REAL-TIME SIMULATION OF EARTHMOVING PROJECTS USING AUTOMATED MACHINE GUIDANCE

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ABSTRACT

Simulation techniques have offered significant boosts toward a cost-and-time-optimized planning of construction projects by enabling project managers to effectively comprehend the behavior of projects. Using historic data from projects of like nature, simulation considers uncertainties involved in a project through accommodating the stochastic modeling parameters. However, the heavy reliance on the statistical data and not taking into account the context-specific features of the project cause the degradation in the realism and accuracy of the simulation models. Similarly, the extent to which a historic pattern could be retrofitted to new projects will decrease in line with the growing uniqueness of the projects and the novelty of construction methods. Furthermore, the existing real-time simulation frameworks are not capable of distinguishing the transient environmental changes, with minimal long-term impacts on the productivity, from the influential changes that will greatly impact an operation. In addition, existing simulation tools are devoid of location awareness, resulting in the inability to consider safety threats in their representation of the project. To address these issues, this research proposes a framework based on the integration of new tracking technologies used in Automated Machine Guidance (AMG) with simulation-driven 4D modeling methods. The proposed framework automates the adjustment of the simulation model based on the updated data from the site, and thus transforms simulation from a predictive tool used at the planning phase to a proactive monitoring platform usable throughout the planning and construction phases. A prototype is developed to test and demonstrate the effectiveness of the proposed approach.

KEYWORDS

Real-time simulation, Automated Machine Control/Guidance, 4D modeling

INTRODUCTION

To maximize the productivity of operations, it is of crucial importance to identify the optimum arrangement of the different types of resources. Although planning and optimization of small-size and some medium-size projects can rely on the professional intuition and experiences, large scale projects require a very meticulous and delicate planning, if productivity and efficiency are not to suffer. Therefore, in order to judge different scenarios for a given operation in a comparative fashion, and thus optimize the operation planning and resource allocation, it is indispensable to develop a digital model of operations, in terms of time-sequenced activities and the flow of resources. To this end, the application of simulation in the construction industry has been investigated and suggested widely in the literature (AbouRizk, 2010; Hassan, Al-Hussein & Gillis, 2010; Zayed & Halpin, 2001; Hassan & Guber, 2008; Halpin & Martinez, 1999).

However, simulation relies mainly upon the statistical data gathered from previous projects of the like nature. Given the volatility and dynamism of a construction system and the high sensitivity of short-term schedules to variations of constituent parameters, very often it is the case that the initially developed model fails to remain valid and representative of the actual work. To compensate for the possible discrepancies and deviations from the estimated values, i.e. time and cost, and also in order to make simulation results more realistic, the assumptions made at the point of the model design need to be constantly modified and attuned based on the actual state of the operation. Consequently, some research has been conducted on a mechanism to dynamically monitor the trend of changes in the model parameters and adapt the simulation model accordingly in real-time (Hammad & Zhang, 2011; Lu, Dai & Chen, 2007; Song & Eldin, 2012; Akhavian & Behzadan, 2012).

On the other hand, new tracking technologies are providing tools for improving productivity and safety by enabling on-site data capturing and decision making using the Global Positioning System (GPS), Real-Time Location Systems (RTLSs), and other geo-positioning technologies (Perkinson, Bayraktar & Ahmad, 2010; Teize, Allread, Fullerton & Hinze, 2010; Peyret, Jurasz, Carrel, Zekri & Gorham, 2000; Hildreth, Vorster & Martinez, 2005). These tracking technologies are integrated with 3D design models and Digital Terrain Models (DTMs) in two modes: Automated Machine Guidance (AMG) and Automated Machine Control (AMC). The growing applications of AMC/G presents the opportunity to leverage the GPS systems mounted on the construction machines, and the stream of location data flowing therefrom, for purposes other than controlling/guiding machines. This will create an opportunity to use sensory data to accurately capture the impact of simulation parameters (e.g. machine speed, weather, equipment conditions, etc.) that will affect the operations. Nevertheless, not all the data updates suggest that model refinement is required. Given the accuracy of the simulation and the level of detail for which the initial model is designed, only certain types of changes in the environment or simulation parameters may necessitate the refinement of the model. To the best of the authors' knowledge, no research on real-time construction simulation considered a robust filtering mechanism to distinguish non-influential, or alternatively low-impact, data fluctuations from the refinement-worthy changes. As a result, the realism and credibility of real-time simulation as a method to reliably capture the environmental and operational changes tremendously suffer.

The present paper explores a novel approach to the location-aware real-time simulation of earth-moving construction operations with the following two main objectives: (1) to improve the accuracy of real-time simulation through the consideration of environmental parameters that may affect the accuracy of the simulation model, and (2) to explore the state-identification rules more in-depth and for all the machines participating in a cyclic operation.

PROPOSED APPROACH

As stated earlier, real-time simulation is a concept based on the continuous update of a model initially developed for a particular process. The initial model is inherently established on a large amount of speculations and postulations, extracted mainly from similar previous projects. These models require constant adjustment and tuning to remain accurate in the face of many anomalies and discrepancies that are rampant in the course of the work execution. The model refinement can be performed using real-time data from the site. In spite of the simplicity of this concept, technical and conceptual challenges for developing a full-fledge framework are manifold. Challenges to be addressed for the development of a real-time simulation include: (1) a simulation tool that can offer the required features for the continuous refinement of the model, (2) a mechanism for data classification and processing to extract meaningful information associated with the models' parameters from raw location data gathered from the site, (3) a method to distinguish the data suggesting major discrepancies between the reality and the model from non-influential fluctuations in the data flow, (4) a framework for adding location awareness to the simulation so that more accurate results can be achieved in view of spatial limitations and possible safety threats.

The structure of the proposed framework for a location-aware real-time simulation is presented in Figure 1. The proposed framework consists of several components including: (1) Rule-based System, (2) Information Filter, (3) Model Analyzer, (4) Model Refiner, (5) Scenario Analyzer, and (6) Simulation Engine.

Rule-based System

The raw data obtained from GPS is not usable unless put under processing. GPS transmits information about the location of particular objects and the time in which the readings were made. However, for these readings to be transformed into meaningful information usable for the simulation purpose, the location data need to be converted to modeling parameters, e.g. durations and speed. To materialize this, it is required to develop a knowledgebase which encapsulates expert and experience-driven rules that help interpret and transform the purely geographical data. For instance, from an array of

GPS readings coming from a receiver attached to a truck, we need to identify when the truck starts traveling to the dumping location or how long it has been in a queue before it is serviced by a loader. Although a similar concept has been proposed before (Song & Eldin, 2012), the proposed rules are restricted to one type of equipment, i.e. trucks, and several states, such as out of service, have not been covered. Additionally the discrepancies between the GPS data and the simulation model representing a permanent change have been treated as an assumption, while in the present framework an information filter is applied to sift the transient from the permanent changes.

The rule-based system transforms GPS data to simulation parameters and comprises a knowledgebase and a reasoning mechanism. The knowledgebase contains all the rules and heuristics which determine the state of machines and their current phase in the operation. These rules are experience-driven and case-dependent. On the other hand, using the knowledgebase, the inference engine helps determine the modeling parameters that are of interest for the simulation.

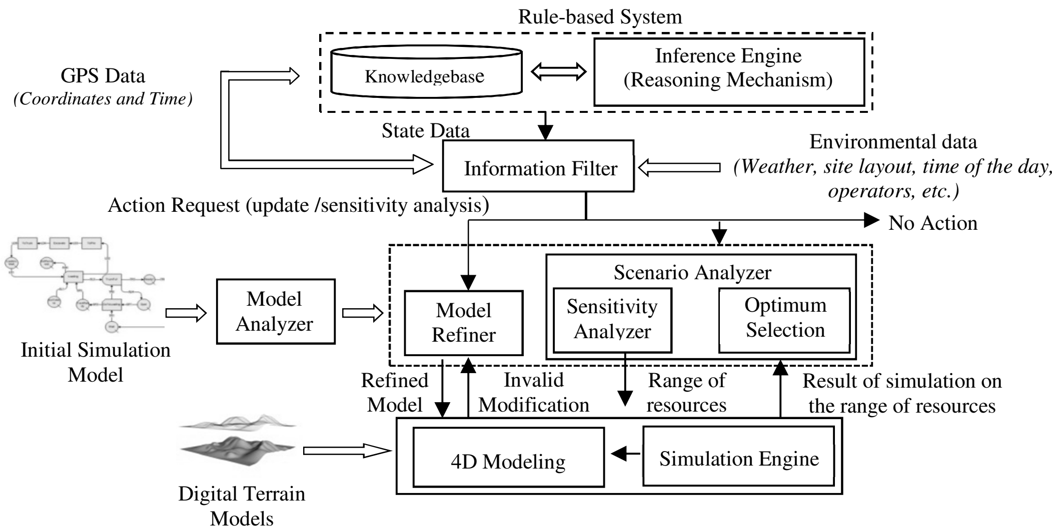


Figure 1 – A framework for real-time simulation

Given the vastness and the large scale of construction projects and types of equipment required, it is almost impossible to extract a general mathematical model that performs the transformation of data to the required modeling parameters for all types of projects and machines. Expert rules need to be developed based on the exclusive characteristics of the project, types of machines in the operation and the topography of the site. The zone-detection is an integral part of these expert rules, especially for equipment whose cyclic operations take place over a geographically scattered area, e.g. trucks. If the approximate area in which a certain activity occurs is known, then it will be possible to associate the coordinates of equipment to a certain activity. For this purpose, geo-fences can be used to create activity-specific zones. Geo-fences are virtual contours drawn around an area that help detect if a unit has entered a known area (Reclus & Drouard, 2009). Although this alone will suffice to infer the initiation of certain types of activities, mainly activities that involved only one resource, when more than one resource need to be engaged for an activity to commence, or when there exists the possibility of the formation of queues, it is required to apply some additional rules. For instance, a truck will be identified in the phase of loading when (1) it is in the loading area and (2) compared to all other trucks in the loading area, it is the closest to the loader. Other determining rules that can be used to convert GPS data to the required information need to be developed based on the modeling parameters of interest and the particular characteristics of the project.

The knowledgebase comprises state-identification rules that are expressed in terms of two variables, namely dynamic variables and constant variables. Constant variables are basically the coordinates of virtual geo-fences that are marked by the exclusive activities that take place within a zone.

Dynamic variables, on the other hand, are auxiliary factors, e.g. distance from the loader, angle of the bed of the truck, machine state, etc., that help more accurately calculate the modeling parameters, e.g. duration and speed.

To provide a tangible example for the framework of the knowledgebase, a simple hauling-dumping project is used. In this example, a team of two trucks, an excavator and a conveyor belt, as the indicator for the dumping point, are assigned to a hauling task. All equipment are equipped with GPS receivers and identified by unique IDs. For trucks, this simple operation forms four distinct areas, each of which is marked with an exclusive activity. The entrance time and the exit time of each truck to the corresponding area can be determined by the juxtaposition of the truck's GPS data and the geo-fences. The entrance to an area and the duration of stay coupled with the additional conditions, e.g. distance from the loader, help compute the precise durations associated with various activities. For instance, the beginning of the loading activity can be determined by the fulfillment of the combined conditions of the truck being in the loading area, truck's zero velocity and the truck being the closest to the loader. Similarly, the end of the loading is indicated by the increase in the truck's velocity and its distance from the excavator. With the above states identified, the loading time can be calculated through Equation 1:

$$LD_{ij} = ELT_{ij} - SLT_{ij} \tag{1}$$

Where:

LD_{ij}= Loading duration of truck i in cycle j
ELT_{ij}= End of loading time of truck i in cycle j
SLT_{ij}= Start of loading time of truck i in cycle j

Following the same principle, ten different possible states can be identified for a single truck in the above simple example, as illustrated in Table 1. The inference engine contains the reasoning mechanism that uses the rules within the knowledgebase to infer the corresponding values of the modeling parameters from the incoming flow of GPS data, i.e. time and coordinates.

Table 1 – Identification rules for the truck's states

State of the truck	Identified Zone	Dynamic Variables	Identification Rule
Under loading	Loading	Velocity & Distance to the excavator	The truck is in the loading zone, it is the closest to the loader and its velocity is zero
In the queue	Loading	Velocity & Distance to the excavator	The truck is in the loading zone but it is not the closest truck to the loader and its velocity is zero
End of loading	Loading	Velocity & Distance to the excavator	The truck is in the loading zone, it is the closest to the loader, its velocity changes from zero and it is getting far from the loader
In hauling	Hauling	Velocity	The truck is in the hauling zone and its velocity is not zero
Out of service	Hauling	Velocity	The truck is in the hauling zone and its velocity is zero
Under dumping	Dumping	Velocity& Distance to the Conveyer	The truck is in the dumping zone., it is the closest to the conveyor belt, and its velocity is zero
In the queue	Dumping	Velocity& Distance to the Conveyer	The truck is in the dumping zone, it is not the closest unit to the conveyor belt and its velocity is zero
End of dumping	Dumping	Velocity& Distance to the Conveyer	The truck is in the dumping zone, it is the closest to the conveyor belt, velocity changes from zero and it is getting far from the conveyor belt
In return process	Returning	Velocity	The truck is in return zone and its velocity is not zero
Out of service	Returning	Velocity	The truck is in the return zone and its velocity is zero

As for excavators, given the higher Degrees of Freedom (DoFs) of the machines and the finer motions that segregate different states, the state-identifications rules are more sophisticated. Five states can be identified for an excavator in the above-mentioned example when it is stationary, namely under loading, swinging with the full bucket, dumping, swinging with the empty bucket and idle. These states can be identified without zone-detection on the account that the information regarding the velocity of the bucket and the direction of its move suffice for the state-identification of the excavator. Table 2 summarises the state-identification rules based on GPS data of the bucket.

In the particular case of the excavator, there exists an additional state of repositioning, when the excavator changes its loading position. The identification of this state presents a more complex challenge as it requires pattern recognition so that the travel of the bucket to an unknown new zone can be detected dynamically. Given that the operation of the excavator is highly cyclic with a relatively predictable pattern, and knowing that the repositioning commences with a deviation from the known cyclic pattern (load-swing-dump-swing back) and results in a new cyclic pattern, pattern recognition can help identify the repositioning state. However, this is outside the scope of the current paper.

Table 2 – Identification rules for the excavator's states

State of the excavator	Dynamic Variables	Identification Rule
Under loading	Velocity & Motion direction	The bucket is predominantly moving in a vertical plane with a low velocity
Swinging (loaded)	Motion direction & Distance to the truck	The bucket is predominantly moving in a horizontal plane and it is moving toward the truck
Dumping	Motion direction & Distance to the truck	The bucket is relatively stationary and its location intersects with the truck's bed
Swinging (empty)	Distance to the truck & Motion direction	The bucket is predominantly moving in a horizontal plane and it is moving away from the truck
Idle	Velocity	The bucket is not moving

Information Filter

The information filter monitors various sources, and should it detect discrepancies that demand a change of the model, it will send a request to the model refiner or scenario analyzer for further actions. If the type of changes is such that it is required to reorganize the resources between various activities, this will be consulted with the scenario analyzer. For instance if a truck runs out-of-service, it might be necessary to investigate the effects of continuing with or without replacement of the defected unit. On the other hand, if the changes in the model only require refinement of the model's parameters, e.g. the hauling speed is slower or faster than estimated, the request is sent to the model refiner.

For this component to be able to distinguish refinement-requiring discrepancies from negligible data fluctuation, it is required to collect data from various sources other than GPS. Parameters that may carry transient implications on the process includes, but not limited to, temperature, humidity, precipitations, operators' skill, equipment condition, working hours, time of the day, dynamic changes to the site layout, accidents, etc. While any of the above parameters could affect the location data, it is conceivable that their impacts are temporary. Accordingly, every machine state and the pertinent simulation parameters need to be processed and analyzed in line with a set of corresponding environmental data. Table 3 represents a set of environmental data that need to be coupled with state data in order to make filtering evaluation possible.

Table 3 – Environmental parameters with implications of the productivity of operations

	Environmental Data	Data representation	Implication
1	Time	hh:mm:ss	Impact of the operator's fatigue
2	Temperature	Cº	Impact of the temperature
3	Humidity	%	Impact of humidity
4	Precipitation	Rain/Snow (mm)	Impact of precipitation
5	Equipment condition	Broken/Out of Fuel/ Inspection required	The efficiency of the equipment
6	Operator's ID	#	Impact of the operator's skill
7	Site condition	Good/Moderate/Bad	Impact of site condition
8	Accidents	Yes/No	Impact of accidents
9	Wind speed	Km/hr	Impact of wind

Model Analyzer

The model analyzer interprets the initial model and translates the simulation's internal logic to a formalized and modifiable format. It then disintegrates the model into the constituent components and formalizes the causal relationships, activities and resources so that they can be individually modified and re-assembled by the model refiner and scenario analyzer for further execution.

Model Refiner

The input for this component is the change request coming from the information filter, representing a major deviation from the existing values in the model, the state of equipment resulting from the rule-based system and the parsed model coming from the model analyzer. The model refiner identifies the parameters that need to be adjusted based on the change request placed by the information filter and updates the model accordingly.

Scenario Analyzer

The scenario analyzer mainly performs sensitivity analysis over a range of resource quantities to help optimize the configuration of the fleet. For example, if a unit falls out of service, this component would allow the management to explore the possible options they can choose from. This component includes an engine for the sensitivity analysis and a module to opt out the most optimum solution.

Simulation Engine

The simulation engine is a platform on which the process model is run and the subsequent report is generated. This component goes through the model simulation and flows the resources amid the network of activities to perform the time and productivity evaluation of the model. However, the selection of the optimum solution is done once all the scenarios are validated by the 4D modeling component regarding safety requirements.

4D Modeling

The 4D modeling and visualization component is used as a means to investigate potential safety threats, time-space conflicts or geometric constraints in the execution. It could also be used to control the progress of the project and warn about delays. It is built on DTM of the site, Work Breakdown Structure (WBS) and the schedule generated based on the simulation. With these inputs, this component illustrates how resources move and interact on the site, with the consideration of the geometric constraints and as-planned schedule. The combined outputs of the 4D modeling and simulation engine validate or abandon the resource configuration and present how the operation is deviating from the schedule. If the model is abandoned, the model is sent back to the model refiner or scenario analyzer for further adjustment. Elaborate explanation of this component and its structure can be found in Setayeshgar et al. (2013).

PROTOTYPE DEVELOPMENT

To demonstrate the applicability of the proposed framework, a prototype application was developed and tested in this research. The prototype is developed in Microsoft Visual Basic for Application (VBA) platform embedded in Microsoft Excel. Stroboscope (Martinez, 1996) is chosen as the simulation engine due to its palpable strengths in extensibility, robustness, availability, compatibility with simulation of construction operations and the ease of use. The main scope of the prototype, at the current stage of the research, is to implement the model analyzer, model refiner and scenario analyzer and integrate them with a simulation engine. In the proposed framework, once the raw GPS data are processed in the rule-based system, and thus transformed to information about the machine state, and then filtered by the information filter, they are either sent to the model refiner or scenario analyzer. However, at the current stage of the prototype, the assumption is that the input GPS data is already processed into the state data and verified by the information filter as influential changes requiring the refinement of the simulation model.

The structure of the model refiner is illustrated in Figure 3(a). The initial simulation model is fed to the prototype, and the model analyzer parses the model and creates the list of durations and features that are used in the model. At this point, the user is asked to choose the variables and parameters that are used in the real-time simulation, e.g. hauling speed, and correlate the chosen variables/parameters with the relevant state data coming from the information filter. For instance, the user determines that the actual speed of truck 1 in the hauling state is the subtraction of state data annotated B and A, i.e. column B and A in an Excel sheet. To establish this correlation, the user choose the hauling speed in the interface of the real-time simulation module and define the new value as (B-A). It is worth noting that the investigation of how this process can be automated is part of the future work of this research. Once the correlations are made, the prototype monitors the flow of state data and updates the model according to the incoming state information. Every time an update is made, the model is re-run in the simulation model and results are published in the Excel sheet.

Figure 3(b), on the other hand, suggests that once the model is parsed by the model analyzer, the user defines the range of parameters' values within which the sensitivity analysis is desired, e.g. a range 1 to 5 for the number of trucks, and the sensitivity analysis module generates the array of all combinations resulting from the input ranges. The outcome will then be sent to the simulation engine for computation of productivity and costs corresponding to each scenario. Consultations with the 4D modeling and further optimization have not been part of the scope of this prototype.

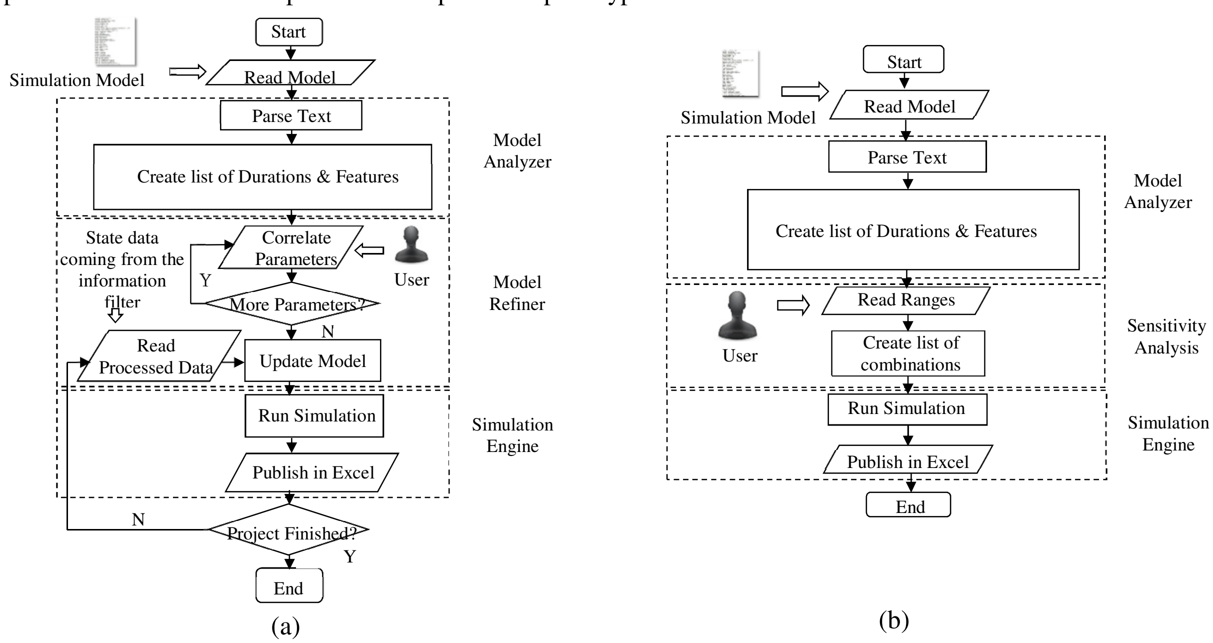


Figure 3 – The process flow of the prototype for (a) Model Refiner and (b) Scenario Analyzer

CASE STUDY

Two case studies were designed to test the feasibility of the proposed approach using the developed prototype.

Case Study One

The first case study is designed to test and validate the proposed method, specifically the scenario analyzer and model refiner components, based on a cofferdam construction project performed by Kiewit-

Alaire partnership in Ontario, Canada, focusing on the sand filling operation. In this operation, the sand is loaded on trucks using a front end loader, and further dumped on a conveyer belt that carries and discharges it to the cofferdam. Once the cofferdam is filled with sand, a vibrating smooth drum compactor is used to compact the sand in order to remove air voids in sand particles and make the platform stable enough for the equipment that will travel over the cofferdam.

The simulation model of the above-mentioned operation is designed using Stroboscope notation, as shown in Figure 4. As for the validation of the model refiner component of the developed prototype, with the lack of actual GPS data for the operation, a series of hypothetical GPS data is devised and processed for the operation of two CAT 777F trucks on an 8-mile long route. In this case study, it is assumed that the speed of the trucks, as a feature defined for the resource type "truck" in the simulation model, is subject to fluctuations, and subsequently the simulation model needs to be updated in relation to the variation of this feature. The assumed speed of the truck is 20 mile/hr and 40 mile/hr for the hauling and return respectively. Three cycles of the truck operation are observed and based on the state-identification rules explained in Table 1 the state data readings are tabulated in Table 4 (Columns A to H).

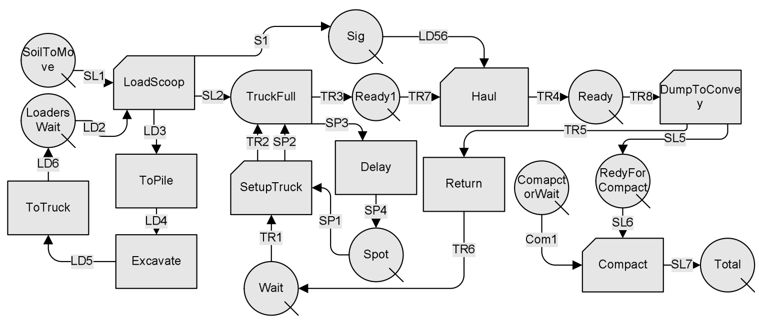


Figure 4 – Simulation model for the sand filling operation

In the prototype, the speed of trucks in the hauling and return is set to be adjusted based on the column of Excel sheet where the relevant state data appear. For instance, with the End of Loading Time (ELT) and Arrival Time to Dumping (ATD) appearing in columns A and B (Table 4), respectively, the speed of truck 1 in the simulation model can be redefined according to Equation 2. Accordingly the speeds of truck one and two in hauling and return were correlated with the pertinent state information.

$$\text{Hauling Speed for Truck 1} = \frac{8(mile) \times 60\ (\text{min})}{ATD - ELT} = \frac{480}{B-A} \tag{2}$$

The implementation of the prototype for the above scenario results in the adjustment of productivity as appears in column I of Table 4.

Table 4 – Results of the real-time simulation component

A	B	C	D	E	F	G	H	I
End of Loading Time Truck 1	Arrival time in Dumping Area Truck 1	End of Dumping Truck 1	Arrival time in Loading Area Truck 1	End of Loading Time Truck 2	Arrival time in Dumping Area Truck 2	End of Dumping Truck 2	Arrival time in Loading Area Truck 2	Productivity
1.75	25.25	25.75	37.45	3.78	30.12	30.87	43.2	617.6402761
38.71	65.58	65.03	78.51	44.21	70	72.08	84.71	612.1163998
79.68	101.76	103.08	114.65	86.21	121.15	122.63	134.08	618.1154277

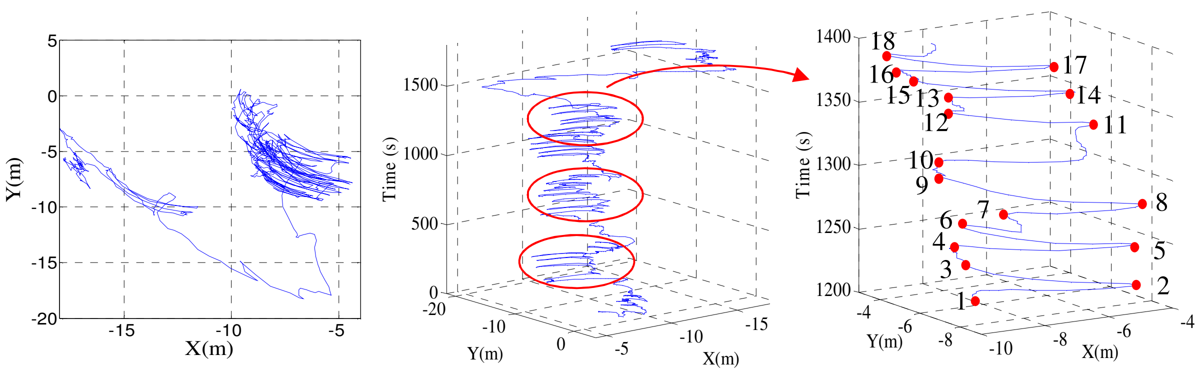
The results demonstrate the feasibility of the proposed model refiner by calculating the simulated productivity of operation based on the varying values of hauling and return speed. The finishing day of the operation is updated according to the calculated productivity values and the required decisions can be made as to speed up or slow down the operation.

It could be hypothetically assumed that two types of trucks, namely CAT 777F and CAT 730, and one type of loader, CAT 980 front end loader, are available for this project. Sensitivity analysis performed, using the developed prototype, at the onset of the operation reveals that the optimum fleet composition is 8 CAT 777F trucks and one loader. However, if one truck breaks during the operation, the sensitivity analyzer module can be run again to identify the possible measures that can be taken. The results of the sensitivity analysis suggest that reducing the number of trucks by one causes the productivity to plummet to 526.69 loose cubic yard (lcy)/hr from the original 600.02 lcy/hr. The decision to proceed with or without replacement of the truck depends on how far the project is advanced in its schedule. It is conceivable that at the second half of the project the manager decides to proceed without replacement of the truck at the cost of few days delay, while such compromise may not be justified at the first half of the project.

Case Study Two

The second case study uses actual data gathered from an AMC/G-enabled Hitachi EX-3600 hydraulic excavator operating at the Obed Mine in Alberta. A 30-min log of GPS data were obtained and plotted in order to investigate how the required simulation information of a chosen activity in the excavation cycle can be extracted from GPS data. It is noteworthy that the obtained data had no Z values. Figures 5(a) and (b) show the total 30 minutes operation of the excavation, where X and Y axis represent the 2D location of the excavator and Z axis displays relative time in seconds. The GPS readings were collected with the speed of 1 Hz and with the accuracy of level two (L2), cm-level accuracy (SX Blue GPS, 2013).

As can be seen in Figures 5(a) and (b), some swinging activities can be discerned in the marked areas. Figure 5(c) provides a magnified view of a number of swinging actions. The starting and ending points of swinging are marked with enumerated points on Figure 5(c), which are identified through visual detection of sharp edges. With the coordinates of these points known, the elaborate status of excavator can be induced as shown inTable 5.



(a) (b) (c)

Figure 5 – State identification using GPS data from AMC/G

Although this state-identification is performed through visual analytics (Nejati, Hammad & Ghadiri, 2012), in post-processing mode, the same rules can be applied for identifying the status of the excavator in real time. For instance, it can be inferred from Table 2 that during loading activities (from point 3 to 4) the coordinates of the GPS do not fluctuate greatly, i.e. small length of move, and thus the speed is low, while during swinging (from point 4 to 5) the moving speed is much higher. Another interesting observation is that the moving speed is always lower when the bucket is full than when it is empty.

A closer scrutiny of Figure 5(c) suggests that starting from point 13 the excavator relocates to a new loading point, points 15, 16 and 18. To validate this assumption, pattern recognition is performed using K-means clustering method in Matlab (Hartigan & Wong, 1979). For this purpose, all the points marked in Figure 5(c) were used as the input values. These data were divided into two input variables, namely the loading points on the left-hand side of the Figure 5(c) and the dumping points on the right-hand side.

Table 5 – The calculation of swing time using AMC/G

Point	X (m)	Y (m)	Time (s)	Action	State	Direction of move	Duration of Move (s)	Duration of cycle (s)	Length of Move in x,y (m)	Velocity in x,y (m/s)
3	-7.501	-4.314	1220	Start load	Loading	N/A	17		0.365	0.021
4	-7.866	-4.296	1237	Start Swing	Swingin g (loaded)	To the truck	8	32	4.814	0.602
5	-4.607	-7.839	1245	Dumpin g	Swingin g (empty)	Away from the truck	7		4.557	0.651
6	-7.742	-4.532	1252	Start load						

Figure 6 illustrates the clusters and their respective centroids, allowing to visually identity patterns that help identify the repositioning of the excavator. Based on K-means clustering, loading points were recognized to form a new pattern starting from point 15. Similarly, point 11 was recognized to be the start of the new pattern in dumping spot. This finding corroborates that the excavator was most likely repositioned after point 13.

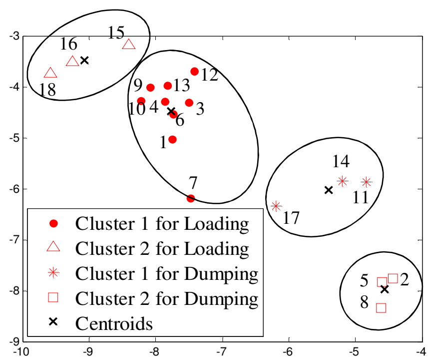


Figure 6 – Patterns of the excavator operation

CONCLUSIONS AND FUTURE WORK

The present paper explored the concept of location-aware real-time simulation of earthmoving projects through the development of a framework and the implementation of a prototype. The proposed framework, encapsulating the components for dynamic filtering and 4D modeling, offers a solution for monitoring simulation models in relation to real-time data from the site and refining the model if any major discrepancies are observed. A prototype was developed using Stroboscope to examine the feasibility of the proposed framework. Two case studies were developed and implemented to (1) validate the functionality of the developed prototype; and (2) investigate how real-time GPS data can be transformed into meaningful information pertinent to the simulation model and further used as the basis for the generation of state-identification rules.

The proposed framework offers a twofold enhancement to the real-time simulation frameworks proposed by other scholars. (1) A filtering module is proposed that can help distinguish the transient environmental changes with minimal long-term impacts on the productivity from the influential changes that will greatly impact an operation, and (2) the state-identification rules were explored beyond what is proposed by other researchers, incorporating rules about the operation of excavators.

In spite of the primary success of the developed prototype, further efforts are required to complement the prototype so that it covers all aspects of the proposed framework. Firstly, a wider range of construction machines and operations needs to be investigated to create a comprehensive rule-based system for state identification. Also, the applicability of advanced soft computing methods, e.g. neural network, for state-identification needs to be scrutinized. Secondly, the information filter component needs to be developed and tested. Thirdly, although 4D modeling and visualization was briefly tested, its full integration with real-time simulation has to be further addressed. Finally, all the components need to be combined and tested against an actual case study for the evaluation of the actual benefits the framework can offer in terms of more realistic representation of construction operations.

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REFERENCES

AbouRizk, S. (2010). Role of Simulation in Construction Engineering and Management. *Journal of Construction Engineering and Management*, 1140-1152.

Akhavian, R., & Behzadan, A. H. (2012). An integrated data collection and analysis framework for remote monitoring and planning of construction operations. *Advanced Engineering Informatics, 26*(4), 749-761.

Halpin, D. W., & Martinez, L. H. (1999). Real World Applications of Construction Process Simulation. *Winter Simulation Conference* (pp. 956 - 962).

Hammad, A., & Zhang, C. (2011). Towards real-time simulation of construction activities considering spatio-temporal resolution requirements for improving safety and productivity. *Proceeding of the 2011 Winter Simulation Conference* (pp. 3533-3544). Phoenix.

Hartigan, J., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. *Applied Statistics*, 100-108.

Hassan, M. M., & Gruber, S. (2008). Simulation of Concrete Paving Operations on Interstate-74. *Journal of Construction Engineering and Management, 134*(2), 2-9.

Hassan, S., Al-Hussein, M., & Gillis, P. (2010). Advanced Simulation of Tower Crane Operation Utilizing System Dynamics Modeling and Lean Principles. *Proceeding of the 2010 Winter Simulation Conference* (pp. 3262-3271).

Hildreth, J., Vorster, M., & Martinez, J. (2005). Reduction of Short-interval GPS Data for Construction Operations Analysis. *Journal of Construction Engineering and Management*, 920-927.

Lu, M., Dai, F., & Chen, W. (2007). Real-time decision support for planning concrete plant operations enabled by integrating vehicle tracking technology, simulation, and optimization algorithms. *Canadian Journal of Civil Engineering*, 912-922.

Martinez, J. C. (1996). *STROBOSCOPE State and Resource Based Simulation of Construction Processes* (Doctrol dissertation), University of Michigan.

Nejati, A., Hammad, A., & Ghadiri, D. (2013). Supply Chain Pre- and Post-Disaster Management Using Visual Analytics: The Case of Canada-U.S. Border Crossings. *3rd Specialty Conference on Disaster Prevention and Mitigation.* Montreal.

Perkinson, C. L., Bayraktar, M. E., & Ahmad, I. (2010). The use of computing technology in highway construction as a total jobsite management tool. *Automation in Construction, 19*(7), 884-897.

Peyret, F., Jurasz, J., Carrel, A., Zekri, E., & Gorham, B. (2000). The computer integrated road construction project. *Automation in Construction, 9*(5-6), 447-461.

Reclus, F., & Drouard, K. (2009). Geofencing for fleet & freight management. *In Intelligent Transport Systems Telecommunications,(ITST), 2009 9th International Conference*, (pp. 353-356).

Song, L., & Eldin, N. N. (2012). Adaptive real-time tracking and simulation of heavy construction operations for look-ahead scheduling. *Automation in Construction, 27*, 32-39.

Setayeshgar, S., Hammad, A., Vahdatikhaki, F. & Zhang, C., (2013). Real Time Safety Analysis of Construction Projects Using BIM and RTLS. *The 30th International Symposium on Automation and Robotics in Construction and Mining (ISARC).* Montreal, Canada.

SX Blue GPS. (2013, 10 2). Retrieved from http://www.sxbluegps.com/intro-carrier-phase.html

Teizer, J., Allread, B. S., Fullerton, C. E., & Hinze, J. (2010). Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system. *Automation in Construction, 19*(5), 630-640.

Zayed, M. T., & Halpin, D. (2001). Simulation of Concrete Batch Plant Production. *Journal of Construction Engineering and Management, 127*(2), 132-141.