A FRAMEWORK FOR REAL-TIME SIMULATION OF HEAVY CONSTRUCTION OPERATIONS

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ABSTRACT

This paper describes a framework of real-time simulation for modeling heavy construction operations. Compared with the traditional offline simulation that uses stationary inputs, the capability of real-time simulation to dynamically incorporate new project data and adapt to changes in the operating environment offers the promise of improving the accuracy of project forecasting. In the proposed real-time simulation framework, dynamic data from construction operations are constantly captured and fed into a process-simulation model for short-term scheduling purposes. A prototype system was developed to demonstrate the structure of the proposed framework and its feasibility. The benefits of this simulation approach and future research requirements for achieving a higher-level modeling automation are also discussed in this paper.

1 INTRODUCTION

Construction operations are mostly repetitive and subject to many resource constraints and the influence of interruptions and uncertainties in a construction environment. This operational characteristic has inspired and motivated more than four decades of research and practical applications of discrete-event simulation in the construction industry. Simulation applications can be found in broad areas of the planning and estimating of construction operations that are repetitive in nature, such as earth moving, tunneling, sewer-line construction, and paving operations in heavy construction projects (e.g., Halpin and Riggs 1992).

While simulation has been recognized as a powerful tool primarily for the early project planning stages, it can be equally valuable for short-term scheduling and project control during the project execution stage. Short-term schedules extend the master project schedule with an additional level of detail so that activities in the near future can be scheduled on a day-to-day or even a task-to-task basis (Hinze 2008). They play a vital role in the organization of tasks performed at the crew level and the management of such resources as time, materials, equipment, and workers. Unlike early project planning, short-term scheduling must constantly adapt to the dynamics of a construction system and develop a schedule that is based on the current system status and the outlook of the future project operating environment. As a result, rescheduling becomes necessary whenever an event, regardless of whether it is a change in current project status or future outlook, significantly invalidates the existing schedule. Ideally, short-term schedules should be constantly updated to reflect conditions as they actually exist. However, this can be a daunting task in the light of inevitable and constant changes in the project environment along the project timeline.

Although simulation is an excellent tool to model uncertainty and schedule repetitive operations, using simulation as a short-term scheduling tool encounters many obstacles. Traditional simulation methods have been primarily designed to predict long-term, steady-state system behavior. They usually assume that the target system is stationary and that models will operate under a given set of system design parameters, for example activity precedence relationships and duration distributions (Banks 1998). In short-term scheduling, the goal is no longer to average out the randomness in the system's behavior but rather to account for and react to system changes on a real-time or near-real-time basis. It requires that a simulation model captures system changes constantly and be updated accordingly so that the changes and their impacts can be evaluated in a timely manner. Therefore, the current set of simulation methods must be revisited and updated to serve the need for scheduling in situations with a relatively short time horizon.

This paper proposes a framework of real-time simulation for short-term scheduling of repetitive construction operations. The purpose is to describe the real-time modeling process and demonstrate its feasibility through a prototype system and an industrial case study. Related research work is reviewed in the next section, and the conceptual framework of real-time simulation and system components

are then defined. This is followed by a description of the prototype system and the case study. The paper concludes with a discussion of future research requirements.

2 RELATED WORK

Simulation is a proven but still-evolving technique in response to the ever-growing needs of the industry. To remain competitive, companies must improve not only their planning and optimization of their operations but also their capability to adapt and respond to the constantly changing operating environment. Real-time or online simulation extends the conventional offline uses of simulation to support online planning and control capabilities (Banks 1998). This section provides a brief review of related research in the simulation community as well as recent applications of simulation to short-term scheduling in the construction industry.

Researchers have already recognized the need for planning and control in real-time system management. Davis (1998) provided a comprehensive review of the need and evolving research requirements for such a real-time simulation environment through a comparison of offline planning and online planning using simulation technology. This review defined the role of simulation analysis and identified the limitations of current simulation approaches as they are applied to short-term planning. New simulation processes are required to address these limitations.

To further improve the control of dynamic systems, simulation has been continuously integrated with other supporting technologies as a critical component for real-time data analysis. Notably, the Dynamic Data-Driven Application System (DDDAS) is a new paradigm in which simulation, measurement, and applications are dynamically integrated (Darema 2004). This system goes beyond the traditional simulation paradigm to one that can dynamically incorporate online and archived measurement data from real-world systems to allow more efficient, accurate, and precise control. In this emerging methodology, simulation continuously gathers data from real-world entities and uses the data to adjust the model itself and make predictions of future system states. This dynamic feedback system promises to refine the simulation model at runtime and guide further data-collection efforts for continuous improvement.

Many applications of real-time simulation have been reported—for example, real-time decision-making applications in manufacturing. These applications use real-time data received from production monitoring systems to support real-time decision making based on online discrete-event simulation (Yoon and Shen 2006). Advanced techniques, such as artificial intelligence, distributed systems, and virtual manufacturing, are applied to allow for short-term or real-time decision making, such as for the next week, the next day, or even the next shift.

The construction industry has also recognized the opportunity for real-time control and short-term scheduling using the voluminous data streaming off job sites that are made available because of new sensing and communication technologies (FIATECH 2004). For progress monitoring and measurement, algorithms were developed to utilize real-time project data for measuring project progress, productivity, and actual consumption of materials (Navon and Shpatnitsky 2005). For performance forecasting, simulation can be a powerful data-analysis tool to turn real-time data into predictive information for project scheduling and control. Repetitive long-term projects provide opportunities to fine-tune simulation input parameters based on actual project progress. Chung, Mohamed, and AbouRizk (2006) collected project data from a tunneling project manually on a bi-weekly basis and used the data to improve simulation input models using Bayesian updating techniques. Their research shows the extent of improvement in simulation input modeling and planning predictions from using actual project data. Lu, Dai, and Chen (2007) developed a real-time decision-support system for planning concrete plant operations. The system tracks activity durations in real time and later uses the data to update simulation input models. In summary, the recent studies focus primarily on leveraging real-time data for improving simulation input modeling. Beyond input modeling, real-time data also bring new opportunities to many other simulation modeling areas, such as model formulation, validation, and updating. The following section defines system components of the proposed real-time simulation framework and explains at the conceptual level how it can improve the existing simulation process.

3 A FRAMEWORK FOR REAL-TIME SIMULATION

The proposed real-time simulation framework contains four components, including real-time data collection, process knowledgebase, self-adaptive modeling, and simulation services, as shown in Figure 1. These system components integrate real-time data and process knowledge to facilitate constant model updating and refinement to reflect changes in the operating environment. Section 4 illustrates how this conceptual framework is implemented in a prototype system for modeling asphalt hauling and paving operations.

3.1 Real-time Data Collection

Real-time simulation is a data-driven modeling process, and a significant amount of data are required for determining current project status and fine-tuning the model's operation logic structure and input models for more accurate short-term scheduling. The proposed data-collection component constantly collects data that can adequately describe current project status and the future outlook of the

operating environment, such as productivity performance, current project progress, and resource allocation for the near future. These data can be collected from various sources, such as data-collection sensors, project personnel, and existing information systems.
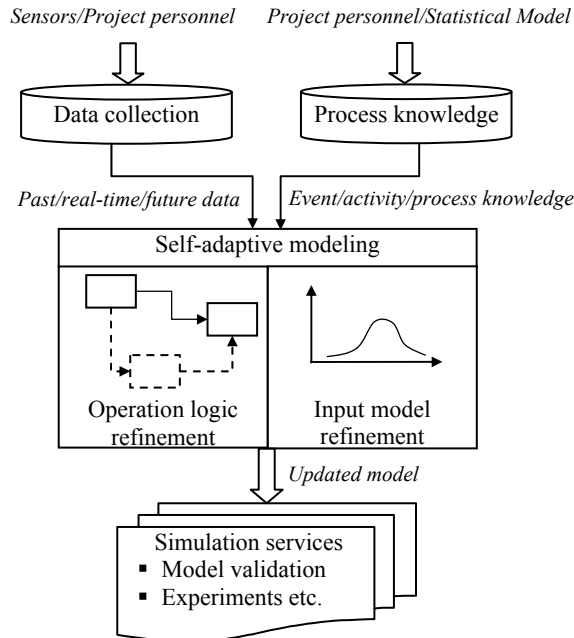

Sensors/Project personnel   *Project personnel/Statistical Model*

Data collection   Process knowledge

Past/real-time/future data   *Event/activity/process knowledge*

Self-adaptive modeling

Operation logic refinement   Input model refinement

Updated model

Simulation services
- Model validation
- Experiments etc.

Figure 1: A framework for real-time simulation.

Collecting data in real time can be challenging. Operation data must be collected constantly to reflect the changes in project performance and the job site environment. The time and cost required to manually collect and process these data is prohibitive, but with the recent advent of sensing and communication technology, a broad range of embedded, wide-area, and satellite-based sensors (e.g., speed, location, motion, and image sensors) are now economically available for wireless, automatic, or remote data gathering. The lack of real-time data is becoming less and less of a factor in the development and implementation of real-time simulation. For example, equipment-intensive heavy construction projects have seen the use of the Global Positioning System (GPS) to track the real-time locations of construction equipment such as earth-moving machines (Ackroyd 1998; Navon and Shpatnitsky 2005) and concrete-hauling trucks (Lu, Dai, and Chen 2007). GPS is also used in the prototype system of this research.

In addition to real-time performance data, short-term scheduling also requires input data about future project operating variables that may significantly impact project performance. Controllable operating variables, such as future resource allocation and shift arrangement, can be collected by schedulers and scheduling systems. Uncontrollable operational variables, such as future weather and traffic con-

ditions, if required for simulation modeling, may be collected from external data sources.

3.2   Process Knowledgebase

As data are made available from a highly sensed construction site, the next logic question is how to make these time-sequenced data meaningful for simulation modeling. Many sensors, such as GPS, are capable of recording and transmitting data with a frequency of a few minutes or even seconds. This high-frequency data collection process improves data accuracy but also generates a significant amount of data that challenge the ways in which meaningful information can be extracted. For example, the information extraction process requires knowledge about the real-world operation. In the proposed process knowledgebase, this knowledge about (1) operation logic and (2) input modeling is obtained from project personnel and pre-defined statistical models. This knowledge determines how raw, time-sequenced data are interpreted for simulation model updating.

3.2.1 Operation Logic Knowledge

Operation logic describes events, activities, and processes involved in an operation and precedence relationships and interactions among these elements. The knowledge regarding operation logic can be represented in a hierarchical structure of events, activities, and processes. In discrete-event simulation, the operation of a system is represented as a chronological sequence of events over time (Law and Kelton 2000). An event occurs at an instant in time, and more importantly it causes a change in the state of the system. An event is the smallest time element in a simulation model, and its attributes can be used to derive higher-level activity and process data. An activity is what transforms the state of a system over a period of time, and it is initiated by the occurrence of an event and is ended by the occurrence of another event. A process is a time-ordered sequence of activities that describe how an entity moves through a system. If one considers vehicle GPS tracking as an example, data records describe in real time a vehicle's location, speed, and direction, and those data can be used to identify events that mark the start and completion of an activity. Based on this event information and the user-defined process knowledgebase, activities and processes represented by the time-sequenced raw data can be determined and analyzed for simulation modeling. To achieve this reasoning process, user-defined rules must be established for the identification of events and for drawing inferences from events to activities and processes. The prototype system presented in Section 4 provides a sample implementation of this approach.

3.2.2 Input Modeling Knowledge

Another aspect of the knowledgebase deals with simulation input models, which specify input probability distributions and their parameters, such as the distribution of an activity's duration. Several methods can be used to represent random inputs to a simulation model, including empirical distribution, standard statistical distributions, and external prediction models. Empirical or standard distributions aggregate effects of all variables affecting a simulation input in a single distribution function representing the variation, such as activity duration or decision making (AbouRizk and Sawhney 1993). To further improve forecasting accuracy, certain uncertainty variables—e.g., weather and staffing level and their impacts on simulation input—can be modeled explicitly using a prediction model. For example, Wales and AbouRizk (1996) developed a continuous-change weather process model and combined it with a simulation-based project CPM network. The impact of weather conditions on activity durations are modeled by neural network models. Zhang et al. (2003) proposed the application of fuzzy logic to discrete-event simulation in dealing with uncertainty in the quantity of resources required to activate an activity. The duration of an activity, which varies with the quantities of resources involved, is determined through a fuzzy rule-based model. To improve the accuracy of short-term scheduling, these advanced forms of prediction models can be stored in the knowledgebase and used at simulation runtime to predict simulation inputs.

3.3   Self-adaptive Modeling

The key feature of real-time simulation is its capability to adapt a pre-defined simulation model to constant changes of the project environment. This capability is achieved by updating both the model operation logic and the input models when they are no longer able to accurately represent current and anticipated future project performance. Updating the model manually is possible but will quickly become impractical for project environments in which frequent changes exist. The self-adaptive modeling component is designed to streamline the model-updating procedure by taking advantage of inputs from the data acquisition and the process knowledgebase components described above. For example, real-time and most-recent values of an activity's duration can detect changes in the duration pattern, and a new statistical distribution can then be determined using those data. As another example, an excavator changes its location as evidenced by its GPS records. Based on the operation knowledgebase, if the two locations are associated with two different job-site locations, then the system will draw an inference that the excavator was relocated from one job to another, and the simulation model will be updated accordingly. This self-

adaptive process is valid if it meets two assumptions. First, the real-time data must adequately capture the signs of system changes and whether these changes are relatively permanent. Second, adequate and accurate operation knowledge must be defined to interpret the signs and inference-system changes. Like any decision-support techniques, this self-adaptive modeling function offers support for model-updating decision making, but it cannot completely replace human judgment. User intervention is still required to confirm or disapprove system changes defined by the self-adaptive modeling procedure.

When a system change is warranted, the simulation model must be updated accordingly to reflect this change. The model can be updated in an offline fashion in which the operation logic and input model are revised first, and then new simulation experiments can be conducted. Updates to the operation logic may include adding or deleting activities and resources and changing precedence relationships. Updates to the input models may involve changes of probability distribution types, distribution parameters, and even input modeling methods. Real-time data sets collected can be used to fit to a set of standard distributions, and the best-fitted distribution can be chosen to replace outdated input models (BestFit 1999). For cases in which a specific type of distribution has been predefined, real-time data sets can help to fine-tune distribution parameters. Applying operation logic and input model changes to a simulation model can be automated, as discussed in Section 4.

3.4   Simulation Services

Simulation services required by real-time simulation include model verification, validation, simulation execution, and output data collection. Many simulation software tools are available that offer simulation functions such as graphical modeling, simulation algorithms, and output data analysis, and they allow end users to construct models, conduct simulation experiments, and perform data analysis. However, a simulation experiment always begins with the assumption that a simulation model has been verified and validated. This checking process is normally conducted manually. In a real-time simulation mode, a system model must be constantly updated to reflect system changes. Therefore, simulation services must also provide support for verifying and validating a simulation model in an efficient way. Figure 2 shows the full cycle of the real-time simulation process. Real-time data provide an opportunity to allow a computer-aided model-validation and model-verification process.

Model verification concerns whether an updated simulation model operates properly and logically. Several objective techniques can be computerized and used to streamline the verification process. For example, simulation trace, which describes simulation model events in an ordered sequence, is one of the most powerful verification techniques

(Law and Kelton 2000). Simulation trace can be combined with real-world data to computerize model verification. To achieve this, the simulation model is given the same set of static input data that are recorded from the actual system. A simulation experiment is then conducted to generate the trace. These simulation trace events can be compared side-by-side with actual events recorded by real-time data, discrepancies can be quantitatively measured, and users can be alerted when there are any significant deviations.
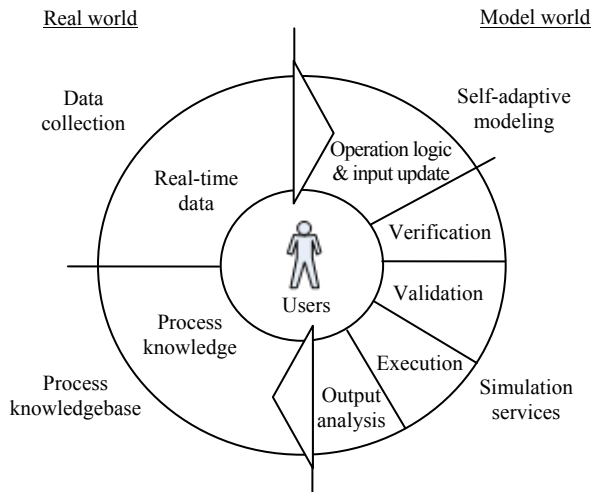

Figure 2: Real-time simulation process.

Validation determines whether a stochastic simulation model is an accurate representation of the real system. When a system already exists, the most objective test to validate a model is to compare the model's output with actual data in the real world. This can be done by validating input-output transformation or validating using historical data (Banks 1998). When real-world data are available, these verification methods can be combined with classical statistical tests to automate model validation. Furthermore, for the case of validation using historical data, a detailed comparison of system and model output at the activity level can also help users to diagnose accuracy issues and identify root causes. The prototype system presented in Section 4 uses a confidence-interval approach to automate model validation.

In summary, real-time simulation challenges the way in which a simulation study is conducted, but at the same time, real-time data give raise to the potential of having a more streamlined modeling and experiment process. As shown in the proposed framework, real-time data inspire the possible automation of the data collection, model updating, verification, and validation processes. When fully implemented, these automated processes can help end users focus on the essentials of project scheduling and control instead of on the requirements for the simulation modeling itself. Users can be freed from time-consuming data-collection activities and can direct their efforts toward building process knowledge. Computer-aided verification and validation changes the responsibility of the end users from model programming and debugging to model health monitoring and decision making. To illustrate some of these capabilities, the following section describes a prototype system developed for asphalt hauling and paving projects.

4 THE PROTOTYPE SYSTEM

Heavy construction work is a highly equipment-intensive process, and contractors work under a unique set of conditions that are characterized by various resource constraints, uncertainty, and interruptions by many technical and environmental factors. These projects are usually spread out over miles, which makes project control and management even more difficult and exposes contractors to greater schedule and financial risks. Successful execution and control of these projects relies on an efficient short-term scheduling approach that can capture dynamic project data and incorporate them into the scheduling of upcoming work. The proposed real-time simulation framework was implemented to support this short-term scheduling effort. An asphalt hauling and paving operation is described, and it is followed by a description of the prototype system.

4.1   Asphalt Hauling and Paving Operation

Hot-mix asphalt is normally produced at a central asphalt plant and transported by trucks to the job site for paving. The operations at an asphalt plant and job sites located in central Louisiana are briefly described here. The central plant features a double-barrel drum mix process that blends, heats, and mixes aggregates and asphalt cement, and the plant produces a continuous flow of asphalt concrete. Fresh asphalt concrete is stored in storage silos, from which it can then be dispatched into dump trucks. Trucks are prepared by spraying a release agent on their beds, and then they are loaded with asphalt concrete. A ticket is issued to each truckload before it leaves for the job site. At the job site, the asphalt concrete is discharged into a shuttle buggy, which acts as a buffer between the dump trucks and the paver. The shuttle buggy can receive asphalt mix while simultaneously transferring the mix to the paver. When a truck is fully unloaded, it returns to the asphalt plant for another shipping cycle.

4.2   Prototype System Implementation

The prototype system integrates GPS tracking technology with simulation for the purpose of short-term scheduling. The data-collection method, process knowledgebase, self-adaptive modeling, and simulation engine and services used are described below.

The hauling and paving operation relies strongly on heavy equipment, and construction activities and events can normally be associated with the location, speed, or travel direction of a piece of equipment. GPS-based location tracking has become commercially available for monitoring heavy construction equipment, such as excavators, trucks, and pavers. GPS uses satellites that transmit precise signals to allow a GPS receiver installed in a vehicle to determine its location, speed, travel direction, and the time. Because these data are stored locally in the vehicle's GPS receiver, making them available in real time for a remote simulation server requires that data be transmitted constantly. This is achieved by attaching the GPS receiver to a modem that sends data through a wireless cell-phone network. Data can be updated in real time when such a request is made by users, or they can be updated automatically at a specified time interval, such as one minute. In addition to GPS devices, other sources of real-time or near-real-time data can also be acquired. In this project, a PC-based control system that manages the asphalt plant provides job number, job site location, material type, and load weight data for progress and productivity measurement. In the prototype system, GPS and other operation data are stored in a Microsoft Access database.

To extract meaningful data for simulation modeling—e.g., truck loading time and hauling time—knowledge regarding various events and activities involved in the operation must be used to assist data interpretation. To associate a truck's location to an event, a concept called "geo-fence" is used. A geo-fence is an area that is defined around a fixed geographic location or a mobile object of interest, such as a paver. Geo-fences must be defined by project personnel for areas such as asphalt plant loading lanes and paver locations. The user interface in Figure 3 shows a set of user-defined geo-fences. When a truck travels across the boundary and into an asphalt plant loading geo-fence, a start-loading event is logged, and when it moves out of the boundary an end-loading event is recorded. When higher accuracy of time measurement is required, the frequency of GPS data update can be adjusted from every few minutes to every few seconds when a vehicle is getting close to or is within a geo-fence of particular interest.

After events are identified, knowledge possessed by project personnel is again needed to draw inferences from events to activities, as well as from activities to processes. As described in the conceptual framework, this knowledge is organized as rules in a hierarchical structure. Sample rules for the dump truck process, for example, are shown in Figure 4. In this project, an effort is made to separate truck waiting time from loading and unloading activities (the reason for this is explained in Case Study 1 of Section 5). Travel time for moving in and out of the work zone are also explicitly modeled as activities in order to collect data for evaluating the impact of work-zone traffic control, but

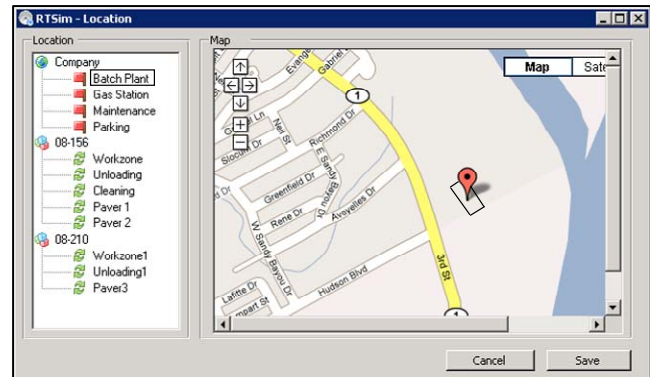this impact evaluation study is beyond the scope of this paper and will not be discussed further.

Figure 3: User defined geo-fences.

Figure 4: Dump truck process.

The prototype system uses a general-purpose simulation tool, Simphony (Hajjar and AbouRizk 1999), to provide basic discrete-event simulation services. Using Simphony's Common Template, processes such as the one shown in Figure 4 can be expressed graphically, as shown in Figure 5. The model assumes that the resources consist of one asphalt plant, seventeen trucks of the same size, one shuttle buggy, and one paver with a hopper capacity of one truckload.

Simphony's Active X library is used to manipulate simulation projects from external applications, such as Microsoft Access, which was employed in this research. Any aspect of a simulation model can be completely controlled through this library, which means that the model can be automatically updated after a change request is made by the self-adaptive modeling component. Operation logic changes to a model include adding and deleting activities,

as well as logic links. Input model changes include changing distribution types and parameters. To automate the input distribution-fitting process, activity duration data sets collected from GPS units are fitted using a distribution-fitting program, BestFit (BestFit 2004), and the best-fitted distribution is then used to update the simulation model. BestFit fits a data set to 28 different probability distributions and these distributions are ranked by fit statistics, including Chi-square, Anderson-Darling, and Komolgorov-Smirnov. The BestFit developer's kit was used to automate the data-fitting function in the prototype system. Optionally, the fitting results can be presented to end users for confirmation, as shown in Figure 6.
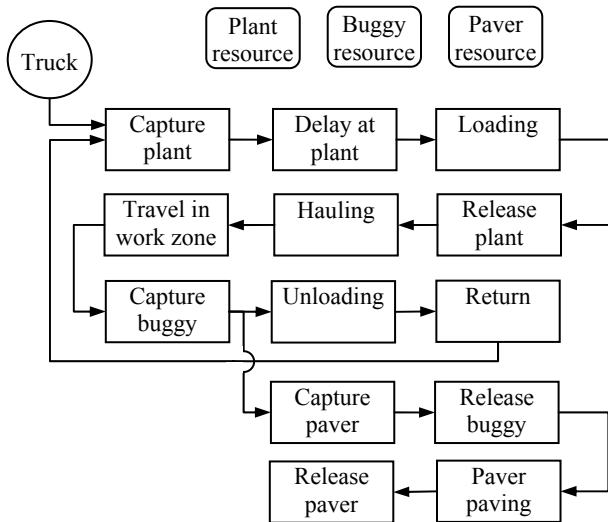

Figure 5: Dump truck and paver process model.

Model validation is automated using a confidence-interval approach based on real-time data. Truck cycle time is an important measure of the performance of the asphalt hauling and paving operation and was selected for model validation. Actual data were collected from the sample project which will be described in the next section. The paired-t approach is used to construct a confidence interval for the difference between the observed average cycle time and the simulated average cycle time (Law and Kelton 2000). The 95% confidence interval for the difference is (-9.9, 10.6). Because the interval contains 0, it was concluded that the observed difference is not statistically significant at a confidence level of 95% because it might be interpreted as sampling fluctuation.

5   CASE STUDIES

This section presents two case studies to illustrate the capability of the prototype system. The first case study shows how the prototype system adapts to changes in the project operating environment, and the second case study demonstrates its capability to model multiple, concurrent projects.
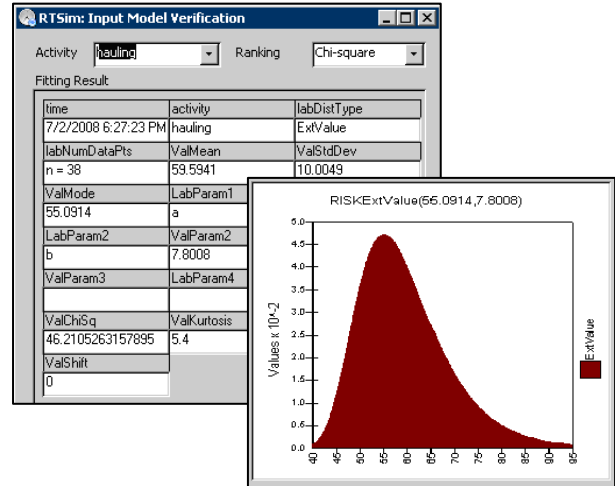

Figure 6: Automated input modeling.

5.1   Case Study 1

The sample project involves grading, drainage structures, asphaltic concrete overlay, and related work for widening a 1.66-mile portion of U.S. Route 84 from a two-lane to a four-lane highway. The contractor originally scheduled 20 dump trucks and 1 paver to this project, and all of them were equipped with GPS units for real-time data collection. A base simulation model, established prior to the project based on the project plan and historical data, defined five activities: asphalt loading, hauling, unloading, paving, and returning. Many changes were observed in the actual operation, and they invalidated the base model. For example:

- Only 17 trucks were actually found working on this project, with the other three trucks being relocated to other jobs for various reasons.
- Actual waiting times at the asphalt plant were much longer than the queuing time measured by the base simulation model.
- Actual hauling and returning times were significantly longer than what had been expected due to work-zone traffic and traffic-control problems.

Experiments showed that these changes misplaced the value of truck cycle time by at least 20%. In this case study, real-time data collected during the first day of the project were used to update the base model for predicting future performance. The prototype system logged trucks working on the project and updated the number of trucks available accordingly. Actual activity durations were used to update operation logic and input models. The system's capability to resolve the asphalt plant waiting-time issue is described as an example below.

In a typical simulation model, queuing time for a service is determined by entity arrival time and server service time. For example, a truck's waiting time at the asphalt plant can be derived from its arrival time, the queue length,

and loading time. Therefore, in the base model, this waiting time was not modeled as an activity but instead was treated as a model output. However, the actual observed waiting time is longer than the normal queuing time derived from the simulation model because the asphalt plan also serves trucks from other projects and other external customers at the same time. Extending the model scope to include these situations is not always practical, but an immediate solution is to model this additional delay explicitly as an activity. In the prototype system, the following model validation and updating procedure was applied:

1. The difference between the actual average waiting time and the simulated average value are measured statistically, and a change request is logged when the difference is larger than a threshold—e.g., a confidence level of 90%.
2. After receiving the change request, the additional delay due to external processes is modeled as a probability distribution. This input modeling uses delay data collected during actual operation, and the delay is estimated as follows:
   Delay = (Start loading time – Enter plant gate time) – Queue length x Average loading time. (1)
3. A delay activity with the fitted distribution is inserted and linked properly to the loading activity in the base model.
4. Simulation experiments are then conducted as a part of the post-request procedure.

In this case study, the additional delay was identified, and an exponential distribution with a mean of 16.3 minutes was generated. A "delay at plant" activity was inserted into the base model, as shown previously in Figure 5, and this change alone reduced the cycle-time prediction error by roughly 6%.

5.2 Case Study 2

This case study is designed to show the system's capability to model multiple, concurrent asphalt hauling and paving projects. In order to reduce the time required to construct the base model, an effort was made to identify common geo-fences in asphalt hauling and paving projects and associate these geo-fences with re-usable simulation elements. For example, geo-fences and the simulation model describing different asphalt plants share similar operation logic. Figure 7 shows two geo-fences typically defined for an asphalt plant, along with events and activities, and the corresponding simulation module. The module is saved and associated with the geo-fences so that when an asphalt plant-type geo-fence is created by a user, its simulation model will also be automatically created. A similar reusable geo-fence element for a paver site was also created. These geo-fence elements were then used to model three concurrent projects that are served by the same asphalt plant but are located at different job sites.

Activities between the plant and a paver site are modeled as traveling time by default. One plant-type geo-fence and three paver-type geo-fences are first defined by the user in a map system. A simulation model is then automatically generated for the three job sites and the asphalt plant. This computer-generated model is identical to a model that is otherwise generated manually, but the computer-generated model requires significantly less time to build due to the integration of geo-fences with reusable simulation elements.
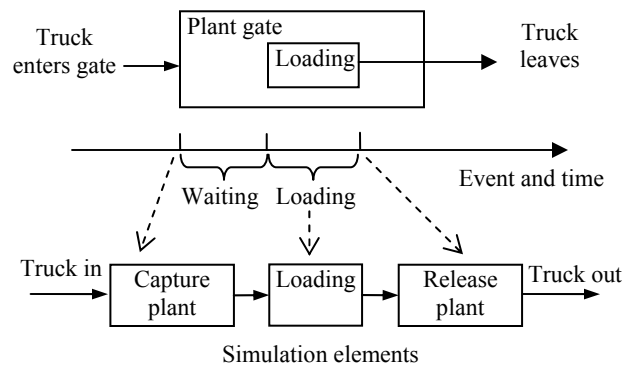

Figure 7: Paver geo-fence element.

6 CONCLUSIONS

This paper describes a framework of real-time simulation for short-term scheduling. It is applicable to repetitive construction operations, and a prototype system for asphalt hauling and paving projects is developed. This framework contains four components: real-time data acquisition, a process knowledgebase, self-adaptive modeling, and simulation services. Real-time data and process knowledge are coupled to enable a self-adaptive modeling process that validates and refines a process simulation model. The prototype system shows that, based on real-time data, it is capable of updating a simulation model's operation logic and input models in order to reflect changes in the project environment. Compared with the traditional simulation, real-time simulation has the potential to improve the accuracy of performance forecasting while reducing modeling burdens on the end users.

While this research shows the feasibility of real-time simulation, a significant amount of research work is still needed to capture the full potential of the concept. This includes defining a more comprehensive real-time data collection scheme, more efficient data fusion and processing, better representation of expert knowledge and a tighter integration of such knowledge with real-time data, automated change monitoring and updating processes, and a simulation platform that supports these new requirements.

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