate since every project is unique. Moreover the use of such data has a great impact on the accuracy of the outcomes of those models since they do not account for uniqueness of construction projects.

In recent years and because of the progressive advancements in information technology, new models and systems have been introduced utilizing different technologies such as; (1) spatial technologies particularly GPS (i.e. Topcon; VisionLink; Alshibani and Moselhi 2007, Moselhi and Alshibani 2007; Montaser et al. 2011& 2012); Radio frequency identification technology (RFID) (I. e. Montaser and Moselhi 2012, Montaser and Moselhi 2013); (2) on board instrumentation system (OBIS). The OBIS is a powerful tool for equipment management, which provides managers and operators with information on a wide range of functions. The system relies on the placement of sensors on many locations on the tracked equipment to detect abnormal conditions in any of the equipment systems. The main function of these sensors is to: (1) diagnose the mechanical health of tracked equipment to improve productivity; and (2) measure physical parameters such as temperature, pressure, and control lever position. These parameters are then used to determine the equipment cycle time and productivity.

The OBIS is used in several earthmoving applications including controlling scraper wheel slippage and transmission shifting, maximizing dozer production, providing increased traction to haul trucks, and preventing loader rollovers. Caterpillar is a leading company in using OBIS. It developed Vital Information Management System (VIMS, CAT Product Link, 2013) to estimate actual productivity and to monitor the mechanical status of its equipment. However, the OBIS are characterized by being expensive in cost and those systems could not forecast eaither fleet productivity nor project cost and time at completion deterministically or stochastically (Montaser et al 2012).

Although the simulation has received a great attention by researched as a powerful tool for analysing complex problem, the main setbacks of the simulation as stated by (e.g. Chung 2007; Shaheen et al. 2007, Hajjar and AbouRizk 2002) are: (1) simulation is expensive and time-consuming; (2) it relies on expert opinions to compensate for lack of numerical data for various construction activities; (3) it requires dedicated simulation professionals and a number of simulation runs to generate meaningful estimates, and (4) it is sensitive to assumptions and /or calculations required not only to quantify correlation coefficients among input variables, but also to develop the probability density functions associated with these variables.

For the purpose of identifying the causes of unacceptable performance, the GPS has many advantages comparing to OBIS. The following advantages can be observed: (1) GPS can identify idle time from activity duration, (2) GPS can collect a large volume of data, which can be utilized in developing realistic probability distributions for activity durations, (3) collected GPS data provides good representation of operating conditions; and (4) the truck loading and dumping time can be identified only if GPS is used. The OBI can only record the aggregate travelled time whereas GPS data are used directly to calculate the time for hauling and return. Even though the use of GPS as tracking tool has many advantages, still there is a need for collecting a large volume of data. This can make the task of the project manager complex since there is a need to manage; process; and analyses such a big volume of collected data.

In an effort to overcome the previous stated limitations of simulation and OBIS, RFID technology has been applied by many researcher as a new technologies. The RFID can offer low cost method of tracking earthmoving operations. The main limitations of RFID is that the technologies cannot help in detecting the causes behind the unacceptable performance since the fixed RFID readers is attaching only to designated gates of projects dumping and / or loading area. In addition, the RFID based systems can track the moving equipment outside the loading and dumping area. As stated above and regardless of the technique used, the models and existing systems require collecting large volume of data from construction site which as result requires the development of information system capable of processing and analyzing the collected data.

This paper presents a practical and easy to use system in an effort to overcome the limitations of current automated systems in estimating onsite productivity and in forecasting project cost and time. The system is designed to be used as a snapshot tool for estimating actual productivity and forecasting project time and cost. The cost and time is forecasted based on the productivity achieved on construction site. The developed system uses limited GPS data samples as alternative approach for collecting large volume of data. The proposed system can help in detecting the causes of unacceptable performance based on the collected GPS data.

2. PROPOSED SYSTEM

The proposed system, neither requires human involvement to collect on site data nor expensive and sophisticated instrumentations for estimating actual productivity and forecasting project cost and time. The proposed system, on the contrary, relies primarily on collecting samples of GPS data in near real time using web-based system. The system uses the collected GPS data to estimate on-site productivity and forecast project time and cost. The collected GPS data includes time, speed, heading, longitude, latitude, and latitude (see Table.4). The GPS receivers are mounted on hauling units to monitor their movement and location. The captured data is required to estimate tracked equipment cycle times for each round trip. For simplicity and efficiency, only one GPS unit is mounted on one of trucks in the fleet that travels the same path. The estimated productivity for the tracked truck represents the entire fleet productivity since the cycle time of that truck can reasonably represent that of the rest of the trucks involved. The latter option can be used when the hauling units in the fleet are deemed to be of good condition, i.e. none will be expected to breakdown during travel. This option is used in the example projects presented in this paper.

In order to reveal actual conditions such as the uncertainties encountered in the durations of the activities involved, up to 75 samples of GPS data were collected in different time, different working conditions, and under different management conditions. The data samples were collected at relatively short time intervals (45 – 50 seconds). This allows capturing the truck locations in loading and dumping areas. The collection of limited volume of GPS data facilitate data managing and processing while satisfying the data needed for estimating actual productivity and forecasting project cost and time. The user can decide on the suitable number of these data samples that fits its need.

The proposed system incorporates five modules and four algorithms as shown in Fig. 1 and Fig. 2. They are: (1) Data collection Module, (2) GIS Module (GIS), (3) Graphical User Interfaces (GUI) Module, (4) Database Module, (5) Uncertainties/Risk Module; and (6) estimating actual productivity and forecasting cost and time algorithms. The data collection Module uses GPS receiver to collect data from construction site of the moving truck. The GIS Module is used to graphically present the tracked hauling units along travel roads based on the collected GPS data. The GUI Module is used to automate data acquisition, analyze the collected GPS data, and to calculate the cycle times from the collected GPS data using the developed algorithm. The database Module is used to store the information pertinent to equipment (specification, cost, etc), project (time, direct cost, indirect cost, quantities of work), and soil characteristics (swell and shrinkage factors). The uncertainties/risk Module is used to model the uncertainties associated with the calculated duration and equipment cost and to assess the risk of the generated report. The module allows the user to select probabilities distributions of uncertain variables and to quantify the risk associated with the operation being considered based on user specified number of simulations.

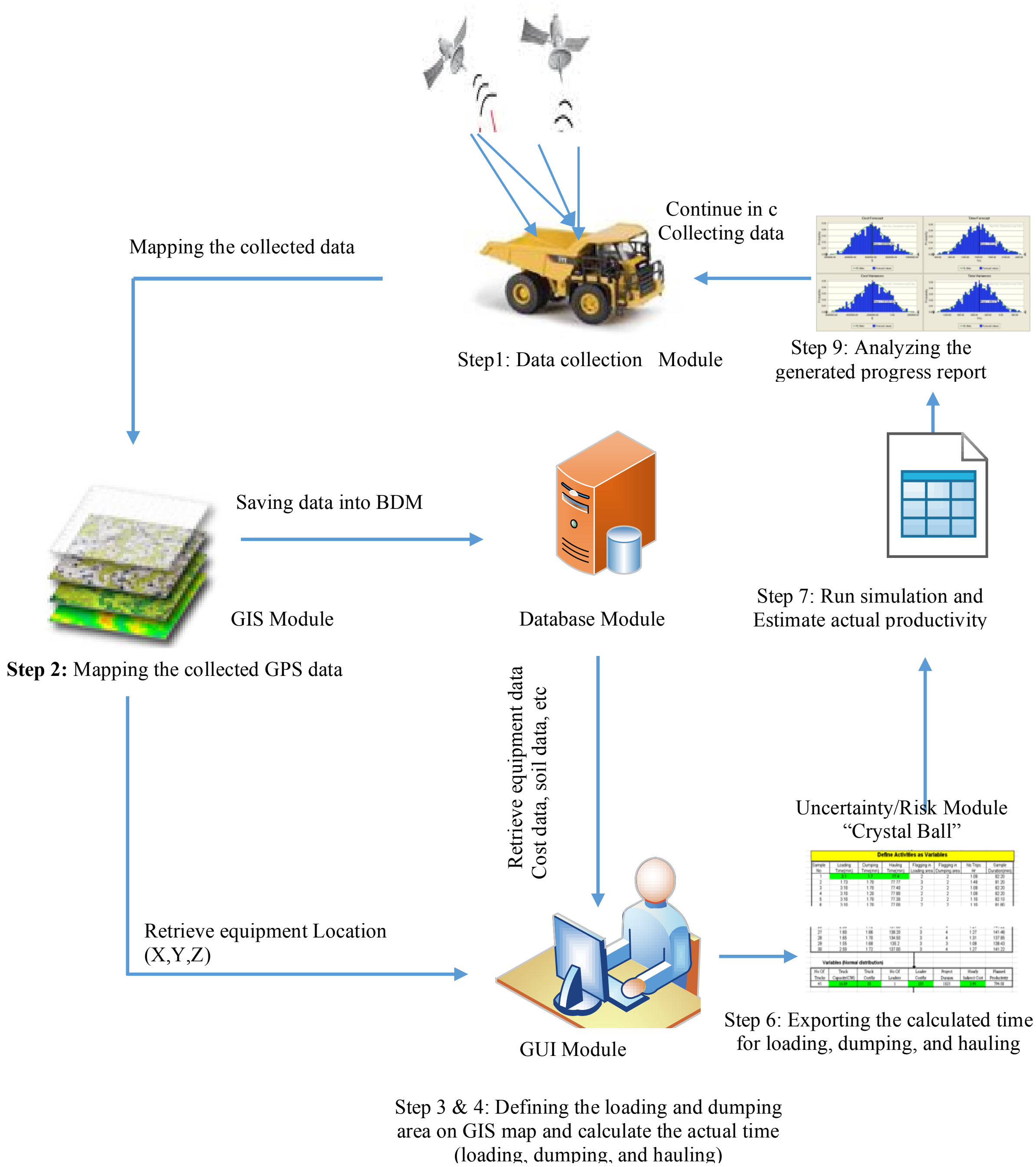


FIG 1: Overview of the proposed model.

The steps required for the application of the proposed system can be summarized as follow:

Step 1: Collecting data from the construction site being considered using GPS receivers by data collection module.

Step 2: Mapping the collected GPS data into the GIS map using the developed GIS module for graphical presentation and for tracking the hauling units along travel roads on a GIS map in real time via internet. The collected GPS data is also stored in the system database Module.

Step 3: Defining the loading and dumping area on GIS map using the developed drawing tool in GUI Module. The developed drawing tool enables the user to define different borrow pit and landfill sites dynamically as the project progresses, when needed.

Step 4: Analyzing the uploaded GPS data to calculate the actual time for loading, dumping, and hauling using the developed algorithm for calculating cycle time of hauling units as will be described in next section.

Step 5: Repeating steps 2 and 4 for the number of data samples considered, e.g. 30 data samples are used here in the first case example and 75 samples are used in the second case example. It should be noted that the proposed system is open to process larger size of data sampling.

Step 6: Exporting the calculated time for loading, dumping, and hauling of the data samples into uncertainties Module in “Crystal Ball” software. The uncertainties associated with the determined duration; truck cost; loader cost; and project hourly indirect cost are then modeled to conduct the risk analysis of the estimated productivity and forecasted cost and time.

Step 7: Having built the probabilistic model that accounts for uncertainties associated with the seven variables referred to above, the simulation is run and the actual productivity is stochastically estimated. The developed algorithm to estimate the actual site productivity is fired simultaneously while the simulation is running. In the risk analysis software, the variables are referred to as assumptions and they are highlighted in green , while the outputs is referred as forecast cells and they are highlighted in yellow as shown in Fig. 5 and 8. The outputs are actual productivity, productivity index, cost forecast, time forecast, cost variances, and time variances. One thousand (1000) simulations are used in the numerical examples presented in this paper. The values of the output variables are displayed automatically in the forecast cells.

Step 8: Analyzing the outputs of the risk module and taking a corrective action(s), if needed, accordingly.

To help project management teams in identifying causes of unacceptable performance, if any, additional indices can also be determined. Detailed description of these indices can be found elsewhere (Moselhi and Alshibani 2008).

2.1. Computation process

The calculated hauling units’ cycle time and number of trips made per hour are used to calculate: (1) fleet actual productivity; (2) productivity performance index; (3) forecasted project cost and time; and (4)cost and time variances as described below.

2.1.1. Hauling units’ cycle time

The core of the developed system is calculating the haul unit cycle time from the collected GPS data. The hauling units’ cycle time is first determined to estimate on-site productivity. The cycle time consists of three main activities; loading, dumping, and hauling (travel and return). In order to accurately estimate of these cycle times directly from the collected GPS, an algorithm has been developed. As depicted in Fig. 4, after mapping the collected GPS data in GIS map, the user is asked to draw boundaries of loading and dumping areas on GIS map using the developed drawing tool of GUI. A circular shape is used to represent loading and dumping areas graphically in a GIS map. The developed system is flexible to allow the user to define a new dumping and/or loading area if those locations change with time due to changes in site topography.

The following steps are applied to determine the truck cycle time.

1. The user needs to define loading and dumping areas graphically in GIS map.
2. The algorithm first counts the number of points (tracked equipment locations) along the traveled road and extracts their position (latitude, longitude, altitude, time, and velocity) from collected GPS data.
3. The algorithm then starts calculating the distance between the position of the point (location) under consideration and the centers of the loading and dumping areas defined by the user in (1).
4. The algorithm then automatically determines, based on the traveled distance calculated in (3) above and the radius of the loading and dumping areas defined by the user, the whereabouts of hauling units. If the distance is greater than the respective radius of loading and dumping areas, the hauler would be recognized as traveling or returning. Otherwise, the dumping time is calculated as the time depicted when the hauler is inside the dumping area, and similarly the loading time is calculated as the time the hauler stays in the loading area. It is essential here to note that the calculated loading and dumping time includes positioning, maneuver, and direct loading and dumping time. Also, travel and return times are distinguished by the direction of the moving unit. For example, if the direction were from loading into dumping, the time would be for travel. The traveling time is calculated as soon as the hauling unit leaves the loading area and just before it enters the dumping area. Similarly, the returning time is determined as soon as the hauling unit leaves the dumping area and just before it enters the loading area.
5. Steps 3 to 4 are repeated until all points on the traveled road are considered. It should be noted that number of trips of a hauling unit is calculated based on determining the number of times the hauling unit crossing the boundaries of loading or dumping area (hitting flag). The model considers the flag has been hit when the hauling unit crosses the loading or dumping area. For example, a hauling unit is considered to have completed one trip when it hits the flag in the loading area twice (one for entrance the loading area and the other when it leaves the loading area) and that in the dumping area once.
6. The following regression equation is used to determine the number of trips a truck makes in a specified time by the user (Collected GPS sample duration).

$$No\ of\ trips = 2.8 \times 10^{-3} \times (X + X1)^2 + 0.2788 \times (X + X1) - 2.08 \times 10^{-2} \times (60/Sd) \quad (1)$$

Where:

X: no of times truck enters loading area (Flagging in loading area).

X1: No of times, truck enters dumping area (Flagging in dumping area).

Sd : Sample duration in minutes and it defined by the user

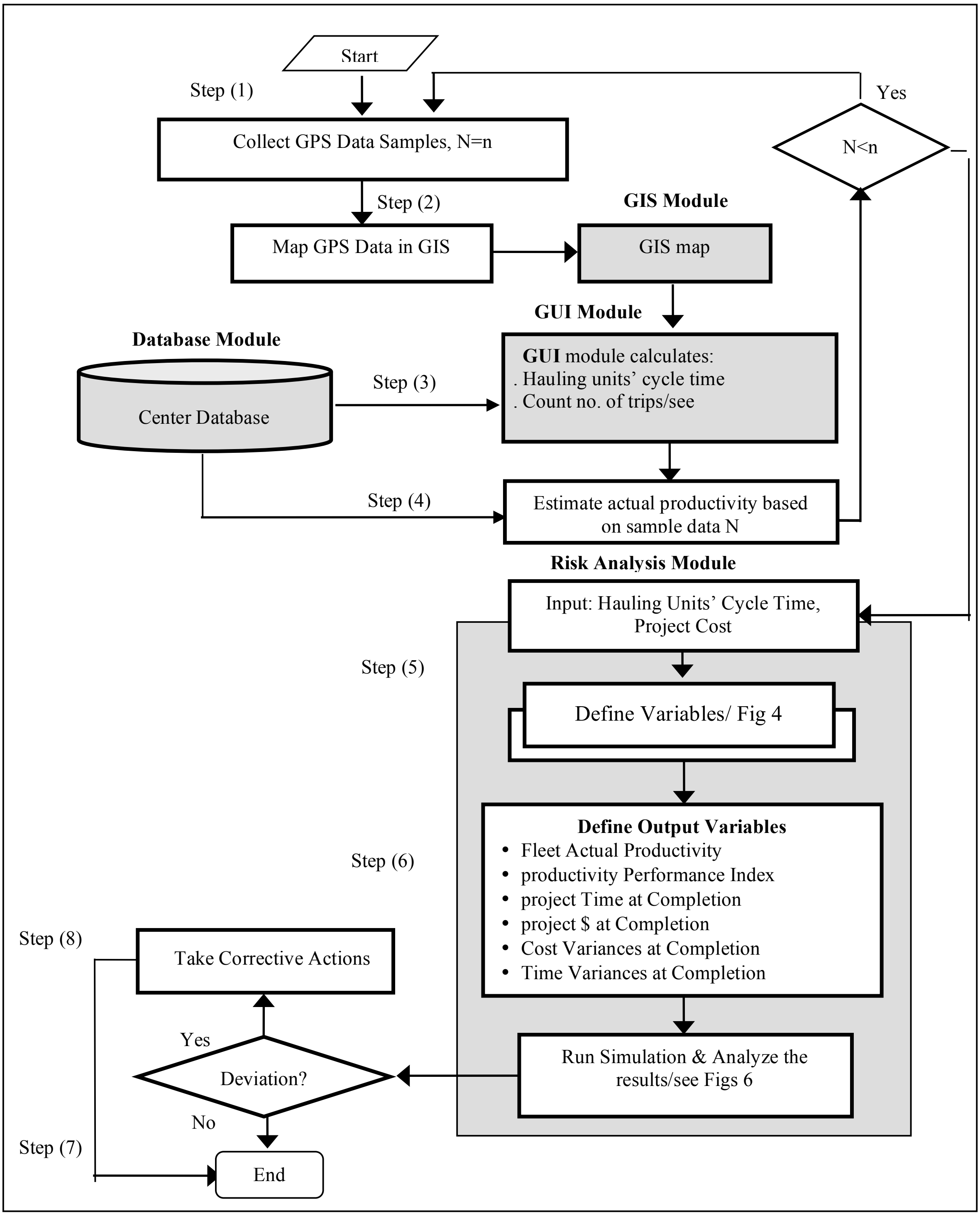


Fig 2: System layout.

Fig. 3 depicts the algorithm developed to calculate the truck cycle time, while Fig. 5 depicts the output of the calculation generated by the developed algorithm for 30 samples of GPS data in example project 1. In Fig. 4, the screen displays the hauler speed profile. The speed profile gives a clear picture of the hauling unit traveling path. In this particular case for example, the profile indicates that the hauling unit has made many stops along their path outside the loading and dumping area. That can be main cause of unacceptable performance.

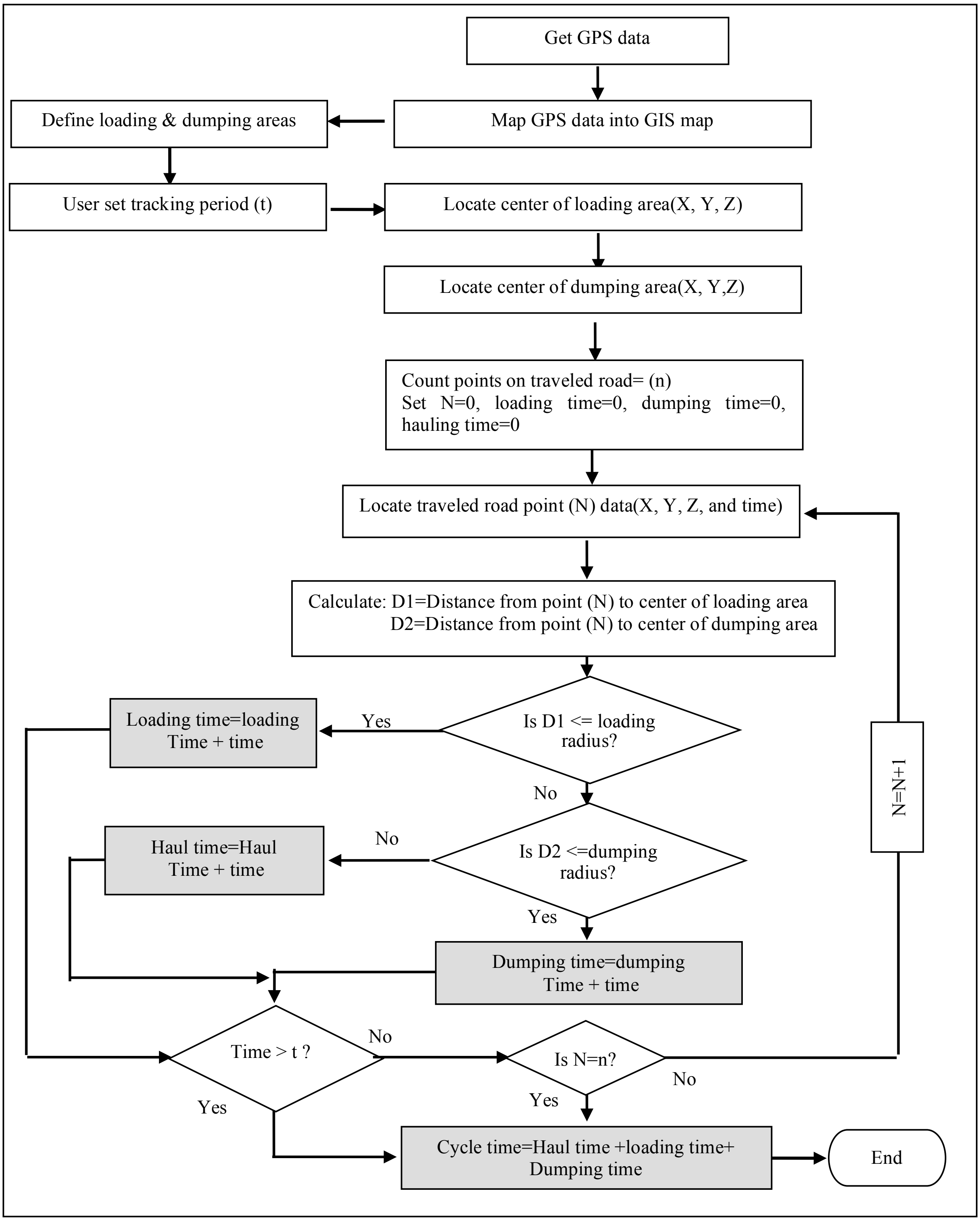


***FIG 3**: Developed algorithm for calculating cycle time of hauling units.*

2.2 Modeling the uncertainties

After calculating the actual cycle time from the collected GPS data (i.e. loading, dumping, and hauling) of the samples GPS data for tracked truck in GUI module, a probabilistic model is built in Crystal Ball software to quantify the uncertainties associated with the operations being considered. Fig. 5 displays the calculated durations of the main activities based on the collected GPS data samples. The cells colored in green represents the model variables, whereas the cells colored in blue represent the model outputs. The figure also presents the data range of the 30 data samples. For example the calculated loading time duration varies from 1.55 minute for data sample No. 29 to 5.13 minutes for data sample No. 7. Since loading, hauling and dumping are stochastic; they are defined by choosing a probability distribution that best fit the data and describes the uncertainty of their respective data. The user can select the distribution that best represent the data involved. In the examples presented in this paper, beta distribution is selected for loading, dumping, and hauling time based on the finding of AbouRizk and Halpin (1992). Normal distribution is selected to represent the uncertainty of the project cost data (loader cost, truck cost, and indirect cost), while triangle distribution is selected to represent the uncertainty of truck capacity. As stated earlier, having the variable and the forecast cell are defined, the simulation is run. 1000 run is applied for the example projects. It should be noted that the algorithm developed to estimate the productivity is defined as forecast cell and it is fired simultaneously while the simulation is running.

2.3 Estimating fleet on-site productivity

Having calculated the truck cycle time and the number of trips it made, the fleet on-site productivity is estimated as:

$$Pa = \sum_{i=1}^{i=n} N_{ti} * C_i * C_{fi} \tag{2}$$

Where:

n: number of hauling unit in the fleet being considered;

P_a : estimated onsite actual fleet productivity;

N_{ti} : the i[th] trips the hauling unit (i) made in one hour (changes during simulation as cycle time defined as variable).

C_i : the capacity of the i[th] hauling unit taking in consideration soil type(defined as variable in risk analysis software);

C_{fi} : adjustment factor that accounts for the equipment operating factor, efficiency, its bucket fill; and on-site job and management conditions and it defines by the user, it has to be greater than zero. The above equation can be reduced to the simple equation given below if all hauling units are identical:

$$Pa = N_h * N_t * C * C_t \tag{3}$$

2.3 Productivity performance index (PPI)

This index provides a measure of the likelihood of finishing the project within its targeted schedule and cost and it is used here to forecast project time. The productivity performance index is determined by comparing the calculated on-site productivity to that planned as follows:

$$PPI = \frac{Actual\ Productivity}{Planned\ Productivity} \tag{4}$$

2.3 Project time and cost forecast at completion

The project time at completion or at any targeted time horizons can be forecasted making use of the productivity performance index and it is calculated as follows:

$$Time\ Forecast = \frac{As\ planned\ Project\ duration}{PPI * \alpha} \tag{5}$$

Where:

α : adjustment factor and it is based on the judgment of project manager and it has to be greater than zero. In assigning value to α , project manager can eliminate productivity consideration from which exceptional conditions are known to have prevailed. For example if a storm occurred in previous period, the project manager can exclude such short declining in productivity performance index. Having the time required to finish the project is forecasted, the project cost at completion also can be forecasted using the following equation.

$$Cost\ Forecast\ @\ completion = Time\ Forecast * \left(\frac{\$}{hr}\right)_p * \beta \tag{6}$$

Where

$\left(\frac{\$}{hr}\right)_p$: planned hourly cost;

β : Cost adjustment factor and it is different from productivity adjustment factor since it is possible the productivity performance is as planned while the project is experiencing overrun. It should be noted that it was assumed that the hour unit cost for the remaining work will be as planned. Other assumption can be used such as the actual hourly unit cost will continue to the completion date.

2.5 Cost and time variances at completion

They are calculated by subtracting the forecasted time and cost at completion as defined in Equations 7 and 8 from that planned.

$$Time\ variance = Project\ duration - Time\ forecast \tag{7}$$

Cost variances at completion can also calculated using the equation given below

$$Cost\ variance = BC@C - Cost\ Forecast\ @\ completion \tag{8}$$

Where:

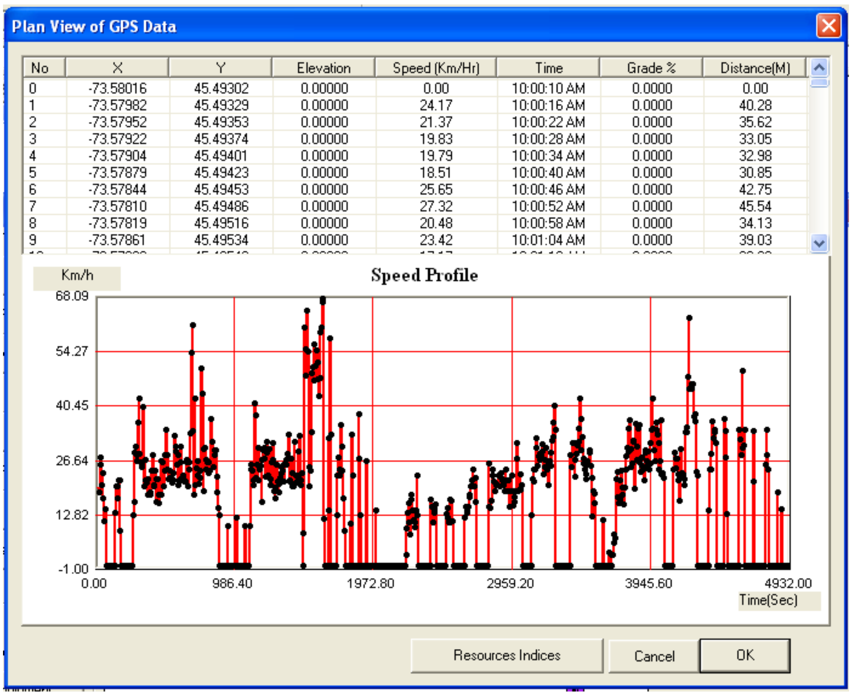
$BC@C$: Budget cost at completion.

3 SYSTEM VALIDATION

3.1 Application example

The project involves excavating and moving approximately 740,000 m^3 (bank cubic meters) of earth from one location, referred to as borrow pit and haul the excavated material to designated area, referred to as landfill site. The material is Gravel sand, weighting 2230 lb per BCY. The landfill site is located at a distance of approximately 21 km (two ways) from the borrow pit location. The traveled road is in urban area with low-rise building. The allowed speed on the traveled road is 50 and 60 Km per hour for traveling and returning, respectively. The earthmoving fleet is considered to consist of one loader and 45 trucks, all are in a good operating condition.

The hourly loader and truck cost are assumed to be \$90 and \$125, respectively. Based on the fleet considered in this example, the project should be completed in 931 hours at a total cost of approximately \$ 3,909,697.733. It is required to track these operations in near real time without human involvement in data collection from construction site. In addition, it is required to estimate on-site productivity, forecast project time and cost at completion while taking in consideration the uncertainties associate with durations of the operations and uncertainties associate with the project cost (equipment cost and project indirect cost), and find the activities that have the greatest impact on fleet productivity.



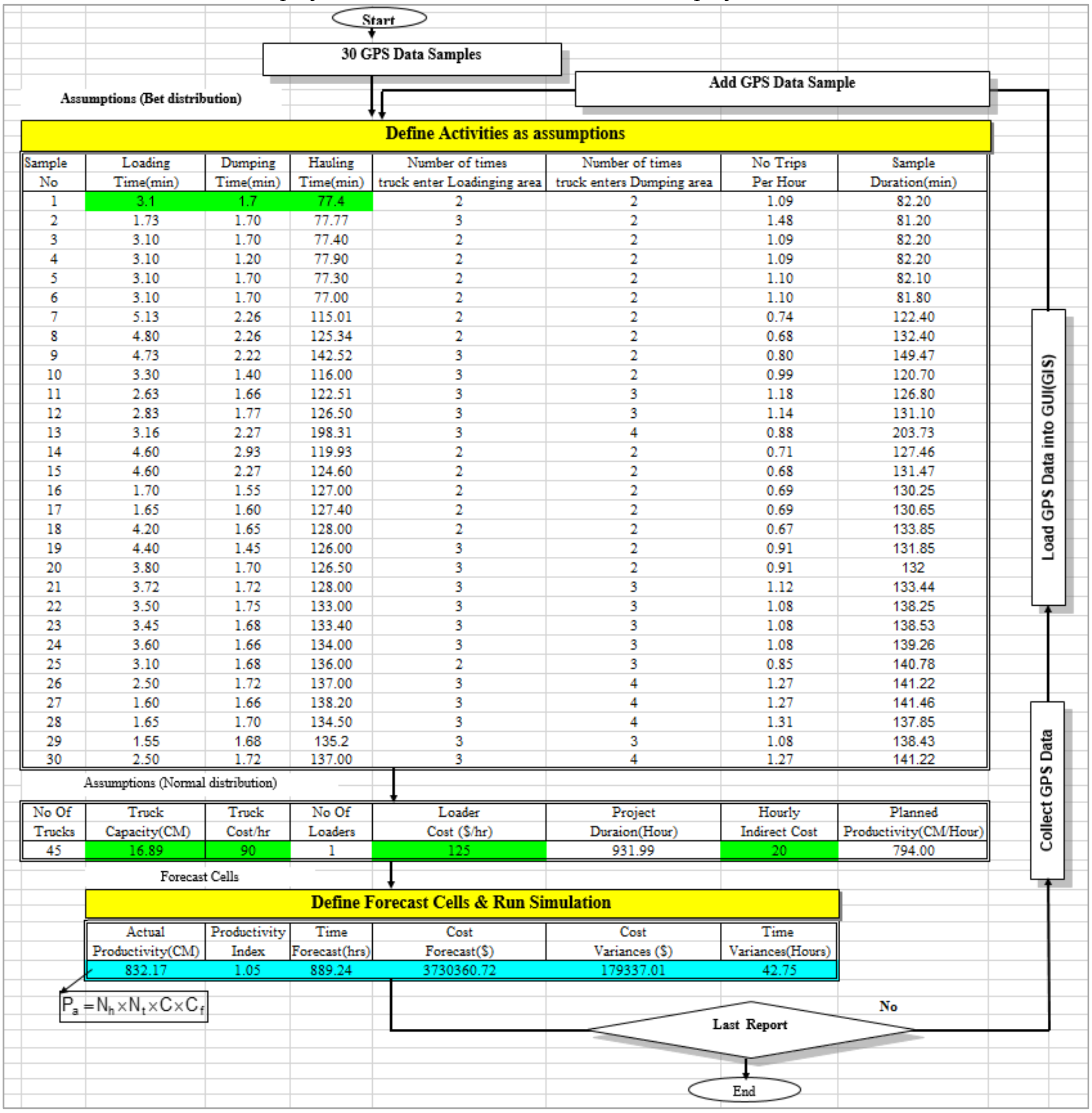
No	X	Y	Elevation	Speed (Km/Hr)	Time	Grade %	Distance(M)
0	-73.58016	45.49302	0.00000	0.00	10:00:10 AM	0.0000	0.00
1	-73.57982	45.49329	0.00000	24.17	10:00:16 AM	0.0000	40.28
2	-73.57952	45.49353	0.00000	21.37	10:00:22 AM	0.0000	35.62
3	-73.57922	45.49374	0.00000	19.83	10:00:28 AM	0.0000	33.05
4	-73.57904	45.49401	0.00000	19.79	10:00:34 AM	0.0000	32.98
5	-73.57879	45.49423	0.00000	18.51	10:00:40 AM	0.0000	30.85
6	-73.57844	45.49453	0.00000	25.65	10:00:46 AM	0.0000	42.75
7	-73.57810	45.49486	0.00000	27.32	10:00:52 AM	0.0000	45.54
8	-73.57819	45.49516	0.00000	20.48	10:00:58 AM	0.0000	34.13
9	-73.57861	45.49534	0.00000	23.42	10:01:04 AM	0.0000	39.03

FIG 4: *Analyzing collected GPS data by GUI Module.*

3.1.2 Analysis of the Results

Considering the condition of the fleet, it was decided to mount only one GPS receiver on one of the 45 trucks. A total of 30 samples of GPS data of the operations involved were collected. The sample duration in minutes is of shown in the last column in Fig. 5. The captured data were then transferred to the web server using graphical user interface (GUI) of the developed system. The system then process and analyzes this data in near real time to calculate actual loading, hauling, dumping, and returning time. Fig. 4 represents the screen printout of data sample No.15. As it can be seen in the figure, the sample duration in the screen printout is 131.47 minutes., the loading time is 4.6 minutes, dumping time is 2.26 minutes, average speed is approximately 12 Km/hr, and the total distance of this data sample is 25.5 Km. Having the cycle time is estimated; the number of trips the truck made for data sample duration (131.47) is then determined using Equation 2. The number of trips made in 131.47 is 1.4592 trips. Therefore, the number of trips made in an hour is 0.68 trips (1/ 1.4592). Knowing the soil type, equipment capacity, and project data, the actual productivity can be easily estimated. One of the features of the developed system is that the system can graphically show the traveled road condition, for example as presented in the screen printout (Fig. 4), although the maximum allowed speed is 50 Km/hr, the driver exceeds this constrain up to 68 km/hr. The Figure also shows that the travel road is flat (Grade % =0).

After calculating the hauling units' cycle time for the 30 samples of GPS data as described above, the user is then requested to define the uncertainties associate with the calculated hauling units' cycle time (loading, traveling, dumping, and returning) and define defines uncertainties associate with the project coat. Based on the data, the user selects the distribution that best represent the data involved in the Crystal Ball, and 1000 trial is conducted. It should be noted that the inputs and outputs variables of the probabilistic model are also defined. Figure 5 depicts the uncertain variables (inputs data) of the example project. The uncertain variables are presented in green while the outputs are presented in blue. The uncertain variables associated with the productivity are the operations activities durations (loading, hauling, dumping, and returning times) and the truck capacity. The uncertain variables associated with the project cost are truck cost, loader cost, and project indirect cost.



Sample No	Loading Time(min)	Dumping Time(min)	Hauling Time(min)	Number of times truck enter Loadinging area	Number of times truck enters Dumping area	No Trips Per Hour	Sample Duration(min)
1	3.1	1.7	77.4	2	2	1.09	82.20
2	1.73	1.70	77.77	3	2	1.48	81.20
3	3.10	1.70	77.40	2	2	1.09	82.20
4	3.10	1.20	77.90	2	2	1.09	82.20
5	3.10	1.70	77.30	2	2	1.10	82.10
6	3.10	1.70	77.00	2	2	1.10	81.80
7	5.13	2.26	115.01	2	2	0.74	122.40
8	4.80	2.26	125.34	2	2	0.68	132.40
9	4.73	2.22	142.52	3	2	0.80	149.47
10	3.30	1.40	116.00	3	2	0.99	120.70
11	2.63	1.66	122.51	3	3	1.18	126.80
12	2.83	1.77	126.50	3	3	1.14	131.10
13	3.16	2.27	198.31	3	4	0.88	203.73
14	4.60	2.93	119.93	2	2	0.71	127.46
15	4.60	2.27	124.60	2	2	0.68	131.47
16	1.70	1.55	127.00	2	2	0.69	130.25
17	1.65	1.60	127.40	2	2	0.69	130.65
18	4.20	1.65	128.00	2	2	0.67	133.85
19	4.40	1.45	126.00	3	2	0.91	131.85
20	3.80	1.70	126.50	3	2	0.91	132
21	3.72	1.72	128.00	3	3	1.12	133.44
22	3.50	1.75	133.00	3	3	1.08	138.25
23	3.45	1.68	133.40	3	3	1.08	138.53
24	3.60	1.66	134.00	3	3	1.08	139.26
25	3.10	1.68	136.00	2	3	0.85	140.78
26	2.50	1.72	137.00	3	4	1.27	141.22
27	1.60	1.66	138.20	3	4	1.27	141.46
28	1.65	1.70	134.50	3	4	1.31	137.85
29	1.55	1.68	135.2	3	3	1.08	138.43
30	2.50	1.72	137.00	3	4	1.27	141.22

No Of Trucks	Truck Capacity(CM)	Truck Cost/hr	No Of Loaders	Loader Cost ($/hr)	Project Duraion(Hour)	Hourly Indirect Cost	Planned Productivity(CM/Hour)
45	16.89	90	1	125	931.99	20	794.00

Actual Productivity(CM)	Productivity Index	Time Forecast(hrs)	Cost Forecast($)	Cost Variances ($)	Time Variances(Hours)
832.17	1.05	889.24	3730360.72	179337.01	42.75

FIG 5: *Risk analysis module as built in Oracles Crystal Ball.*

The outputs of the developed model is referred to as forecast as presented in Fig. 5. They are project total cost at completion, project time, cost variances, time variances, fleet actual productivity, and productivity index. The result shows that the project is experiencing cost underrun and ahead schedule status. This status has been indicated by the calculated productivity performance index (1.05). This good productivity can lead to cost underrun of $ 179, 337 and ahead of schedule of 42 hours. It should be noted that the cluster of columns near the mean indicates the most likely value. For example, the most likely time forecast is between 1450 and 1500 hours. The certainty level of the project has good productivity index is about 4 %.

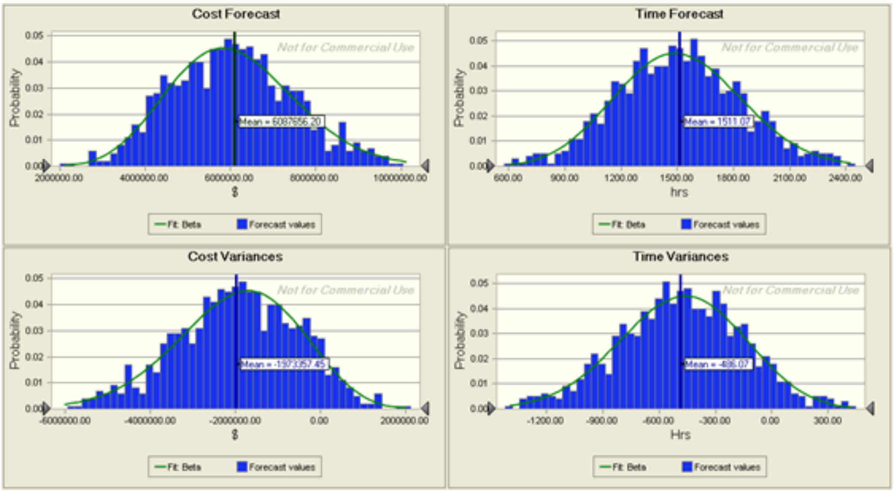


Fig 6: Output of the developed model.

As showed by Scatter Charts (Fig. 7), the Hauling time has a strong positive correlation with cost and time forecast of 0.8487 and 0.9247, respectively. In addition, although the truck hourly cost is less than the loader hourly cost, the truck cost has greater positive correlation (0.38) with the cost forecast than loader cost (0.0052). The dumping and loading time, on the other hand, have the weakest correlation with time forecast. Furthermore, the correlation between hauling time and on-site productivity is a negative value, which means that are inversely related.

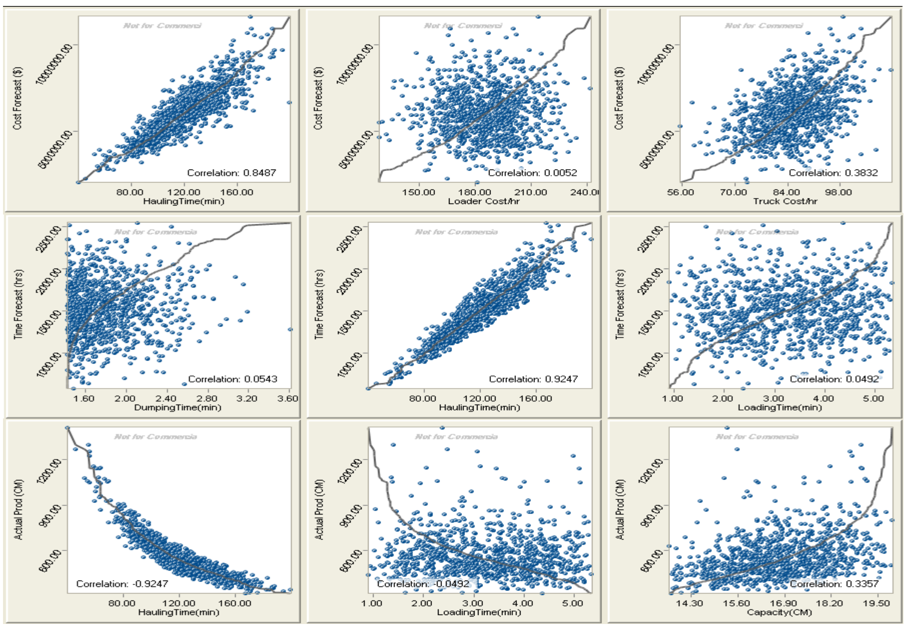
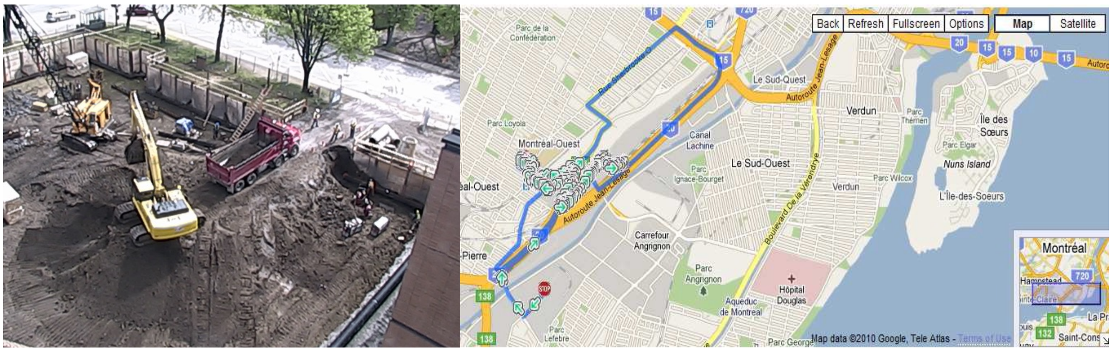


***FIG 7:** Scatter Charts.*

3.1. Application example II

The developed system was additionally tested in a second example project to investigate its capability in estimating onsite productivity and forecasting project cost and time using larger volume of collected GPS data. The project involves the construction of a research laboratory building of 4 floors including a basement. The excavation area is approximately 1,800 m^2 with an average depth of 7.70 m. the project is located in west end of Montreal. The contractor wishes to estimate, with high level of confident, onsite actual productivity and forecast project cost and time. The project data is summarized in Table. 1. Figure 8 shows the excavation work of the project under consideration and the equipment involved. Figure 8(b) shows the site, its surrounding area, and travel road in google map. The fleet used by the contractor in this project consists of an excavator, type VOLVO ECR235CL and 4 CAT 725 trucks. A 75 GPS data samples were collected of the example project in support of data processing and simulation modeling. A 75 cycle times were extracted from the collected GPS data using the developed GUI.



(a) (b)

FIG 8: *Project site overview.*

The GPS data were collected at different time intervals, and at different hours of the work day to represent a wide range of possible conditions. The system parameters and the probability distributions considered for each of its variables are shown in Table. 2.

TABLE. 1: Project data.

Parameter	Value
Earth-moving volume (m^3)	10381.76
Swell factor	0.81
Bank density (Kg/m^3)	2900
Daily Indirect cost	$2000
Daily working hours	8 hrs
Length of haul-road (Km)	15.6 km
Job conditions	Favorable
Available number of trucks (CAT 725)	4
Truck hourly cost	$ 100
Truck capacity(m^3)	14.30
Available number of excavators (VOLVO ECR235CL)	1
Excavator hourly cost	$ 150
Heaped bucket capacity	1.73(m^3)

Table. 3 shows seven set of captured GPS data (positions), while Table. 4 depicts ten of extracted cycle times from a total of 75 samples of GPS data. As it can be seen from the table, there is variation in the calculated cycle times. This variation was due to the fact that (1) the project was constructed in urban area where travel time is sensitive to traffic congestion; (2) the weather conditions such as rain fall slowed down traffic; (3) the project has two dumping areas; located at different distances from the construction site.

TABLE. 2: Parameters of the developed module.

Simulation parameter	Data source	Probability distribution	
Loading time	Extracted from GPS data	Logistic	Input data
Hauling time	Extracted from GPS data	Beta	Input data
Dumping time	Extracted from GPS data	Maximum Extreme	Input data
Truck cost	($100/hr)	Triangular	Input data
Excavator cost	($150/hr)	Triangular	Input data
Project indirect $	($20/hr)	Triangular	Input data
Number of trucks	4	Input data	Constraint
Number of Excavators	1	Input data	Constraint
Excavator productivity(Cu m/hr)	calculated	Input data	Input data
Simulation outcomes			
Truck productivity	calculated	Forecast	Output
Project final cost	calculated	Forecast	Output
Project cost time	calculated	Forecast	Output
Cost variance	calculated	Forecast	Output
Time variance	calculated	Forecast	Output
Unit cost ($/Cu m)	calculated	Forecast	Output
Productivity index	calculated	Forecast	Output
Match index	calculated	Forecast	Output

TABLE. 3: Part of sample of collected GPS data

Latitude	Longitude	Date	Time	Information	Speed (KM/h)	Heading
45.43993	-73.6389	12/04/2010	6:35:13	Moving	25	SW
45.43797	-73.6428	12/04/2010	6:36:43	Moving	19	NW
45.4409	-73.6459	12/04/2010	6:37:28	Moving	17	NW
45.44266	-73.6471	12/04/2010	6:38:58	Moving	12	N
45.44516	-73.6425	12/04/2010	6:39:43	Moving	63	NE
45.45008	-73.6355	12/04/2010	6:40:28	Moving	42	NE
45.45329	-73.6332	12/04/2010	6:41:13	Moving	29	NE

TABLE. 4: Calculated cycle times of hauling unit

Cycle No	Cycle time (min)	Loading Time (T1) min	Travel Time (T2) min	Dumping Time (T3) min	Return Time (T4) min	No of trips/ hour
1	33.63	4.50	19.13	6.00	4.00	1.78
2	33.75	7.75	10.00	8.00	8.00	1.78
3	31.00	3.00	10.00	8.00	10.00	1.94
4	29.08	3.08	9.00	5.00	12.00	2.06
5	33.54	4.13	10.78	5.00	13.63	1.79
6	28.00	2.13	9.87	7.00	9.00	2.14
7	25.00	2.75	8.25	6.00	8.00	2.40
8	27.00	4.00	9.00	5.00	9.00	2.22
9	28.00	3.10	8.90	5.00	11.00	2.14
10	27.05	3.05	8.00	6.00	10.00	2.22

The contractor selected a fleet consisting of one excavator and 4 articulated trucks to carry out the work, all in good operating conditions. The GPS data is collected to track the operations involved in time interval of 45 seconds. The 45 seconds interval is used to enable the system to track the fleet configuration in loading and dumping area. For example, if the fleet is not well configured, a waiting time can be displayed in loading and /or dumping area. That is one of the advantage of using GPS data comparing to that of OBIS and RFID.

3.2.2 ***Discussion of the results***

A total of 75 cycles were extracted from GPS data and these cycles were used to estimate actual productivity and project cost and time. The collected data samples were uploaded into GIS map using GUI of the developed system. The actual loading, hauling, dumping, and returning time are then estimated from the collected GPS data. Having the cycle times are estimated; the number of trips made in one hour is then calculated using Equation 2., the user defines the input and output variables of the probabilistic model, selects the distribution that best represent the data involved in the Crystal Ball, and 1000 trial is conducted. Fig. 9 depicts the input data of the example project. The uncertain variables associated with the project cost are truck cost, loader cost, and project indirect cost. The system determines the mean of actual productivity and project cost and time for each simulation run. Fig. 9 shows the system outputs of onsite actual productivity and project cost and time at completion the probability distribution of the mean obtained from 1000 replications. The result shows that the project is cost underrun and ahead of schedule status. This status has been indicated by the calculated productivity performance index (2.63). The good productivity leads to cost underrun of $ 94,523.5 and time saving of 165 hours. Match index indicates that although the actual productivity is higher than the as planned, the fleet configuration can be adjusted by increasing the trucks number. This would even further improve the actual proactivity rate and shorter the project duration. It is clear that the contractor underestimated the production rate at planning stage. That is probably happened due to overestimating of the hauling time of truck.

Cycle No	Cycle time (min)	Loading Time (T1) min	Travel Time (T2) min	Dumping Time (T3) min	Return Time (T4) min	No Trips/Hour
1	33.63	4.50	19.13	6.00	4.00	1.78
2	33.75	7.75	10.00	8.00	8.00	1.78
3	31.00	3.00	10.00	8.00	10.00	1.94
4	29.08	3.08	9.00	5.00	12.00	2.06
5	33.54	4.13	10.78	5.00	13.63	1.79
6	28.00	2.13	9.87	7.00	9.00	2.14
22	29.75	8.00	9.75	5.25	6.75	2.02
23	31.25	8.75	9.00	5.25	8.25	1.92
68	32.12	7.08	9.03	8.00	8.00	1.87
69	31.28	5.33	9.23	6.00	10.72	1.92
70	27.28	3.28	10.00	6.00	8.00	2.20
71	24.00	2.00	10.00	4.00	8.00	2.50
72	26.00	3.65	8.35	6.00	8.00	2.31
73	27.75	2.00	10.00	6.00	9.75	2.16
74	38.00	9.67	10.33	8.00	10.00	1.58
75	22.00	4.00	6.00	4.00	8.00	2.73
76	30.00	2.42	9.58	8.00	10.00	2.00

Define Assumptions

No Of Trucks	Truck Capacity (Heaped CM)	Truck Hourly Cost	No Of Excavator(s)	Excavator Hourly Cost	Project Duraion(Hour)	Project Hourly Indirect Cost	Planned Productivity (Cu M/Hour)	Quantity Cu M	Project Planned Unit $/Cu M
4	14.3	100	1	150	267.57	20.00	38.80	10381.76	14.69

Forecast Cells

Define Forecast Cells & Run Simulation

Actual Productivity(CM)	Productivity Index(Actual/Planned)	Project Time Forecast(hrs)	Cost Forecast at completion	Cost Variances($)	Time Variances (hrs)	Forecasted Unit $	Match Index
102.04	2.63	101.74	57992.05	94523.50	165.83	5.59	0.68

FIG 9: *The system outputs of the example project II.*

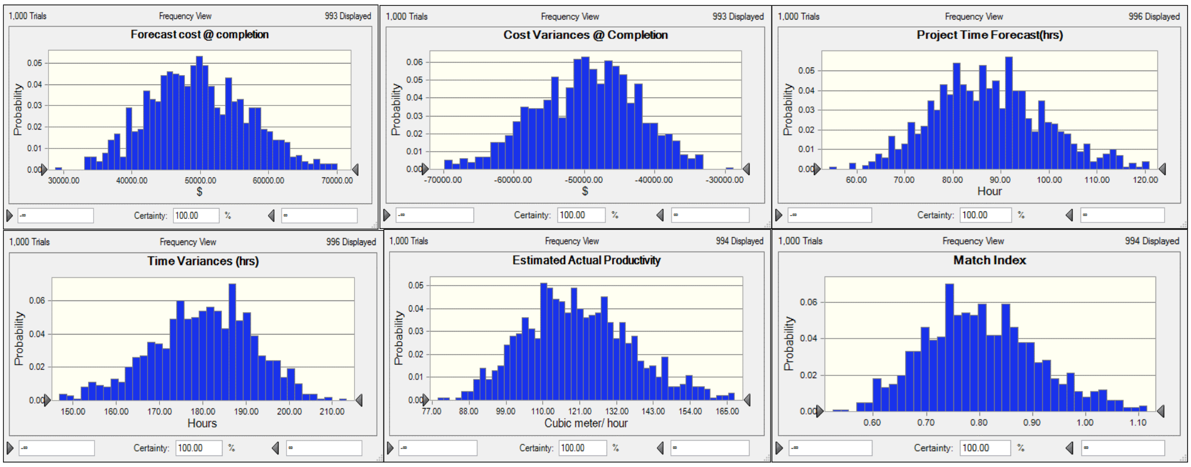


FIG 10: *The system forecasts.*

4. SUMMARY AND CONCLUDING REMARKS

This paper presents a new system for estimating onsite productivity and forecasting project cost and time of earthmoving operations. The developed system uses limited GPS data, collected from construction site using GPS receivers mounted on hauling units. The collected data is used to estimate equipment cycle time and subsequently estimate fleet productivity, which is then used for forecasting project cost and time. The developed system utilizes only samples of GPS data as alternative approach to current systems that require collecting a large volume of data. The system is can be used during construction phase by reconfiguring fleet dynamically while operations are in progress to support needed corrective actions.

The develop system is limited to earthmoving operations which involve the use a fleet of loaders and trucks. The system has not been tested in tracking earthmoving operation that involve the use of pushers/scrapers fleet. The system also is applicable only for open cut excavation as in highway construction projects.

The system can be enhanced with RFID and other remote sensing technologies where the use of GPS alone becomes inadequate. This enables its application to underground earthmoving operations and to construction sites in urban area with high rise buildings that prevent receiving satellite signals.

The system accounts for uncertainties associated with activity durations (loading, dumping, and hauling) and project direct and indirect cost. The system is expected to support contractors in making optimum use of available resources during project execution. Two example projects were analyzed to demonstrate the capabilities of the developed system. The results indicate that the proposed system can be used successfully in tracking and control of earthmoving operations. It also provides contractors with a tool that enables them to assess the risk associated with the fleet selection process. Analysis of the results obtained indicates that using GPS facilitates data exchange among members of project teams, which enables timely corrective actions. Displaying GPS data graphically can help project managers in identifying causes behind unacceptable performance, if any.

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