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Artificial Intelligence Integrated Construction Simulation Method

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the requirements for the Degree of Master of Philosophy

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CERTIFICATE OF ORIGINALITY

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Abstract of the dissertation entitled:

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On one hand, the interactive, complicated system environment of a construction site renders the conventional site layout planning and scheduling techniques inadequate in coping with the materials handling system design in construction. On the other hand, simulation provides a promising solution to construction planning by predicting the future state of a real system from computer model based experiments. However, the complexity and time requirement involved in constructing a simulation model along with the difficulty in decoding simulation output data keep practicing engineers from employing simulation tools in practice. In an attempt to facilitate simulation application in construction, this thesis research has (1) formalized the procedure of setting up a construction operations simulation model in accordance with the Simplified Discrete-Event Simulation Approach (SDESA) and (2) experimented with data mining and knowledge discovery from the data produced by valid construction simulations by applying Artificial Neural Networks (ANN).

Implementation and validation of the research findings are based on a real world case for improving the effectiveness of the materials handling system on a precast viaduct construction project in Hong Kong. How to apply the simulation methodology of SDESA is elaborated and illustrated step by step, with the case study. Particular emphasis is placed on

the procedures of establishing a simulation model, the validation of the simulation model, the design of simulation experiments, and the analysis of simulation results.

With the same case of simulation modeling, this research further demonstrates the application of neural networks (NN)-based sensitivity analysis in support of construction operations simulation modeling. Four input factors relevant to operations and logistics planning in site are identified and assessed, namely (1) the number of trailer trucks rented for hauling segments, (2) one-batch vs. two-batch precast segment delivery modes, (3) the proportion of segments placed in the remote storage area, and (4) the haul duration from the remote storage area to the working span. The NN-generalized input sensitivity information was corroborated by experienced site managers and engineers, which in turn (1) helped validate the operations simulation model, (2) provided valuable insight into the behavior of the operations simulation model, and (3) enhanced the understanding of the real construction system.

On the case study project, the field managers were convinced of the functionality and effectiveness of the artificial intelligence integrated construction simulation method being proposed. They took advantage of findings from the research in designing the actual materials handling system. In short, it is hoped that by implementing the simplified, intelligent construction simulation method as developed, practicing engineers would be capable and confident to draw up the best construction plan that would lead to the enhancement of cost-effectiveness and productivity in the field.

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1. INTRODUCTION

1.1. Problem Statement and Research Objectives

Construction planning is the most crucial, knowledge-intensive, ill-structured, and challenging phase in the project development cycle due to the complicated, interactive, and dynamic nature of construction processes (Halpin and Riggs 1992). The complex interactions among resources on the construction site and various constraints in the harsh construction environment hamper a systemic, detailed, and cost-effective approach to construction process planning and control. The present common practice of construction planning is the use of a critical path method (CPM) based schedule in the form of an activity-time 2D bar chart (Gantt chart) on both long term (i.e. the whole project period) and short term basis (i.e. the month/week ahead or even particular days). Nevertheless, lack of resource and spatial considerations in a CPM plan has resulted in the difficulty of identifying mistakes of the construction plan and the inconsistency of interpreting the project schedule (Koo and Fischer, 2000). As a result, field managers have been relying on rules of thumb, past experience and intuition to draw up action plans in response to different situations in reality.

Simulation entails the creation of a computer model of the real system based on real life statistics and operations. The methodology of discrete-event simulation, which concerns ‘‘the modeling of a system as it evolves over time by a representation in which the state variables change only at a countable number of points in time’’ (Law and Kelton 2000). It has been researched to analyze and design construction operations for over three decades (Martinez & Ioannou 1999) for (1) productivity level estimation for complicated processes,

(2) improved scheduling for repetitive processes, and (3) planning adequate resource assignment that minimizes time and cost (Gonzales-Quevedo et al. 1993).

Ever since the inception of CYClic Operation Network (CYCLONE) technology (Halpin 1977), simulation models for typical construction systems have been delivered as electronic realistic prototypes for engineers to experiment on, aimed to boost the field operations productivity, efficiency, and bring in monetary saving. Nonetheless, operations simulation has lagged CPM and other types of scheduling packages in acceptance and implementation in the construction industry (Paulson 1995; Shi and AbouRizk 1997) and has remained largely software exercises at the academic and experimental level (McCahill and Bernold 1993). The main obstacles to widespread use of simulation by construction practitioners are identified to be (1) the complexity of the simulation methodologies and (2) the difficulty in extracting management insight and tactics from the simulation outputs.

The complexity of the simulation methodologies not only requires the construction practitioners to go through a painful, long learning curve but also consumes unreasonably long time to construct valid simulation models in tackling construction management problems. For some simulation methodologies, modelers have to possess both programming skills and advanced statistics knowledge in forming models even for simple construction operations (such as earth moving). Although many research endeavors have been devoted to developing simplified construction simulation methodologies, to date, construction simulation remains largely difficult to learn and inefficient to apply.

As an attempt to make construction operations simulation as easy as applying critical path scheduling, Lu (2003) adapted existing event- and activity-based simulation algorithms into a simple, effective construction simulation technique, called the Simplified Discrete-Event

Simulation Approach (SDESA). SDESA was extended to allow the site layout definition of a construction system, and to synchronize the operations modeling in a dynamic construction system with the construction site layout planning (Lu et al. 2003). Some previous case studies have proven that SDESA can capture most construction operations details with simple modeling notations and concise schematic models. **However, the uniqueness in simulation strategy justifies the formation of a SDESA model setup procedure which is aligned with practical modeling needs in construction and the simulation functionalities of SDESA.** Therefore, the first objective of this research is to formalize SDESA model setup procedure based on the experience gained from previous practical operations simulation case studies.

To further enhance the applicability of construction simulation, the conversion of simulation output data into useful information is facilitated by taking advantage of the latest advances in the research of Artificial Neural Network (ANN). Unlike the conventional regression methods, ANN allows the mapping of a number of inputs to multiple outputs without increasing data processing effort. The capabilities of handling a large amount of data at a time and approximating complicated, non-linear relationships within a system make ANN an ideal tool in construction research, such as applications on structural analysis, soil property prediction, and productivity estimation. In this research, ANN is integrated to construction simulation to map the relationships between various influential factors (e.g. resource configuration, material arrivals) and the overall performance indicators of a construction system (e.g. productivity, resource utilization). The ANN model is trained with data resulting from simulation experiments. We can further perform sensitivity analysis on ANN such that the significance of each input factor in relation to the operations system performance can be estimated. With the simple and explicit presentations (e.g. chart or table) of the sensitivity analysis results, construction professionals, who may not be familiar with simulation modeling or ANN at all, can benefit from construction simulation in making sound decisions.

1.2. Research Framework

This research attempts to improve the existing construction operations simulation technology by (1) formalizing of the SDESA model setup procedure and (2) developing a simulation-based knowledge-discovering method by ANN integration (Figure 1.1). The following Section 1.2.1. and 1.2.2. provide more comprehensive descriptions on the background, motivation, as well as the methodology of this research. In Section 1.2.3., the background of the demonstrative case study, in which the proposed methodologies were successfully implemented, is introduced.

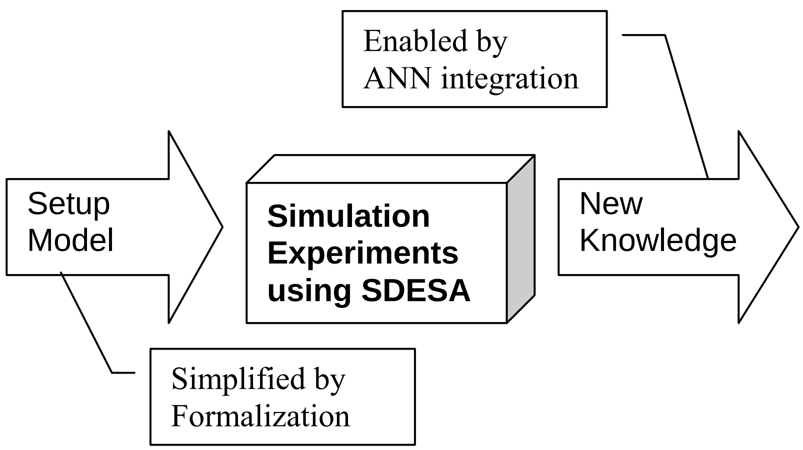

Figure 1.1: Research Framework

1.2.1. Formalization of Construction Operations Modeling Procedures

Martinez and Ioannou (1999) examined the implicit characteristics of discrete-event simulation systems commonly used in construction and grouped them into three general strategies, i.e., activity scanning, event scheduling, and process interaction. Activity

Scanning (AS) and Process Interaction (PI) were identified as the two main strategies most commonly adopted, while Event Scheduling (ES) was viewed as an accessory to the former two. Each simulation strategy views a real-world system from a particular perspective (Pidd 1998, Zhang et al. 2005b) and has a strong impact on the thought process that leads to model development as well as on the way a model is presented to the computer (Evans 1989).

AS models are set up from the point of view of activities and the conditions under which they take place. Hence, AS is believed to be suitable for modeling complex operations system in which many resources with distinct properties collaborate to trigger activities (Hooper 1986). For simulation advancement, AS scans activities for time eligibility and other start conditions, and then executes the activities that are due to happen. (Zhang et al. 2005b) The well-known construction simulation approach CYCLONE is a typical AS simulation approach. To set up an AS model, the modeler follows a standard modeling procedure: (1) identify activities in the system, (2) list the start-up conditions for each activity, (3) draw activities in blocks and conditions in circle shapes, (4) link activity blocks and condition circles according to the construction logic, (5) initialize the system by assigning simulation entities (or called tokens, representing the initial system state) to condition circles. The schematic model composed by the activity blocks and condition circles is called Activity-Cycle-Diagram (ACD).

ACD model facilitates the communication between construction practitioners and modelers, and provides an intermediate medium to convert the conceptual model into the digital model. Figure 1.2 depicts the relationship between the conceptual model, ACD, and the digital model. Using a simple concreting operations as an example, modelers who adopt an ACD based simulation approach first identify the activities (e.g. Unload Concrete to Barrow) and their corresponding activation conditions (e.g. Full Truck and Barrow available), then these activities nodes and condition nodes are organized into a complete ACD model (Figure 1.2) before inputting it into the simulation program.

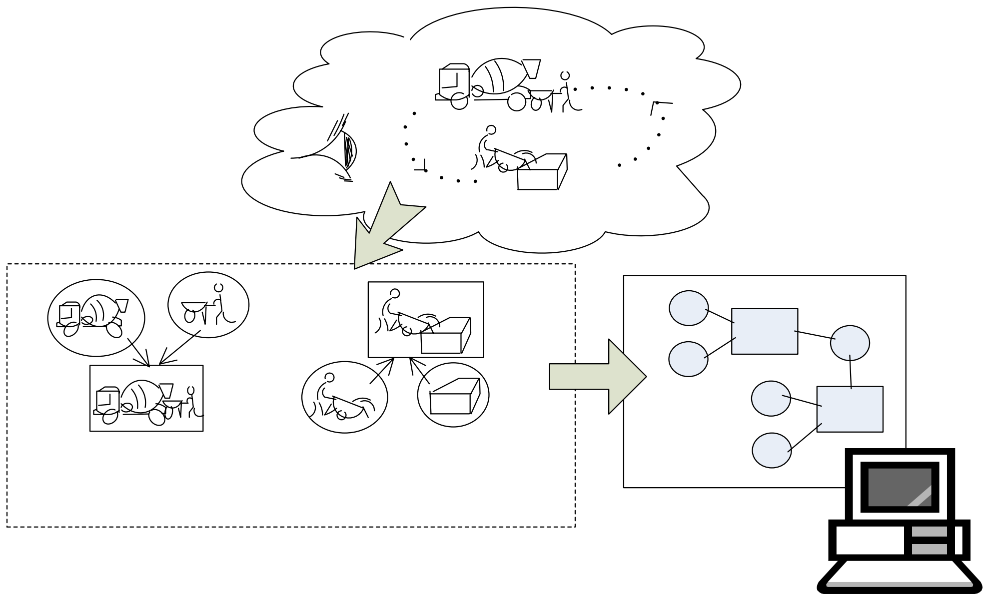

Figure 1.2: Converting a Construction Operations System into an ACD Digital Model

The brevity of the modeling notations and clear modeling procedures exonerate the modelers from tedious coding and considerably shorten the learning time for modeling. However, the inherent difficulty in characterizing resources in ACD based model imposes constraints on its applicability. This difficulty is due to the interchangability of token identity in ACD based model, in which the meaning of an entity keeps changing when it flows from one QUEUE node to another. For instance, if the QUEUE node is defined as the number of empty trucks, then the entities in this node represent empty trucks; but if the next QUEUE node means soil units arrived, the identity of the entities will change into soil unit. The instability of token identity hinders modelers from characterizing a token with properties. As a result, (1) the model size may be enlarged as more nodes are required to represent different properties or statuses of a resource, (2) the accuracy of the model may be compromised by neglecting some resource properties, and (3) additional programming and extended features may be inserted to the simulation system for the ease of resource property definition. Some recent developments are STROBOSCOPE (Martinez 1996) and RISim (Chua and Li 2001), which used different means to allow the inclusion of resource properties. However, the added features inevitably compromised AS modeling the brevity and simplicity.

Looking at the operations from a different view point, Process Interaction (PI) modeling strategy differentiates scarce resource and production unit (or customer waiting for service). A production unit arrives, undergoes some processing facilitated by scarce resources, and exits the system. PI based simulation has been implemented manufacture and services enterprises throughout the world; such a simulation strategy can successfully improve the design and operation of complex systems (Diamond et al. 2002). Despite the success of it in manufacturing and service industry, PI modeling strategy is unfeasible to be directly applied to model construction operation system (Lu and Wong 2005). The reasons can be partly attributed to (1) the project nature that construction is a project-oriented business that produces unique products and (2) the product in construction is stationary, while the production facilities are mobile (Ortega and Bisgaard 2000). Additionally, the differences between construction and manufacturing make PI modeling strategy difficult to apply on construction operations system in which the production unit is no more obvious as in an industrial system (Martinez & Ioannou 1999).

As an attempt to improve construction operations simulation from its basic modeling strategy, Lu (2003) combined the strengths of both PI and Activity Scanning (AS) into an adapted PI simulation approach - the Simplified Discrete-Event Simulation Approach (SDESA) by viewing a construction system as a group of material handling workflows. To shorten the learning curve, SDESA models are designed to use simple simulation flowcharts. To form a SDESA model, modelers first break down the operations system into work flows (i.e. production lines in a manufacture system), then they enrich the definition of the work flows by adding resources, flow entities, and resource transit information to produce a complete SDESA model (Figure 1.3).

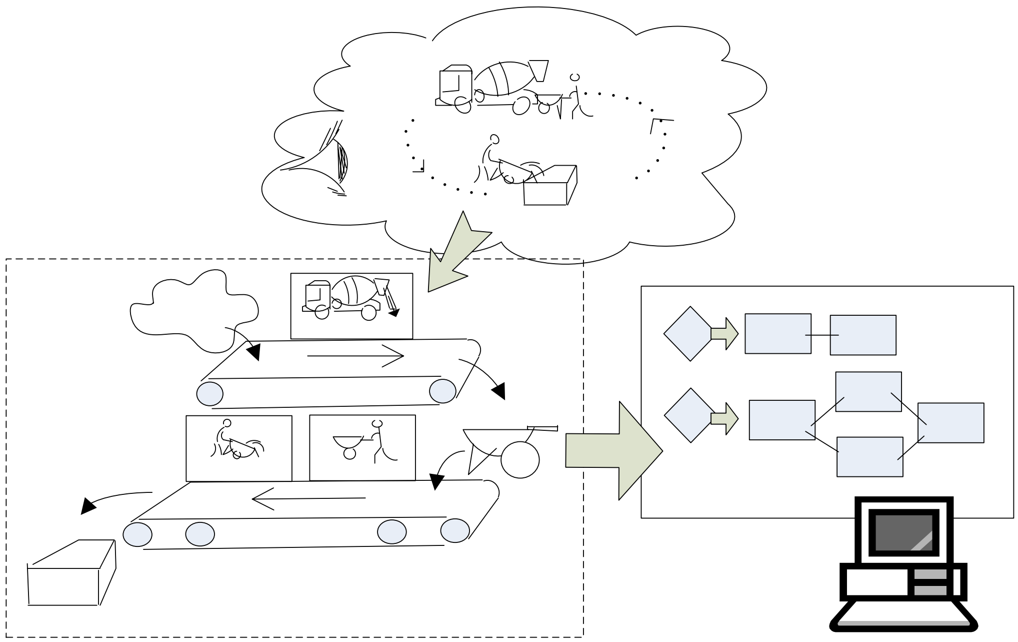

Figure 1.3: Converting a Construction Operations System into a SDESA Digital Model

Just like other AS based simulation methods, SDESA also needs a systematic modeling procedure that leads a construction engineer to define work flows of a construction operation system and form a SDESA model step by step. A systematic and efficient SDESA modeling procedure is developed from the present thesis research. At the mean time, the definition of material-handling work flows in SDESA simulation makes it natural to combine the site layout planning into the modeling procedure. The process and site layout integrated SDESA model is conducive to studying the dynamic, interactive, and complicated relationships between resources and technology constraints associated with the site operations.

1.2.2. Discovering Knowledge Hidden in Simulation Outputs by Artificial Neural Network

Based on experiments on the valid SDESA simulation model, the subsequent NN sensitivity analysis is intended to gain insights and deriving new knowledge on the real system for work efficiency enhancements. Sensitivity analysis in the context of simulation modeling, as given by Law and Kelton (2000), is to find out which of possibly many parameters and structural assumptions have the greatest effect on a performance measure. Often, procedures for seeking the optimum of a target output can be facilitated and informed by the knowledge of input sensitivity of a model.

The traditional sensitivity analysis method is to apply regression techniques onto a set of input-output data collected from running simulation experiments and further to estimate the input sensitivity by determining the partial derivatives of the regression equations. This method relies heavily on the regression model's validity, corroborated by analysis of variability, normality, heteroskedaciticity, correlated residual (Draper and Smith 1998).An independent input-output regression analysis is required for each output measure of concern (Porta Nova and Wilson 1989). Additionally, the regression approach does not well address the uncertainty of inputs and outputs, due to the stochastic nature of simulation modeling. Although substantial research has been undertaken into developing more efficient ways of sensitivity analysis for simulation, including the perturbation-analysis method (the single-run sensitivity-estimation method based on likelihood ratios (Kleijen & Rubinstein 1996)), and the use of light-traffic theory for queuing simulations (Simon 1989), a surrogate method for queuing networks (Vazquez-Abad & Kushner 1993), the procedures are still tedious and convoluted, as the simulation model is required to execute repeatedly to evaluate and observe the model's response (changes in outputs).

ANN mimics the learning process in the human brain to generalize an artificial intelligence model from observing patterns within historical data as provided on a complicated problem. ANN model can be used as a decision support tool for factor analysis, pattern recognition, classification and prediction on new scenarios in the problem domain (Lu et al. 2005). ANN is gaining popularity as a data mining approach that supplements the data warehouse, the enterprise resource planning (ERP) system for creating business intelligence. The ANN model - which was calibrated on the input-output data obtained from simulation - can be viewed as a function to substitute the simulation model itself for system performance prediction. Moreover, such a function also facilitates the simulation model sensitivity analysis, which guides the construction practitioners with sound decisions, and ultimately leads to the best arrangements on the simulated operations system. Compared with a regression model, the undistorted artificial neural network (ANN) sensitivity analysis technique (Lu et al. 2005) is able to map a set of inputs onto multiple outputs simultaneously, and capable to take into account the uncertainty dimension for one simulation output (for example, taking the mean and standard deviation of a simulation output variable as ANN outputs). This is deemed particularly useful and significant to sensitivity analysis for simulation modeling.

1.2.3. Implementation and Validation: the Precast Viaduct Construction Case Study

A precast viaduct construction project in Hong Kong is used to demonstrate the proposed methodologies as for (1) formalization of the SDESA modeling procedures; and (2) integration of Artificial Neural Network (ANN) with simulation. In this case study, the material inventory problem in the precast viaduct project is firstly described, then the application of SDESA simulation methodology is elaborated to illustrate the design and evaluation of the materials handling system in the precast viaduct construction. Particular emphasis is placed on the procedures of establishing a simulation model, the validation of the simulation model, the design of simulation experiments, and the analysis of simulation results (Chan and Lu 2005). Finally, the simulation experiment output data is used to train an ANN model which is capable of encoding the input-output relationships of the operations system by sensitivity analysis.

1.3. Research Methodologies

To establish a systematic modeling procedure for SDESA, most of the established discrete event simulation methodologies were reviewed. Several construction simulation methodologies, such as CYCLONE (Halpin 1977) and STROBOSCOPE (Martinez 1996), were studied in terms of their model setup procedures, functionality, and limitations. Then the functionality of the in-house simulation platform of SDESA was reviewed in detail. The simulation elements in SDESA (including the Flow Entities, Resources, and Locations) were defined clearly in terms of their usages, characteristics and application circumstances. The functionalities of all SDESA model elements and the proposed modeling procedure were illustrated and documented in the SDESA User’s Guide based on the experience gained in applying SDESA in different real projects. Typical site operations in Hong Kong were covered in these applications, the knowledge generated from the simulation was fed back to site personnel for better site management decisions. Finally, possible improvements of the existing SDESA system are identified for improvements in future research.

For the integration of ANN with construction simulation, the ANN technique was studied at the application level and some recent developments of this technique were reviewed. The simulation output data generated in the case of precast viaduct installation were used in training, validating, and verifying the ANN model. And finally, the SensitivityNN (Lu 2001) tool was studied and applied in training ANN model and conducting sensitivity analysis, which transfers the simulation output data into explicit and immediately applicable construction operations management knowledge.

1.4. Dissertation Structure

Chapter 1 introduces the motivation, and the objectives of the research. It also discusses the observed weaknesses of conventional Activity Scanning (AS) based construction simulation methodologies, and presents the brief idea of the proposed systematic modeling procedure for SDESA as well as the integrated Artificial Neural Network (ANN) simulation approach for simulation knowledge discovery.

Chapter 2 gives literature review on the existing approaches for operations simulation and ANN, with particular focus on construction applications. This chapter can help readers to understand more on the development of construction simulation and shed light on the motivation for this research.

Chapter 3 introduces the formalized ANN-integrated simulation modeling methodology. The frame work of how to employ the ANN to facilitate the knowledge discovery from simulation and the site-layout planning integrated simulation modeling procedures are presented. A typical earth-moving example is used in this chapter to illustrate the modeling procedure application.

Chapter 4 shows the implementation of this research on a local (Hong Kong) viaduct construction project. The operations system concerned in the viaduct construction project was modeled following the proposed modeling procedure and the simulation results collected were used to train an ANN model. This chapter demonstrates the applicability and usefulness of this research in practical settings. The last chapter (**Chapter 5**) concludes the research by recapitulating the contributions and giving suggestions for future research directions

2. LITERATURE REVIEW

2.1. Introduction

The objective of this research project is to (1) formalize the Simplified Discrete-Event Simulation Approach (SDESA) modeling procedures and (2) facilitate the knowledge discovery from simulation output by integrating Artificial Neural Network (ANN) with simulation. This literature review chapter provides background on construction simulation and ANN.

Section one is about construction simulation which reviews the development history of construction simulation on its simplicity and functionality enhancement, and the inherent limitation of Activity-Cycle-Diagram (ACD) simulation approach.

Section two reviews the applications of ANN on construction and gives a brief review on the invention and development of ANN. There is also a summary of ANN application research in construction in recent years. The summary of the ANN applications explains the reasons of ANN's popularity in construction and the most common application settings of ANN.

The last section places its focus on the ANN applications on construction simulation. This chapter reviews different approaches of ANN and construction simulation integration and gives comments to each of these approaches.

2.2. Construction Simulation

Discrete-event simulation is a powerful method to imitate the behavior of a real-world system over time by modeling repetitive processes in which durations of operations are stochastic and many resources interact (Law & Kelton 2000). It keeps track of the changes of the state of a system occurring at discrete points in time (Pidd 1992) and experiments with the system on a computer through a digital process model (Prisker 1986). The statistical data generated from the experiments provides users with insight into system's resource application, interactions, and constraints (Tommelein et al. 1994).

Though discrete-event simulation has been around for decades, this technique has not gained widespread use in industry. It is in part because (1) existing implementations did not represent many of the relevant characteristics of project components or construction resources, and (2) it is tedious to collect and assemble all required input data and to construct simulation networks (Tommelein et al. 1994).

CYCLONE (short for CYClic Operation Network, developed for construction operations simulation by Dr. Halpin at the University of Maryland in the early 1970s) is probably the best-known discrete event simulation system used in construction. Compared with the general simulation tools available (e.g. SLAM II) at that time, CYCLONE is much more simplified and easier to learn. It uses only a small set of modeling elements and lends itself well to system modeling in the construction context. Since the inception of CYCLONE, many enrichments based on the blueprint of CYCLONE have been proposed to extend its merits, including INSIGHT (Kalk 1980), MICROCYCLONE (Lluch & Halpin 1982; Halpin 1989), and UM-Cyclone (Ioannou 1988), DISCO (Huang and Halpin 1993), and STROBOSCOPE (Martinez and Ioannou 1999). The more recently developed "offspring" of

CYCLONE is STROBOSCOPE (Martinez 1996), which is a programmable and extensible simulation system designed for modeling complex construction operations. Nevertheless, none of these tools has gained widespread use in construction industry because of the limitations of these simulation methodologies in representing the characteristics of a real project, or the difficulty of applications in developing a valid simulation model (Tommelein et al. 1994; Paulson 1995).

With the objective of making the simulation of construction operations as easy as applying critical path scheduling, Shi (1999) developed Activity-Based Construction simulation method (ABC) to simplify the construction simulation by using one single element "activity" for modeling general construction processes −which is analogous to Critical Path Method (CPM). ABC is composed of the modeling module (ABC-Mod) and the simulation module (ABC-Sim). Similar to the activity-cycle diagram (ACD) of a CYCLONE model, ABC-Mod is a static schematic model which assists modelers to portray a real system with an ABC-compatible diagram by using only activity blocks and arrows to represent the operations logic. Yet, ABC carries the same shortfall of other PI modeling methods in coping with how to represent a resource's transit between various locations. Upon completing one activity, resource entities −which are shared by various activities− are generally released to the resource pool before being reallocated; as such, it is difficult and complicated to model the transit duration of resources between different activity locations with ABC. Zhang et al. (2002) mounted an animation layer on the ABC to visualize the queuing status and dynamic resource movements with icons, which, however, does not enhance the accuracy and flexibility of ABC in regard to modeling resource transit between site locations.

Another attempt in construction simulation simplification is the development of Simphony, which provides an integrated simulation environment for tailoring Special Purpose Simulation (SPS) templates, resulting in domain-specific, tailor-made simulation tools within a relatively short time (Hajjar and AbouRizk 1999; AbouRizk and Mohammad 2000). Despite the fact that SPS tools can facilitate the adoption of simulation by simulation novices in the construction field, customizing a stand-alone SPS tool still requires a large initial investment of time and resources. The designing, coding, and testing of the SPS tool entail the close collaboration of a construction expert with knowledge and experience in a special construction domain and a computer simulation expert.

These attempts of construction simulation simplification help shorten the modeling time by reducing the number of simulation notations or by providing tailor-made icons for model setup. However, the inherit limitations of simulation in portraying the real construction operations has not been investigated. One of the inherit limitations of Activity-Cycle-Diagram (ACD) based simulation is the difficulty of including activity location and site layout information in the model. To date, unless sophisticated model settings were involved, typical ACD based simulation tools, such as CYCLONE and most of its extensions, can only handle the "space" dimension in an implicit way (e.g. set one token as one parking bay) and disallowed a "tight coupling" approach that draws on simulation for evaluating site layout alternatives.

However, it is obvious that activity location and site layout consideration is essential to construction planning. Insufficient work space available in site results in productivity loss, potential safety hazards and poor-quality work (Riley and Sanvido 1995). And a good layout of transit paths and storage spaces on site for handling materials also contributes to the efficiency of overall construction operations (Li et al 2001). In general, how to place temporary facilities within the confines of a construction site so as to achieve efficiency and safety in the movement of resources is referred to as the site layout planning problem. The current practice of site layout planning largely relies on a planner's experience and common sense (Tam et al. 2002). The complicated space needs for production activities change as construction work progresses, which highly depends on the activities, equipment, and material involved (Tommelein et al. 1992). Different needs of space use including material deliveries, staging areas, and locations of major equipment and plants on site are usually foreseen and plotted in a two-dimensional chart at the beginning of a project and will not be updated until the project reaches the next phase of construction (Riley and Sanvido 1997).

Some researchers have proposed different approaches trying to integrate the space dimension into the construction simulation. Choo and Tommelein (1999) proposed the WorkMovePlan model consisting of (1) the site layout tier, (2) the physical flow tier, and (3) the process flow tier; their idea was to integrate the three tiers for linkage with process simulation modeling so as to quantitatively assess site layout alternatives. Yet, the linkage of simulation with the WorkMovePlan remained as "loose coupling", only to provide input to a separate undertaking of simulation modeling. Tommelein (1999) applied a simulation model ─built with the STROBOSCOPE software─ to investigate the amount of time construction workers spent traveling and waiting to receive service at a temporary facility (tool rooms). It is noted that much learning and modeling time was entailed in building the simulation model. Hand-coding efforts were required in linking up the simulation and site layout models. Therefore, an interface with a graphical package (such as CAD) describing the product as well as the layout characteristics can lend significant support to simulation modeling (Xu et al 2003). On a concrete dam construction project, Zhong et al. (2004) applied the geographic information system (GIS) to inform a CYCLONE model with the travel distance and quantity data. Their integrated system also featured 3D-animation for detecting simulation logic errors and reporting simulation results. So far, such interfaces between product and process models have only been instrumental in facilitating data exchange as of soil information and travel route information in earthmoving simulation applications. Another related work was the VITASCOPE system developed by Kamat and Martinez (2001) to enable accurate 3D visualization of specific construction operations modeled with STROBOSCOPE −spatially and chronologically. Applying VITASCOPE requires the knowledge of the syntax of a special marker language and is limited to depict the motion of resources and the states of completion on a constructed facility in a local area. Zhang et al (2005a) described the integration of a cell space model with a CYCLONE simulation model for bridge decking operations. The cell space model divides space into cells and the change of each cell's state over time reflects the space occupancy by a resource or an activity. As pointed out by Zhang et al (2005a), a tight coupling of CYCLONE with the space model is difficult due to the absence of a site layout representation in CYCLONE's schematic model and the lack of flexibility for assigning attributes to resource entities in a CYCLONE model.

Based on the modified process-interaction simulation paradigm, Lu (2003) developed a simple, effective construction simulation technique, called the simplified discrete-event simulation approach (SDESA). Besides the formation of a process flowchart model being simplified, SDESA is also capable to link its simulation model to a 3D site layout view produced with computer graphics, so as to use the site layout view as the animation backdrop in visualizing the operations being simulated and verifying simulation results. The process mapping and simulation methodology formalized in this research is essentially an extension of SDESA by explicitly defining activity locations in the site space and incorporating the site layout model in the generation of an operations simulation model. The main characteristics of SDESA are summed up below:

- Differing from the manufacturing-oriented PI, work flows in SDESA are not limited to linear processes (production-line work flow), and accordingly, the associated flow entities are not limited to product units (e.g. units of material, parts). Some construction resources (e.g. vehicles) can be readily identified as flow entities undergoing a close looping of activities (i.e. vehicle-loop work flow), as long as such resources are interchangeable and are bound to one work flow instead of being shared by multiple work flows. The vehicle-loop work flows are commonplace in construction and also constitute basic resource cycles in forming a CYCLONE model. Flow entities associated with all the work flows in a model are organized into one queuing structure, which is dynamically manipulated by the simulation executive according to the SDESA algorithm.

- In a SDESA simulation model, resource entities are classified into non-disposable (manpower/machinery resources) and disposable resources (material or information units that are generated by one activity and requested by another; they can constitute part of resource availability constraints in matching resources for invoking activities). All resources are organized in the resource entity queue of the model, which is the equivalent of the resource pool in a PI model. Note SDESA uses the disposable resources to logically connect multiple work flows in a construction system.

- The SDESA executive program marshals two dynamic queuing structures (namely, the flow entity queue and the resource entity queue) on first-in-first-out basis, so as to advance the simulation clock and execute activities that satisfy the logical and resource-availability constraints as specified by the modeler in the network diagram model.

2.3. Artificial Neural Network Applications in Construction

Artificial Neural Networks (ANN) are inspired by the structure and functions of brain neurons of the human brain. ANN considers Processing Elements (PE) as the basic unit (i.e. neurons in a neural network) and mimics the neural system by having a large number of connections between these PE. Each of these PE has N inputs and 1 output for signal transmission. PE does not execute instructions alone but responds to the inputs from connected PEs. Similar to the learning process of a human brain, a certain amount of learning examples are presented to the ANN during training process, in which the weight values associated with inter-PE connections are modified until the ANN is capable to generate the expected output (Hegazy et al. 1994).

The first Artificial Neural Networks (ANN) model can be traced back to the cybernetics and automate studies by McCulloch and Pitts in 1943. ANN is under the umbrella of Artificial Intelligence (AI). However, the development of ANN lagged behind the development of other AI development, such as expert system and robotics despite their parallel start since the early 1950s and until people had realized the high maintenance cost and the limitations in achieving intelligence of other AI approaches (Gallant 1988, Wasserman 1989). Therefore, after the early slow development, there has been a growing interest of ANN research, resulting in an increasing number of applications in civil engineering since the mid 1980s (Flood & Kartam 1994).

Several important reasons are highlighted by Flood and Kartam (1994) which makes ANN appealing to civil engineering applicants:

1) the ability of ANN in learning and generalizing from examples is superior to conventional regression models

2) the ability of ANN in generating "solutions" even the input data contains errors or is incomplete
3) once the ANN model is trained, short time is needed in response to a new question
4) relatively less demanding in the speed and memory of a computer as compared with other AI approach (this factor was especially significant in 1980s)

ANN applications in civil engineering domain published over the past two decades were studied, including journals and conference proceedings. The review results (in Appendix) contribute to the understanding on ANN methodologies and the application trend of ANN in construction domain.

Figure 2.1 summarizes the applications of ANN in different research areas within the civil engineering domain. It can be observed that most of the ANN applications are around construction management, including productivity estimation (43%) and tendering (10%). It is believed that the construction management problems, which involve many complicated factors and intertwined relationships, can be handled by ANN more effectively than conventional quantitative or heuristic methods. Other ANN applications relate to structural analysis (23%), geotechnical related problems (10%), and maintenance management (10%).

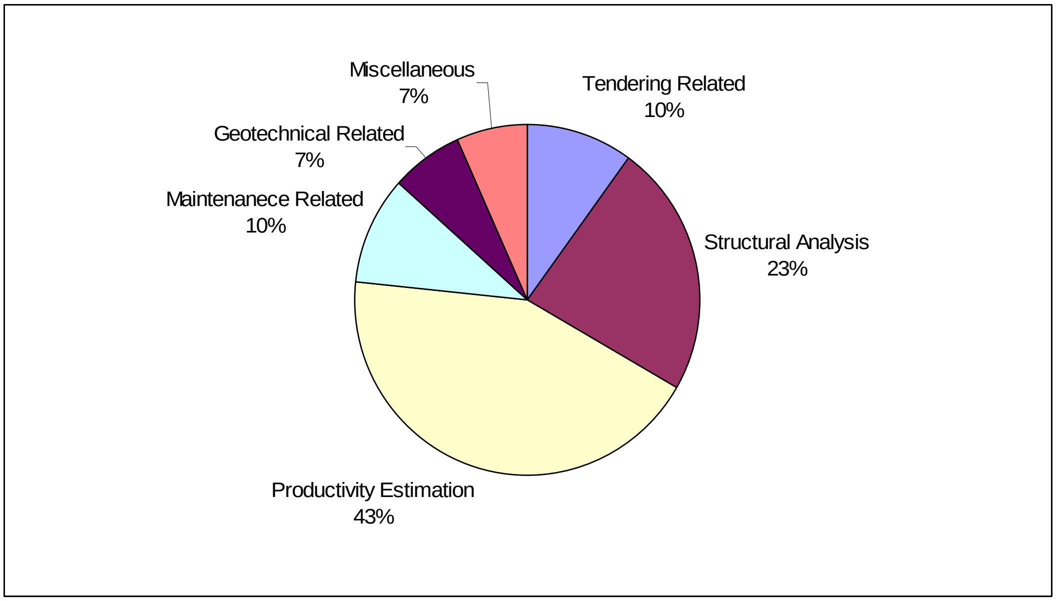

Figure 2.1: Applications of ANN on Different Research Areas in Civil Engineering Domain

Figure 2.2 presents proportions of different ANN algorithms in the civil engineering related applications. It is found that Back-Propagation Neural Network (BPNN) approach (Rumelhart et al. 1986) is the most commonly used (up to 83%) in search. The finding is consistent with Moselhi & Eldeen (2000) and Adeli (2001) that BPNN is the most commonly used type of ANN for civil engineering applications. The popularity of BPNN applications in the construction field is ascribed to its close analogy to the regression technique and its capability of approximating high-dimensional and nonlinear functions (Lu et al. 2001).

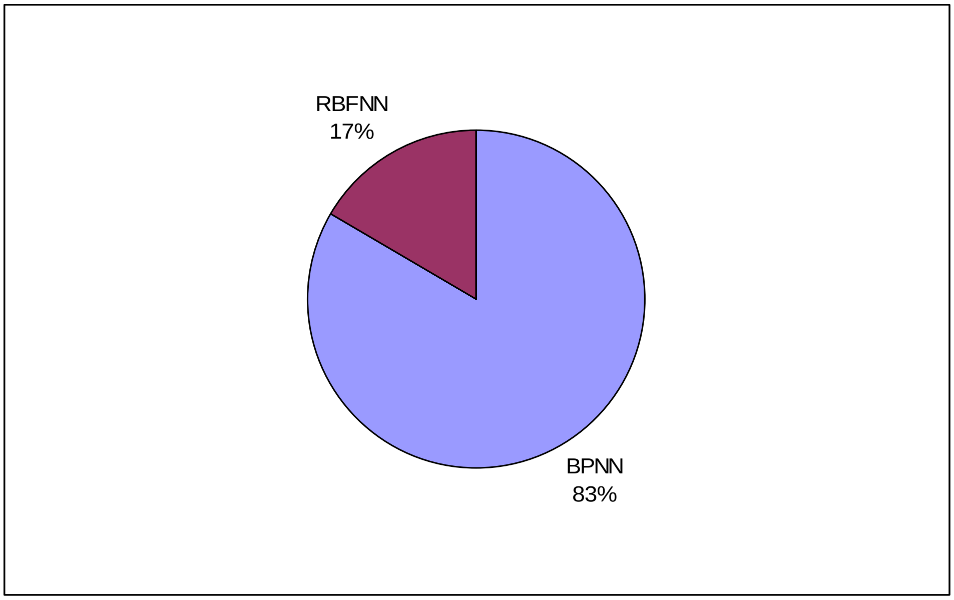

Figure 2.2: The Use of Neural Networks Approaches in the Construction Research

2.4. Artificial Neural Network and Construction Simulation

As for the applications of ANN in connection with construction simulation, the underlying approaches for integrating ANN with simulation can differ and they can be classified into three categories (Figure 2.3). The first approach replaces statistical distributions with ANN models in representing the uncertainty of input data for the simulation model (Chao and Skibniewski 1994; Hajjar et al. 1998). The second approach replaces the core simulation engine (i.e. the simulation event advancing mechanism) by ANN to update the state of the simulated system in order to speed up the simulation run (Flood and Worley 1995). The third approach (Zoe et al. 2002; Chao and Skibniewski 1994) suggests training ANN model by simulation results and uses the trained ANN model to approximate a complicated simulation model.

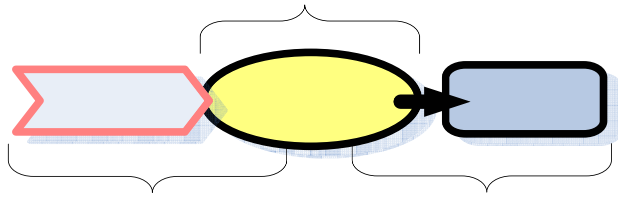

Figure 2.3: Three Different Integrating Approaches of Artificial Neural Networks and Simulation

The First Approach

Chao and Skibniewski (1994) trained a neural network for earthmoving productivity estimation. Their research used Artificial Neural Networks (ANN) to mimic the real excavator operations and generate more descriptive activity duration distribution for the simulation model. The ANN trained based on the observation data from a physical excavator is then embedded into an earthmoving CYCLONE model. The trained ANN translates multiple input factors (i.e. the digging depth and the orientation of the excavator) into a simple activity duration distribution. Another similar research by Hajjar et al. (1998) proposed a generic approach for integrating neural networks with simulation. An earth moving model was setup in which the productivity of the excavator in the model was dynamically linked to a trained neural network model which was trained by site observation data. The trained neural network model recalled the excavator's productivity during the simulation run and the change of the working environment was reflected as the work environment parameters were part of the neural network input. The proposed integration of ANN with simulation replaced the conventional Monte Carlo sampling in providing more interactive and dynamic activity duration approximation. Nevertheless, the proposed NN model duration estimation is incapable to fully reflect the activity productivity fluctuation due to operation variations in that only the mean value of the duration is generated.

The Second Approach

Flood and Worley (1995) proposed a neural network based method for construction simulation aiming to speed up the simulation execution through parallel computer processing. They used radial-Gaussian neural networks to form different modules to mimic subsystems in a construction operations system. Similar to a recursive function, the core neural network module was designed to recall its output to the module itself such that the previous state would be reflected in the next state of the simulation model. A typical earth-moving operations system was used to demonstrate the viability of the proposed approach. Flood and Worley’s approach is undeniably the most complete integration such that the modularized ANN completely replaced the discrete-event simulation engine. However, such replacement presents difficulty in the model validation as the integrated ANN modules are much more complicated to verify than conventional simulation models. Moreover, the proposed approach is incapable to generate and recall other operations information (e.g. resource utilization) except duration, which hinders the exploration on the simulated system in different aspects. Additionally, a large amount of training and validation on data can hardly be collected in reality. As such, the training and validation of the ANN simulation model inevitably rely on the conventional discrete-event simulation method in obtaining data.

The Third Approach

Zou et al. (2002) proposed a neural network embedded Monte Carlo simulation approach to account for uncertainty in water quality modeling. The Monte Carlo simulation was used to generate random inputs and the corresponding outputs were calculated by a mathematical model to form a dataset. Then the dataset were used to train an ANN model in order to replace the complicated mathematical model by simple ANN mapping. However, in this research, simulation is only used for sampling data and does not have a close coupling or interaction with the ANN.

Lu et al. (2001) deduced the partial derivative between the ANN input and output in establish an ANN model to estimate the productivity of spool fabrication. The approach is relatively accurate in identifying the significant factors with the input and output ranges were normalized before analysis. In this research, sensitivity analysis of Back-Propagation Neural Network (BPNN) as proposed in Lu et al. (2001) is used to gain insight into the BPNN which is trained with the construction simulation experiment data. This kind of ANN-simulation integration ease both simulation model validation and ANN model training, as noise-free data for calibrating ANN can be obtained from the valid simulation model. At the same time, ANN sensitivity analysis is conducive to understanding the behavior of the simulation model and further verifying the simulation.

2.5. Chapter Summary

Simulation provides a good alternative to assist construction managers in decision making. However, established construction simulation tools (such as CYCLONE) are still found difficult to model many operations which commonly occur in a construction site. This has called for further research to make construction simulation more straightforward or more flexible. Nevertheless, the stagnation of promoting construction simulation to industry practitioners leads to the rethinking of the inherent simulation paradigm of the CYCLONE-like simulation tools. The weakness of AS simulation paradigm is identified such that the "space" (or site layout) dimension is hard to be included in a natural manner in this paradigm. Therefore, the adoption of the alternative PI simulation paradigm is considered. The first task of this research is to formalize the modeling procedure suitable to Simplified Discrete-Event Simulation Approach (SDESA), which is based on an adapted PI simulation paradigm. The new modeling procedure will seamlessly consider activity locations and site layout planning in forming a SDESA simulation model.

The previous Artificial Neural Networks (ANN) application research efforts have fully demonstrated the advantages of ANN. Based on the literature review, it can be found that ANN is capable of handling large amounts of data and perform function approximation or prediction well without demanding substantial computing resources and modeling efforts. The research on integrating ANN with simulation in the past suggested several various ways of integration. However, it can be observed that "using simulation output data to train an ANN model to make ANN an approximating tool of the simulation model" is relatively practical and useful as the precision of the ANN modeling depends on the availability of a large amount of training data which can be provided from simulation output. Meanwhile, ANN-based sensitivity analysis helps in understanding the behavior of a complicated simulation model.

3. FORMALIZED ANN-INTEGRATED SIMULATION MODELING METHODOLOGY

3.1. Introduction

To improve the productivity of a construction operation, the existing practice relies on human intuitive judgment and experience. A scientific and systematic method for operations design and analysis has been called for to enhance construction operation productivity. The desired method should be (1) easy to pick up by industry practitioners, (2) flexible in handling diversified construction operations, (3) efficient to generate decision-support information in short time. The simulation modeling procedure proposed in this research provides engineers with a straight-forward and systematic means to describe common construction operations. The valid simulation model resulting from the proposed procedure can be used to estimate the responses of the operations system under different operation settings (e.g. different resource configurations, site-layout arrangements, construction methods). To amplify the usefulness of the simulation model, an Artificial Neural Networks (ANN), which can accurately map highly complicated relationships among multiple inputs to multiple outputs, can translate the experiment data from the simulation experiment to managerial knowledge in terms of input sensitivity measures. Eventually, the critical input factors identified can facilitate the seeking of the optimum operation setting and the managerial knowledge derived can be directly applied in improving construction management (Figure 3.1).

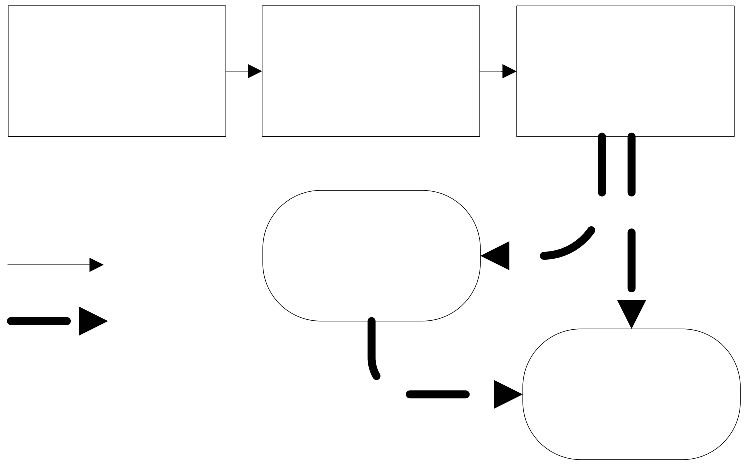

Figure 3.1: Flow Chart for the ANN-Integrated Simulation Method

3.2. The Framework of the ANN-integrated Simulation Modeling Method

The formalized ANN-integrated simulation modeling method includes three steps, they are:

(1) Setup simulation model for experimenting with postulated scenarios on computers,

(2) Train an ANN using the simulation experiment data, and

(3) Perform ANN sensitivity analysis.

The first step – "Setup simulation model"– is recognized as a bottleneck of the proposed ANN-integrated simulation modeling method. It is hard to find one construction operations modeling approach which is cost-effective while fully satisfying construction practical needs, although simulation has been researched for long time in improving its simplicity and applicability. To expedite the construction simulation, an innovative simulation modeling procedure synchronized with site layout planning is proposed in this research, which will be presented in detail with step by step demonstrations in the last section in this chapter.

When a valid simulation model is formed, a series of simulation experiments can be launched to examine the simulated operations system. The output data collected from the simulation experiments will be used for the training of the ANN model. The simulation output data is presented to the ANN model for the tuning of the network's linkage weights until the ANN is "fit" enough to make accurate output predictions. The ANN training algorithms and application methodologies are already well established in the literature. The Back Propagation Neural Network (BPNN) is recommended and adopted in this research.

The well trained ANN is capable of approximating the simulation output so as to allow non-simulation specialist to take advantage of simulation without conducting further simulation experiments. Moreover, and more importantly, the significance of each input factor toward the construction performance can be readily revealed by the established ANN sensitivity analysis procedure. Compared with a regression model, an ANN model is able to map a set of inputs onto multiple outputs simultaneously. ANN's convenience in handling multiple outputs at one time also makes it possible to take into account the uncertainty dimension for one simulation output, which is deemed particularly useful and significant to sensitivity analysis on a simulation modeling. The sensitivity analysis based on ANN adds value to construction simulation by converting the discrete simulation experiment records into valuable information for construction management in terms of both designing the optimum operation setting and assisting in making the sound action plans.

Since the invention of ANN, several different sensitivity analysis approaches were proposed to assist acquirement of insights from it (Craven & Shavlik 1994). For instance, Knowles (1997) added up the absolute value of weights from one input node to every hidden processing element in an ANN model trained for pipe installation productivity estimation. The total weight value of the connections to an input nodes is used to gauge the importance of the corresponding input node. Li et al. (1999) adopted a heuristic approach, which was first proposed by Fu (1994), to extract rules from a trained ANN and try to explain how the construction markup percentage was suggested by the NN. Sinha and McKim (2000) used statistic analysis methods to identify the dominant factors of an ANN model trained for construction organization effectiveness measurement. However, these methods were found to be either inaccurate in rule extraction from ANN or constrained to handle only simple small-scale ANN networks. Adopting the sensitivity analysis approach, Lu et al. (2005) made use of a trained ANN to account for the relative effects of each input factor upon the target outputs in undistorted terms. Compared with a regression model, an ANN model is able to map a set of inputs onto multiple outputs simultaneously. ANN's convenience in handling multiple outputs at one time also makes it possible to take into account the uncertainty dimension for one simulation output, which is deemed particularly useful and significant to sensitivity analysis for simulation modeling.

Because ANN approaches have been well established in the literature, this dissertation will not present the training algorithms and application mechanisms of ANN. However, ANN application will be demonstrated in a local viaduct construction case study in the next chapter. The remainder of this chapter presents the process mapping and simulation methodology for integrating site layout and operations planning in construction. A simple earth-moving case is used to demonstrate the application of the new methodology, resulting in the generation of a SDESA simulation model. The complete application of ANN-Integrated simulation modeling will be given in Chapter 4, which resorts to a real-world project for problem definition, data collection, simulation modeling, and ANN sensitivity analysis of the resultant simulation model.

3.3. Process Mapping and Simulation Modeling Method

Work space needs on activities change as construction work progresses and highly depend on the activities, equipment, and material involved (Tommelein et al. 1992). Insufficient work space available in site causes productivity loss, potential safety hazards and poor-quality work (Riley and Sanvido 1995). A good layout of resource transit paths and temporary storage spaces on site for handling materials is always critical to the efficiency of overall construction operations (Li et al 2001). In order to include the spatial consideration in term of activity location and site layout in simulation, this research proposes a systematic procedure to seamlessly synchronize the process modeling and the site layout modeling for construction planning. A general-purpose, flowchart-based simulation modeling methodology is linked to a site layout model to formulate an integrated simulation model for studying the dynamic, interactive, and complicated relationships between (1) the resource/technology constraints associated with the site operations and (2) the spatial constraints imposed by the site layout.

3.3.1. Terminology Definitions

Construction operations entail moving materials (dirt, concrete, steel, wood), precast or prefabricated components and assembling them into the final building products at specific locations in the site. This is facilitated with manpower and machinery resources and dictated by product designs (i.e. the blueprint drawings) and construction technologies (i.e. technical specifications prescribing activity sequences and quality standards). The resource-driven nature of construction engineering presents the distinct challenge of modeling the dynamic allocation, transit, and matching of an assortment of construction resources (manpower/machinery/material) at certain activity locations, subject to the space, resource and technology constraints. Executing activities in a construction system is in general contingent on the availability of all required resources and subject to all relevant logical/technological constraints. Thus, the characteristics of a construction operation make it difficult to be described and modeled in a systematical way. Hence, one key objective of this research is to **give guidance on how to identify and organize scattered activities and dynamic resources into workflows for easy formation of a construction operations simulation model.**

The workflow defined in SDESA is close to the production cycle defined in Method Productivity Delay Model (MPDM), which is a productivity measuring and evaluating method for construction systems proposed by Adrian and Boyer (1976) in 1970's. The first step in applying MPDM is to collect the production cycle duration and productivity delay data. Then productivity indexes, such as the ideal productivity and the method productivity, are calculated based on the collected data. The calculation results along with the site observation data help engineers to the gauge the construction activity performance and identify the critical delay factors. MPDM provides construction firms with a simple means to perform productivity measurement and evaluation. Nevertheless, the manual data collection and assumptions of the analysis limit its applications to simple construction operations. Moreover, MPDM is incapable to perform activity productivity estimation for postulated (i.e. not existent yet) construction operations systems as the reliability of the method is highly dependent on accurate and actual operation data. However, MPDM has established a systematic framework for portraying a construction system with production units, resources, activities, and workflows.

According to Adrian and Boyer (1976), a **workflow** (termed as **production cycle** in Method Productivity Delay Model (MPDM)) is a group of construction activities involved in the handling, processing, or moving of a **flow entity** (termed as **production unit** in MPDM), which is facilitated by scarce resource (termed as **leading resource** in MPDM). A flow entity is an amount of work descriptive of the production which can easily be visually measured flowing around the work flow. Typical examples of flow entities are (1) a scraper of soil being transported and dumped, (2) a bucket of concrete being poured, and (3) a precast segment being installed. By observing the flow entities in a construction operations system, a modeler can define workflows such that each workflow handles only one distinct type of flow entities. Usually, the method productivity reflects the sufficiency of the resource provision in an operation system. Typical examples of leading resources include (1) loaders for earth moving; (2) a tower crane for the pouring of concrete; (3) a lifter for precast element installation. Although MPDM is only concerned with one leading resource in site observations, SDESA allows the considerations of multi-resource for each activity in order to portray the practical work situation. Taking the typical earth-moving operation as an example, the truck-load (i.e. soil carried by trucks) is the flow entity; the loaders which load the trucks are the resource; and the work cycle of moving soil from the cut site to the dump site forms the workflow.

3.3.2. Build up the Complete SDESA Model

The general steps for process mapping and simulation modeling with SDESA are as follows:

Step 1: <u>Breakdown the construction operations system into workflows and mark down all the key locations by hollow circles in a site layout plan</u>.

Step 2: <u>Mark a production activity with a square node</u> around its corresponding location circle; while <u>a transit activity is denoted with a thick arrow</u> linking two location circles corresponding with the origin and destination locations. There could be some additional precedence relationships between production activities defined at the same location cycle and the precedence logic between these activities should be clearly specified.

Step 3: Initialize the quantity and arrival times of Flow Entity (FE) associated with each work flow in a diamond block connecting to the first activity of each work flow.

Step 4: Allocate the resources to activities and initialize the type and quantity of resources in the resource pool. Note both the available time and the current location of each resource in the resource pool are initialized prior to the start of simulation, which are continuously traced and dynamically updated in order to reflect the current state of the system as simulation proceeds. Disposable Resource (DR) representing the intermediate products or signals is defined and used for linking up activities in different work flows. DR may be generated at the end of the activity or initialized in the resource pool before the dynamic run.

Step 5: Specify activity times as constants or distributions. Alternatively, a transit activity's duration can be defined as the travel distance divided by the resource's moving speed. The travel distance can be directly informed by the site layout model (e.g. the Euclidean distance between the center points of two location circles), while uncertainties −relating to (1) conditions of the resources involved and (2) activity interruptions due to interfering traffic in the site or other environmental factors− can be contained within a statistical distribution which describes the resource's moving speed.

Step 6: Specify any additional transit times as incurred by resources in serving different activities at various locations in the resource transit information system (RTIS), in which information of resource transit from one location to the other is specified. During simulation, RTIS will be queried for updating the state variables of the system. As such, the model structure can be considerably streamlined, and the model definition significantly simplified in comparison with an Activity Cycle Diagram (ACD) modeling approach (such as CYCLONE).

Step 7: Automatically map location circles in each work flow onto their corresponding positions in a site layout model so as to complete the formulation of the simulation model in a site layout view. In the prototype computer platform of SDESA, a production activity is represented as a square block placed at a location circle and a transit activity with a line section connecting two location circles. Since more than one activity may overlap in space, we apply different color schemes onto the square block (or the line section) so as to distinguish different activities and highlight the currently activated ones in the animation of the dynamic process simulation.

3.4. Small Illustrating Example

To illustrate the above terminology definitions and modeling procedures, let us consider a simple earth-moving operation case: at the cut, a pusher and a scraper work together to push-load soil into the scraper's bowl. The pusher then backtracks for loading the next scraper, and the scraper hauls a soil unit (i.e. one scraperful) to the fill, dumps, spreads, and then returns to the cut. Once 20 push-loads are completed, the pusher moves toward the side and trims the side. After side trimming, the pusher then moves back to continue push-loading scrapers. Each scraper handles a soil unit of 20 m^3. The objective is to find the optimum number of scrapers that match one pusher tractor in moving 10,000 m^3 from the cut to the fill. Figure 3.2 illustrates the problem statement and shows the ACD model in the CYCLONE form.

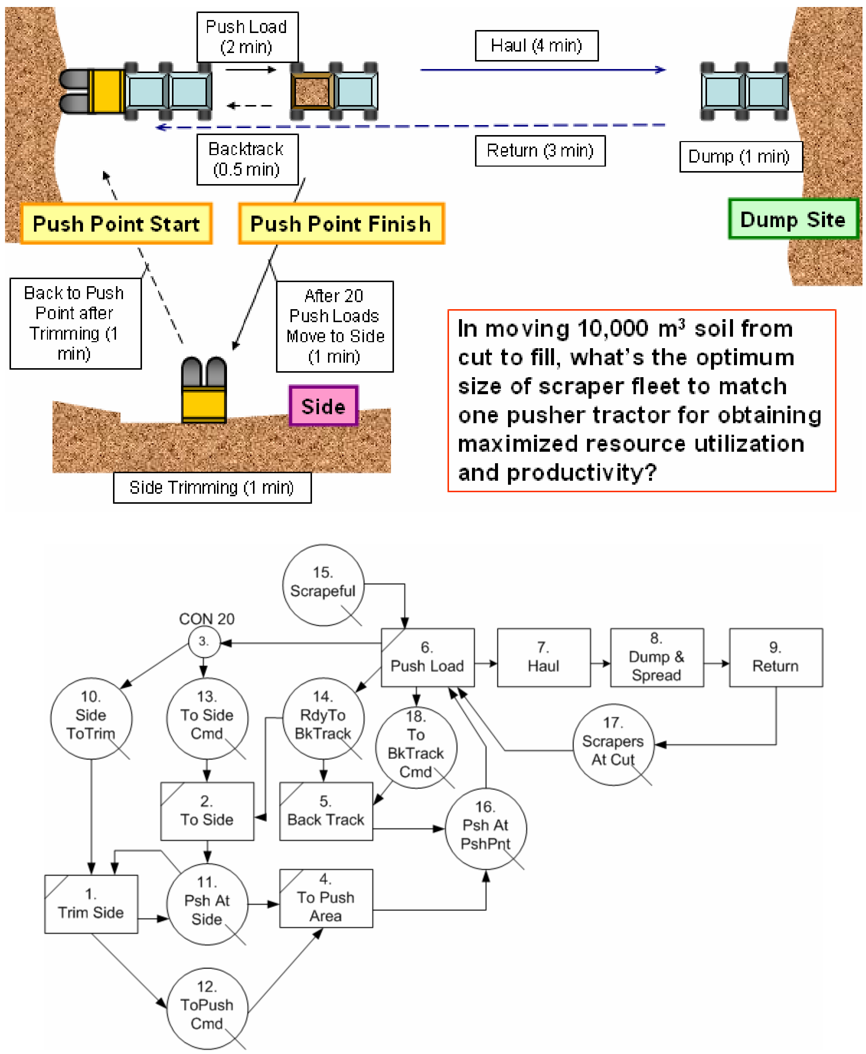

Figure 3.2: Typical Earth-Moving Operations and the Corresponding CYCLONE Model

The modeling procedures being proposed are applied step by step as follows:

Step 1: In this case, two workflows can be readily identified as "the earth moving" workflow and the "side trimming" workflow. By tracing the movement of a scraper, the modeler can circle the key locations in the site space where a scraper performs the "earth moving" work flow and define their coordinates in the site space, including "Push Point Start", "Push Point Finish", "Dump Site" (Figure 3.3). In addition, in order to realize the logic of trimming side during earthmoving, one location "Side" is marked for the "side trimming" workflow.

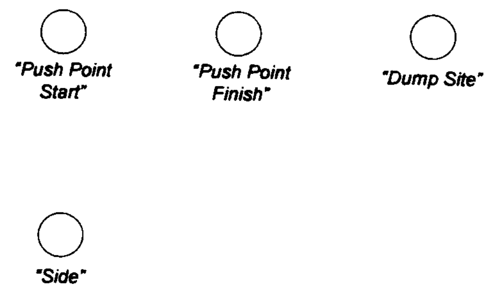

Figure 3.3: Define Key Locations in workflows

Step 2: In the "earth moving" work flow, three transit activities ("PushLoad", "HaulToSite", and "ReturnToSource") are denoted with thick arrows linking related location circles; and one production activity "DumpDirt" is denoted with a square node on the "Dump Site" location circle. For the side trimming work flow, the production activity "TrimSide" is also marked on the "Side" location (Figure 3.4).

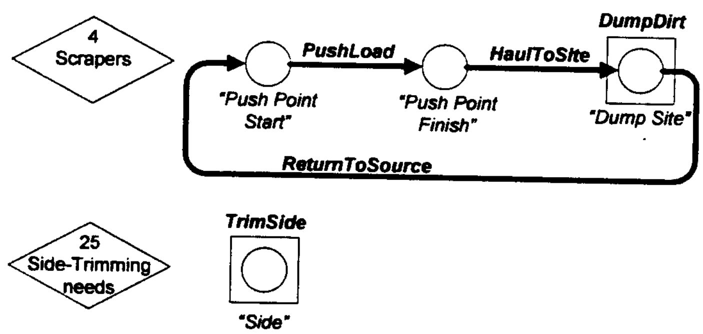

Figure 3.4: Allocate Activities to Key Locations and the Determination of Flow Entities

Step 3: Assuming 4 scrapers are used for the "earth moving" operations, 4 FE are initialized for the first work flow. On the other hand, for 25 times of side trimming in connection with the earth moving operation, 25 FE are initialized - representing the "side-trimming needs"- for the "side trimming" work flow.

Step 4: One soil unit (+SU on top of the activity "PushLoad" arrow) and one pusher (1 PU) are required resources for processing one scraper by the "PushLoad" activity (Figure 3.5).

DR called "Push Load Finished" (PLF) which is generated at the end of "PushLoad" activity (dashed rectangle in Figure 3.5). As for the "TrimSide" activity, 20 such PLF (Disposable Resource) plus one pusher ready at the "Side" location define its resource needs (Figure 3.5). 1 Pusher, 500 +SU (i.e. 10000m^3 divided by 20 m^3 per scraperful), and 0 +PLF are initialized in the resource pool prior to executing the simulation.

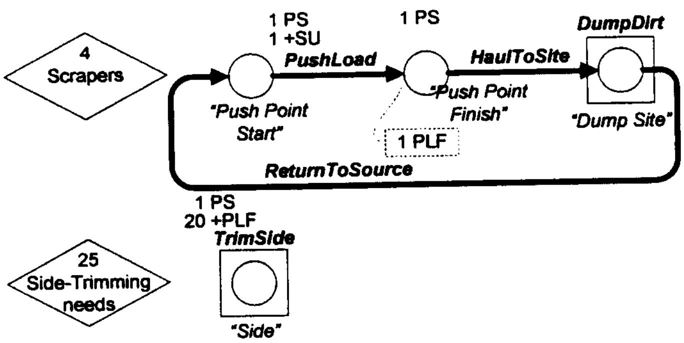

Figure 3.5: Allocate Resources to Activities

Step 5: Specify activity times according to time data given (as shown in Figure 3.2.)

Step 6: The pusher, as a shared resource between the two workflows, serves two activities (i.e. "PushLoad" and "TrimSide") and it takes certain time for the pusher (1) to backtrack from "Push Point Finish" to "Push Point Start", (2) to transit from "Push Point Finish" to "Side" and (3) to return from " Side" to "Push Point Start". The three transit paths of the pusher are marked with three dashed arrows in Figure 3.6. This transit information of the pusher is specified in Resource Transit Information System (RTIS) of the current model (Figure 3.7).

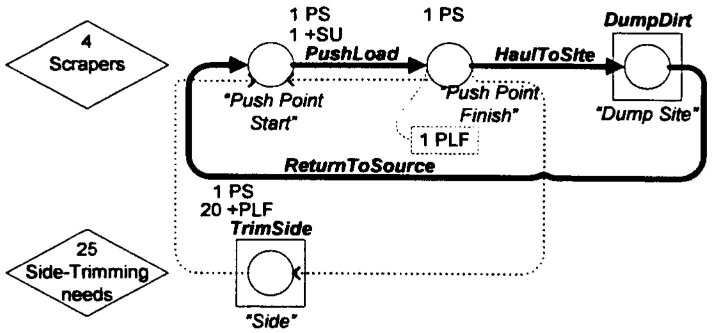

Figure 3.6: SDESA Model of the Earth Moving Operations with the Transit Path of the Pusher

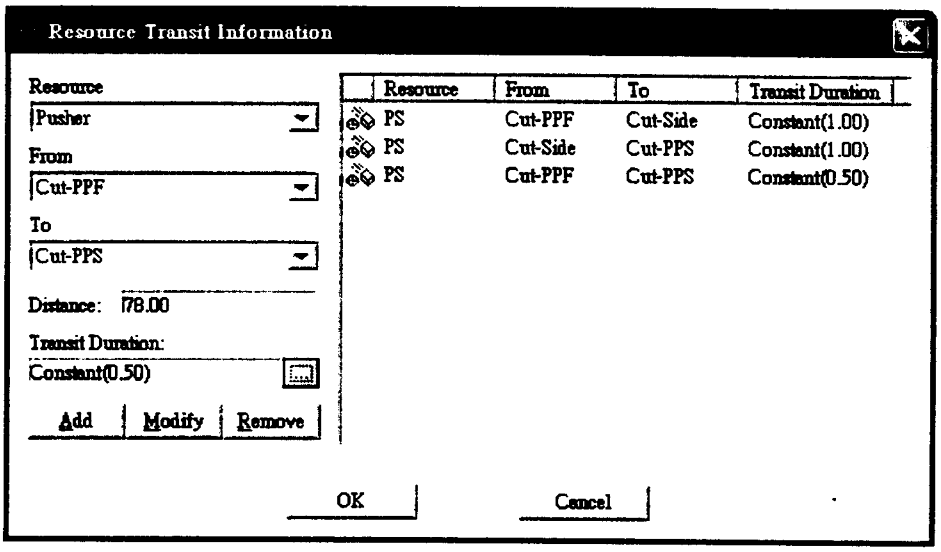

Figure 3.7: Interface of the Resource Transit Information System (RTIS) in SDESA

Step 7: After mapping the location circles onto their corresponding positions in the site layout model, the formulation of the simulation model is completed and the simulation model placed in the site layout view can be automatically generated (Figure 3.8), based on which, simulation analysis and the ensuing animation replay of simulation computations are conducted.

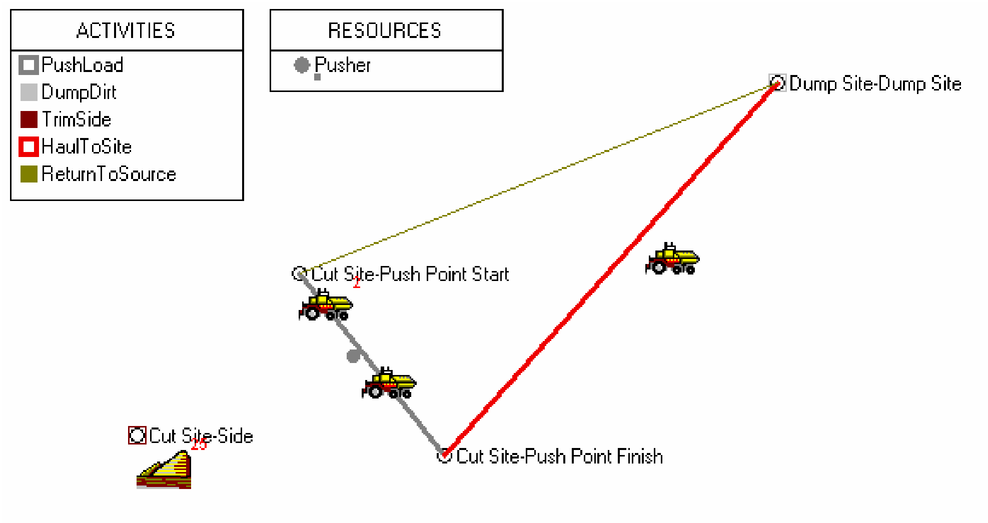

Figure 3.8: Formulation of Simulation Model in Site Layout View

3.5. Chapter Summary

Integrating Artificial Neural Networks (ANN) to simulation helps analyze simulation results and make available simulation-generated knowledge to non-simulation specialists. The ANN-based sensitivity analysis also facilitates the identification of controlling factors upon the output variables by (1) shedding light on the reasoning logic, and (2) gaining insight into the problem definition. In this chapter, the framework of how to amplify the benefit from construction simulation by using ANN to sublimate discrete simulation output data into valuable management knowledge are presented.

To facilitate the use of simulation in conducting operations planning and evaluating site layout alternatives in construction, a generic process mapping and simulation methodology is proposed. The proposed modeling procedure explicitly defines activity locations in the site space and hence incorporates the site layout model in the generation of an operations simulation model. Following the modeling steps, the process model (flowchart) is developed and then linked with a site layout model so as to automatically generate the simulation model in the site layout view. The underlying simulation engine program (SDESA) draws on site layout information and resource transit information system from the simulation model definition to trace and update the state variables (such as resources' available time and current location) during simulation. The simulation model development and validation is also simplified through visualization and animation of the dynamic site operations in the site layout context.

In short, the proposed formalized ANN-integrated simulation modeling method provides construction practitioners with a scientific and systematic method for operations method improvement, which is (1) easy to pick up by industry practitioner, (2) flexible in handling diversified construction operations, (3) efficient enough to generate insightful information in short time. Also, the site layout planning synchronized simulation methodology can simplifying the modeling of typical, repetitive construction processes and potentially augments conventional approaches for site layout planning and materials handling system design.

4. IMPLEMENTATION – Precast Viaduct Construction

4.1. Introduction

The proposed simulation modeling methodology coupled with Artificial Neural Networks (ANN) analysis of simulation output described in the previous chapter was applied on a precast viaduct construction project for the effectiveness improvement of the materials handling system on site. This chapter first describes the material inventory problem in the precast viaduct project, followed by the elaboration of how to apply the simulation methodology as illustrated with the case study of designing, evaluating the materials handling system in precast viaduct construction. Particular emphasis is placed on the procedure of establishing a simulation model and the design of simulation experiments. Then, the data collected from the simulation experiments based on the valid simulation model established were analyzed by graphical analysis methods. After that, the ANN modeling and ANN based sensitivity analysis were performed to quantify the effects of each input factor upon the output measures of performance.

4.2. Background of the Case Study

The Deep Bay Link North project connects to the Shenzhen Western Corridor - the artery to link Hong Kong with the city of Shenzhen – the fast-growing manufacturing and business hub in southern China. The main scope of contract is to construct a 4.2 km long Deep Bay Link mainline consisting of at-grade concrete road and viaduct, which is built of precast segmental box girders and crosses over existing main roads and railways (such as Castle Peak Road, Kolwloon Canton Railway, Light Rail Transit, and West Rails). The client is the Highways Department of the Hong Kong SAR Government. The contract value totaled to HK$1,716 million (US$220 million), and the construction period was October 2003 - October 2005. Gammon Construction Ltd (GCL) was appointed as the main contractor, under whom more than 70 subcontractors were employed.

On the Deep Bay Link North Project, the stepping girder precast construction method was utilized to erect over 227 spans of post-tensioned viaduct in order to minimize the interferences with the existing traffic on the roads and railways crossing the viaduct under erection. A complete cycle of one span viaduct erection comprises three main phases: namely, (1) placing the precast segments in positions as designed by use of a giant gantry riding over two piers of the current span, (2) concreting the stitching joints plus post-tensioning the segments, and (3) advancing the stepping girder to the next span by using a group of powerful hydraulic jacks. Figure 4.1 shows the giant gantry of the stepping girder.

Figure 4.1: The Giant Gantry of the Stepping Girder for Erecting Precast Segments

4.3. The Simulation Objective

The precast segments were fabricated in the neighboring Guangdong province of the mainland China and only allowed to be hauled to the Hong Kong site during the night time – which was restricted by the highway traffic regulations. In some locations along the viaduct, the workface area under the span was spacious enough to store all the segments within the handy reach of the crew, while for many other spans, it became too narrow to freely move a heavy-duty crane around, let alone to stock up the bulky precast segments (12m x 2.5m x 2.8m each; Figure 4.2).

Figure 4.2: Bulky Precast Segments (12m x 2.5m x 2.8m Each) Temporarily Stored around the Working Span

As a matter of fact, such congestion problems are commonplace in precast construction with several activities concurring near the workface area, presenting safety hazards and hampering construction productivity (Low and Choong 2001). Therefore, the site management realized that it was ineffective and unsafe to strive for sufficient storage space for accommodating up to seventeen precast segments in the close vicinity of many spans under construction. To alleviate the congestion around the temporary storage area under a working span, an alternative solution was to partially store the precast segments at a relatively remote storage area, as illustrated in Figure 4.3.

However, in postulating such alternatives, it was not straightforward to address two questions: (1) how far the remote storage area would be located to ensure a smooth, efficient segment erection process; (2) how many precast segments could be stored there such that the targeted cycle duration would be maintained. Note, any disruption to the site progress would translate into considerable losses; for instance, any logistical hiccups in supplying the precast segments might disrupt the rhythm of construction, potentially leaving the specialist crew (manpower and plant) idle for considerable time. As a result, the five-day cycle duration for erecting one current span would be prolonged. Further, this might cause a negative ripple effect on the progress of the succeeding spans and the completion of the whole project. According to the Critical Path Method (CPM) plan obtained from the site, the tasks concerning the precast segment installation resided along the critical path of the project schedule. As such, a one-day delay to the target cycle duration on a particular span would potentially lead to a one-day extension to the contract period, subjecting the contractor to paying for liquidated damages.

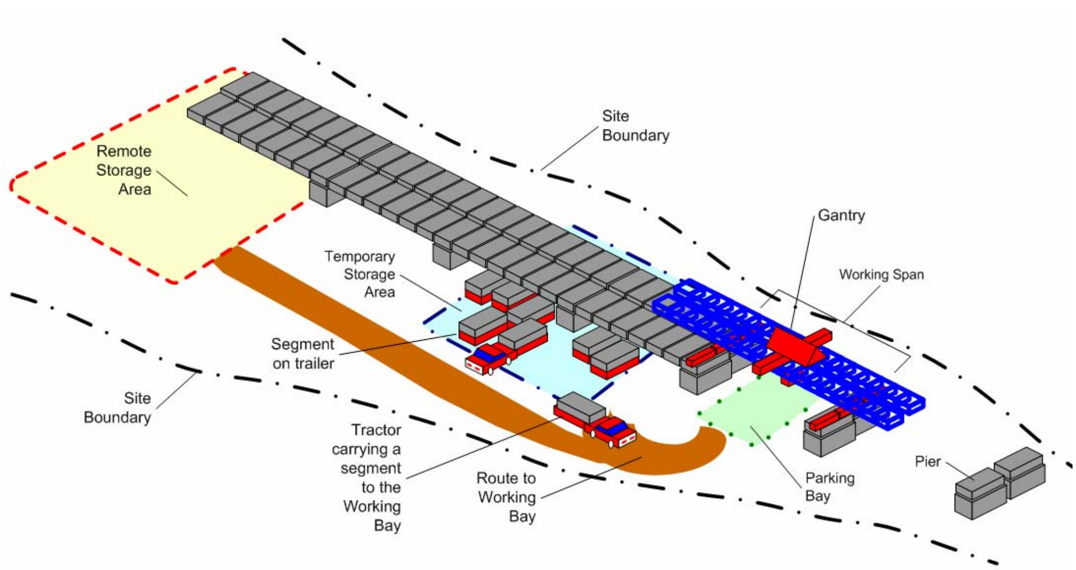

Figure 4.3: Alternative Materials Handling System Design: the Precast Segments Partially Stored at a Relatively Remote Storage Area and then Hauled to the Working Span Using Tractors

In designing the materials handling system for the precast viaduct project, four relevant factors were identified and their effects on the cycle duration for installing one span viaduct were assessed through simulation modeling and simulation-based experiments. The four controlling factors identified are (1) the storage capacity of the remote storage area which supplemented the temporary storage area immediate to the working span, (2) the positioning of the remote storage area, (3) the number of tractors rented for hauling precast segments from both the temporary and remote storage areas to the working span, and (4) the batches and times of the precast segment deliveries (the precast supplier delivered all the segments for one span in one batch before site erection operations started or in two batches over the first two nights of the five-day cycle.)

4.4. Mapping the Operations to SDESA Simulation Model

This simulation study is based on (1) the direct site observation of the precast segment installation cycles, (2) the interviews with the experienced site staff, and (3) the assessment of site records (such as the method statement, the work schedule, the daily report) during July/August 2004. The following information was obtained as model inputs: (1) the CAD illustrations for the construction operations and processes; (2) the brief work breakdown structure; (3) the resource requirements for activities; (4) the activity durations; (5) the resource availability and working hour constraints; and (6) the working hours and process interruptions. Note, the working hours (08:00 ~ 23:00 in two shifts, Mon ~ Sat) and regular activity interruptions (i.e. lunch/dinner breaks, non-working hours at night) applied to all the site activities, except for the activity of curing of the “stitching” concrete (twelve hours).

The observed erection cycle of the precast segments started when a tractor hauled the first segment from a staging area in the site (a temporary storage close to the current span) to the workface area under the current span. The spreader beam (a mechanical hoist attached to the stepping girder) hoisted the segment off the tractor’s trailer to its designed position and finished the erection cycle after the segment was placed in position and firmly locked onto the hanging bars of the stepping girder. Once all the segments (14 segments for the observed span) of the current span were placed, epoxy was used to glue them together, also serving as a lubricant to facilitate the segment installation and forming watertight joints as the epoxy hardened. The gaps between the end segments and the piers were then stitched with ready-mixed concrete. Adequate curing of the "stitching" concrete required 12 hours before all the precast segments could be post-tensioned into one complete span of viaduct. At last, the stepping girder was disengaged from the current span for advancing to the next one.

The modeling steps for the precast viaduct installation are explained in detail below:

Step 1: Breakdown Operations System into Workflows and Identify Key Locations

The precast segment is readily identified as the flow entity in this viaduct construction operation. Two types of resources carry the segments horizontally and vertically respectively, namely (1) the tractors which carry the segments from storage areas (either the temporary or remote storages) and (2) the spreader beam mounted on the gantry which offloads a segment from a tractor to its designed level and position. For the ease of simulation experiment, the segment hauling processes from the remote storage area and the temporary storage area are broken down into two work flows. The key locations identified along these two workflows are marked with circles in a bird's eye view shown in Figure 4.4.

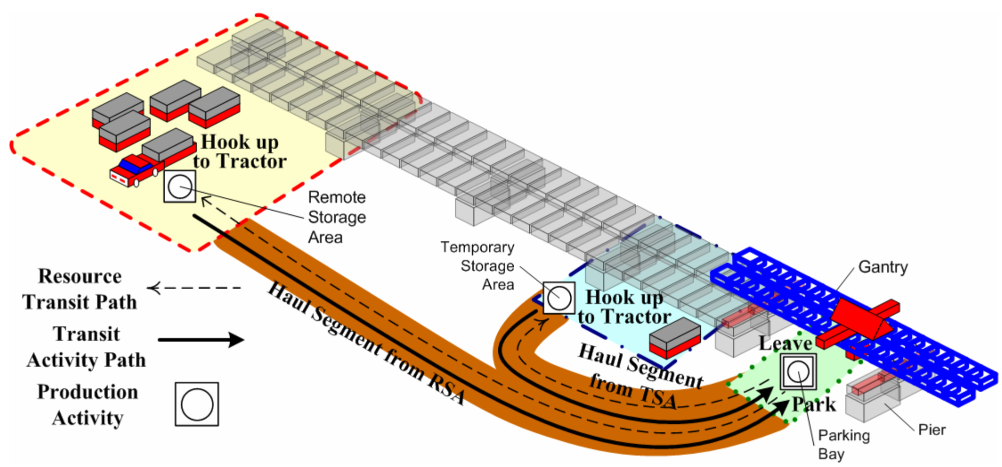

Figure 4.4: Illustration for the Segment Hauling Work Exercises

Similarly, the key locations of the segment erection are identified as the segment unloading spot under the span and the temporary hanging position along the gantry. These key locations are marked with circles shown in Figure 4.5 .

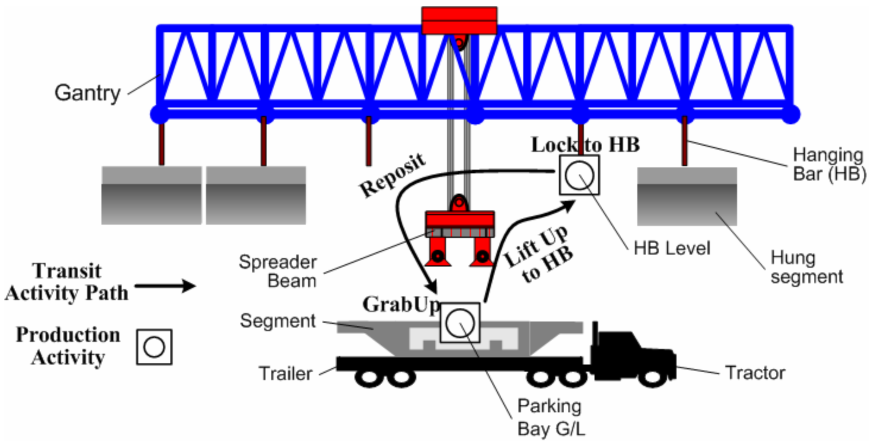

Figure 4.5: Illustration for the Segment Erecting

Another auxiliary workflow on post-erection operations is considered to complete the simulation model for one span work cycle. The job order for post-erection operations (i.e. the completion work after the temporarily hanging all segments on the gantry) is defined as the flow entity.

Step 2: Assign Activities on the Key Locations

At the temporary storage area, a tractor (TRT) hooks up a trailer loaded with one segment at the temporary storage area. Then the tractor hauls the segment from the temporary storage area to the working span. When the parking bay (PB) under the span is empty, the tractor pulls in and parks under the working span for unloading the segment. Upon the segment is lifted up by the spreader beam of the gantry, the tractor leaves the parking bay. In a similar way, the second work flow for hauling segments from the remote storage area to the working span can be interpreted. The transit and production activities of the segment hauling workflows are represented by thick arrows and square boxes respectively in Figure 4.6.

The spreader beam mounted on the gantry undergoes the cyclic process of segment erection: it lifts a segment off the tractor and places it onto the hanging bars of the gantry; then the segment is locked to the hanging bar as a temporary support and the spreader beam repositions itself and returns for handling the next segment. The transit and production activities of the segment-erecting work are represented by lines and square boxes respectively in Figure 4.7.

Step 3: Define and Initialize Flow Entity

The tractor is identified as a scared resource while the precast segment is the Flow Entity (FE). For the horizontal segment transportation work flows, segments (the flow entity) at the two storage areas along with their delivery times are initialized for the two segment hauling workflows. For example, 4 FE and 10 FE are allocated to the "Segments at RSA" and "Segments at TSA" diamond blocks respectively in the base-case model, indicating four segments are stored in the TSA while the remaining ten in the Remote Storage Area (RSA).

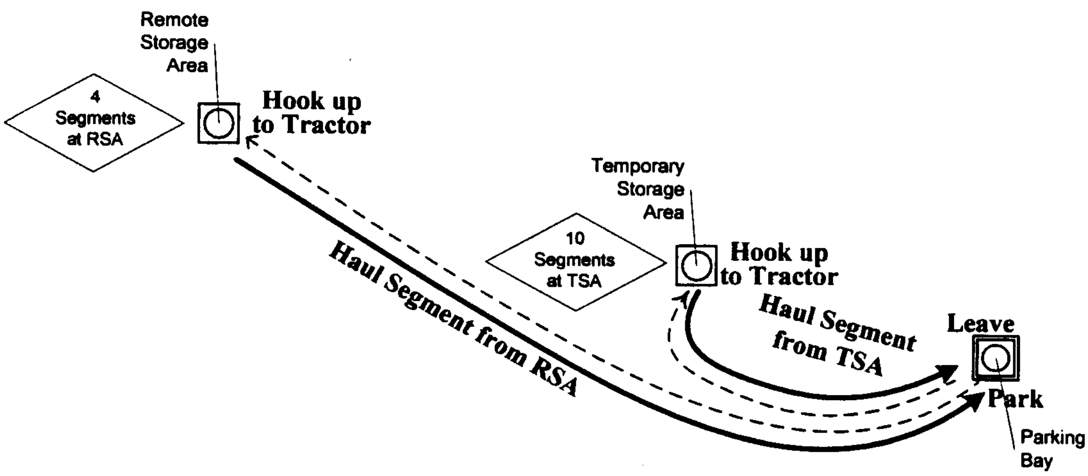

Figure 4.6: SDESA Model of the Segment Hauling Work Flows

For the segment erection work, because the spreader beam (a crane mounted on the giant gantry) is not a shared resource while the arrival of segments is not scheduled (it depends on the tractor deliveries), the spreader beam is designated as FE and, hence, the work flow is formed in a loop (Figure 4.7).

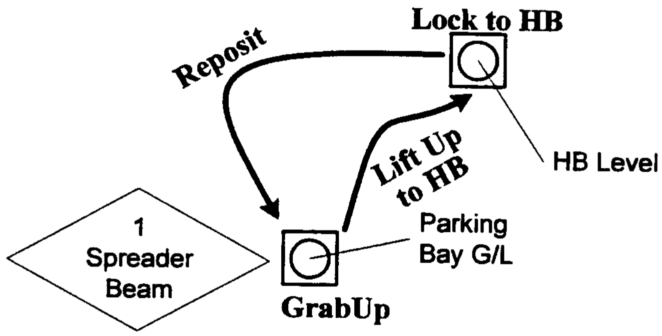

Figure 4.7: SDESA Model of the Segment Erecting Work Flows

Step 4: Allocate and Initialize Resources

In a SDESA simulation model, activities (i.e. both transit and production activities) are symbolized in rectangles and the precedence logic is specified by arrows. The SDESA model shown in Figure 4.8 composes of four workflows: (1) Segments at Temporary Storage Area (TSA) (the 1st workflow); (2) Segment at RSA (the 2nd workflow); (3) Spreader Beam (the loop workflow); and (4) Post Erection (the last workflow). The Post Erection work flow includes the consolidation of the assembled segment structure and launching the giant gantry to another span (Activity No. 13 to 18 in Figure 4.8). The Post Erection work flow is to produce accurate output measurement (i.e. the total installation cycle time for one span). It can be viewed as a series of activities carried out after all segments are temporarily locked to the gantry.

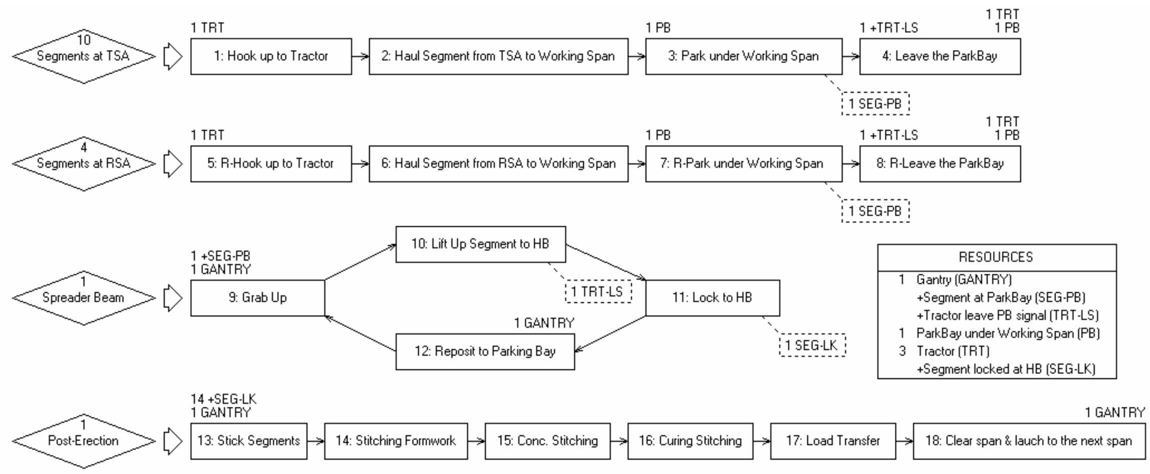

Figure 4.8: Complete SDESA Model for the Segment Installation Operations in Activity-On-Node Style

All the resources that need to be matched and used on each activity are identified. In Figure 4.8, , “1 TRT” marked at the top left corner of Activity “1: Hook up to Tractor”, means a tractor (TRT) is required in executing the activity; the tractor is released until the end of the activity “4: Leave the ParkBay”, which marked at its top right corner of that activity with “1 TRT”. Similarly, the unoccupied parking bay (PB) is the essential resource to trigger the start of the activity “3: Park under working span” and it is released together with the tractor at the end of Activity “4: Leave the ParkBay”. Note, the prefix “+” indicates the disposable resource, which represents an intermediate product or signal linking different work flows. For instance, “1 +TRT-LS” marked above the activity “4: Leave the ParkBay” denotes a “tractor leaving signal” generated by the activity “10: Lift up Segment to HB” in the segment erection work flow. Another disposable resource “+SEG-PB” produced upon the activity “3:Park under working span” represents the precast segment which has been delivered to the parking bay. The disposable resource “+SEG-PB” is requested to trigger the activity “9: Grab up” in the segment-erecting work flow. The activity “9: Grab up” requires both the gantry and a segment delivered to the parking bay, which is symbolized as “+SEG-PB”. The disposable resource “+TRT-LS”, which is generated at the end of the “10: Lift up segment to HB" activity, would invoke the "Leave the parkbay" activities in the two segment hauling work flows. Finally, the accumulation of fourteen "+SEG-LK" disposable resources, representing that fourteen segments have been temporarily locked to the gantry, triggers the start of the post-erection operations, which is modeled by six activities (Activities 13 through 18) in relation to the "stitching" concreting and post tensioning work in completing a span (Figure 4.8).

Next, the type and quantity of resources in the resource pool are defined and the initial resource provisions are configured. According to the actual situation, one gantry, one parking bay under the working span, plus three tractors are initialized in the resource pool of the SDESA model while the quantities of the three disposable resources ("+SEG-PB", "+TRT-LS" and "+SEG-LK") are set to zero at the initial state of the simulation (see the RESOURCES table in Figure 4.8).

Step 5: Specify Activities Durations

Specify activity times for each activity in statistical distributions based on the site observations, site daily records, operations method statement, and proposed schedule program (Table 4.1).

Table 4.1: Summary of the Activity Durations for the Segment Installation Operation

#	Activities	Durations in Hour			
		Distribution Type	Low	Mean	Upper
1	Hook up to Tractor	Constant		0.03	
2	Haul Segment from TSA to Work Span	Triangular	0.03	0.05	0.06
3	Park under Working Span	Uniform	0.07		0.08
4	Leave the ParkBay	Constant		0.01	
5	R-Hook up to Tractor	Constant		0.03	
6	Haul Segment from RSA to Work Span	Constant	Varied in scenarios		
7	R-Park under Working Span	Uniform	0.07		0.08
8	R-Leave the ParkBay	Constant		0.01	
9	Grab Up	Constant		0.01	
10	Lift Up Segment to HB	Triangular	0.13	0.18	0.33
11	Lock to HB	Uniform	0.17		0.23
12	Reposit to Parking Bay	Uniform	0.05		0.08
13	Stick Segments	Triangular	6.02	6.58	6.72
14	Install Stitching Formwork	Triangular	4.00	6.00	7.00
15	Concrete Stitching	Triangular	1	1.5	2
16	Curing Stitching	Constant		12	
17	Load Transfer	Uniform	7		7.5
18	Clear span & launch to the next span	Uniform	20		21

Step 6: Specify Resource Transit Time

The time incurred in the resource transit between activities in different work flows is not included in any transit activity but is defined in a datasheet format in SDESA - the Resource Transit Information System (RTIS). For the tractors, upon releasing them from the parking bay after unloading, they return to one of the two storage areas. The corresponding transit time distributions are specified in the RTIS of the SDESA model (Figure 4.9). Similar to activity duration distributions, the transit time distributions are queried and sampled during simulation for updating the current location and available time of the tractors, following the simulation algorithm of SDESA.

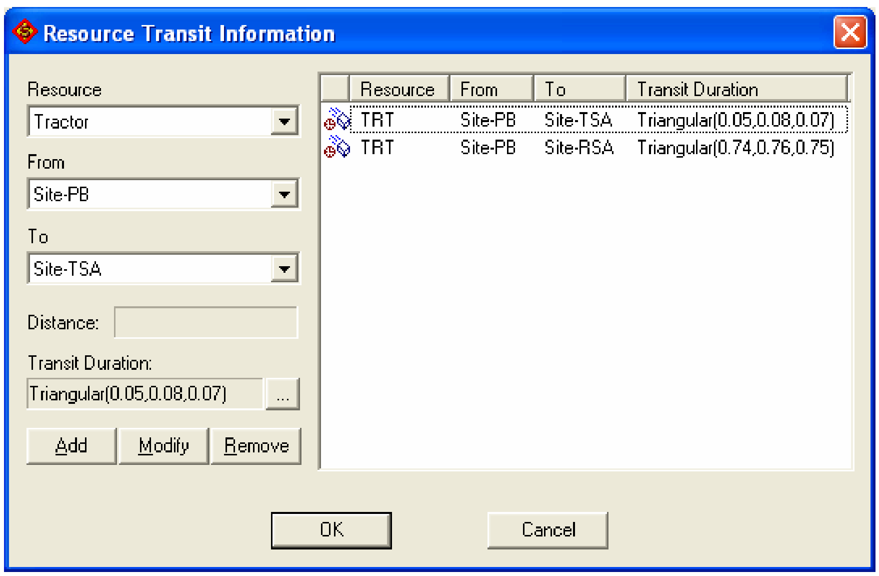

Figure 4.9: Screen Capture of the Resource Transit Information System (RSIT) in SDESA

Step 7: Animation of the Dynamic Process Simulation

Map the activity location definitions onto their corresponding positions in a site layout model so as to complete the formulation of the simulation model in the site layout view. In the dynamic process animation, the currently activated activities are highlighted by thickened lines or blocks, while moving resources are represented with circular dots, illustrated in Figure 4.10.

(1) two tractors are hauling segments from temporary storage area (TSA) to parking bay (PB)

(2) spreader beam is lifting one segment

(3) one of the tractors is returning to remote storage area (RSA) while the spreader beam is being lowered

(4) two tractors are hauling segments from RSA to PB

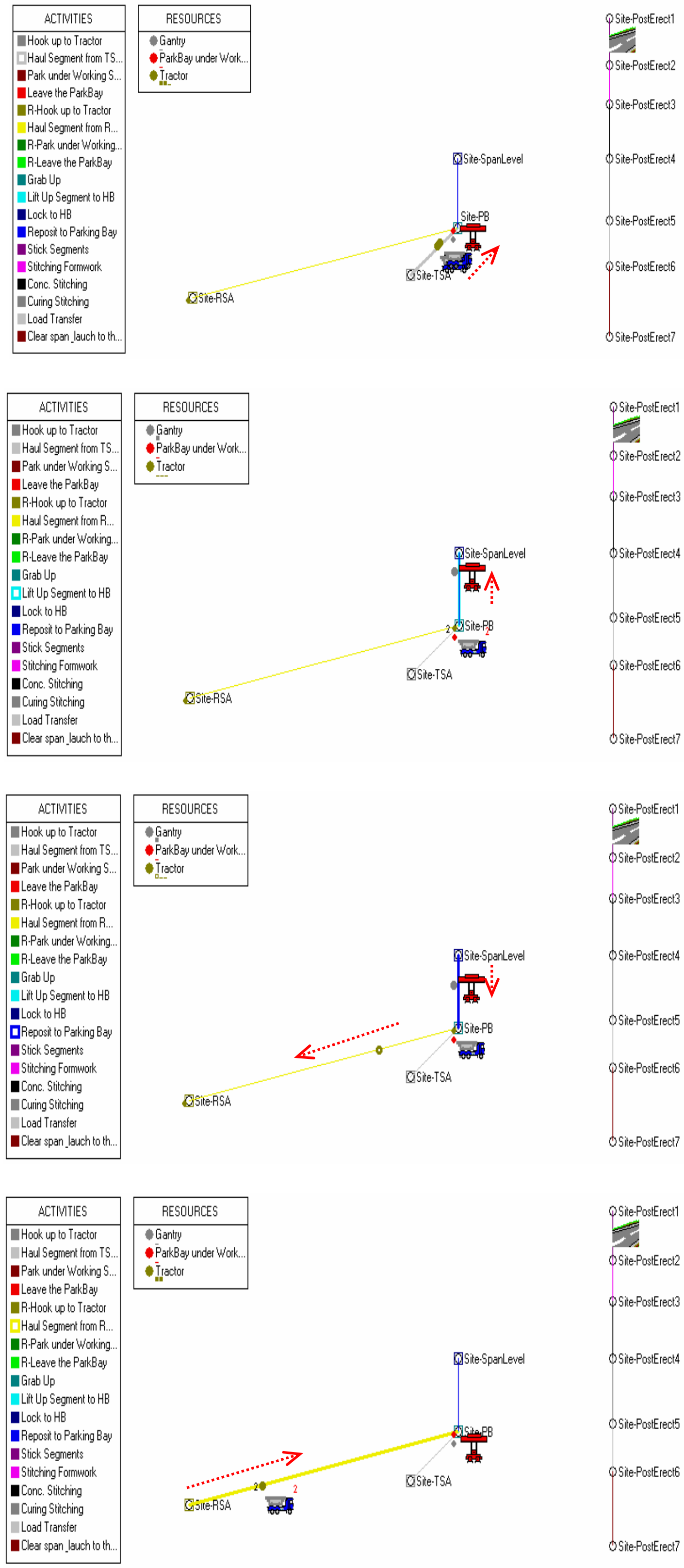

Figure 4.10: Animation Snapshots of the SDESA Model Mapped in the Site Layout View for the Segment Installation Operation.

4.5. Model Validation

In this case study, the visualized simulation outputs in terms of simulation animation as well as the cross-checking between actual and simulation operations performance indexes provide evidences for validating the simulation model. First, an animation based on a single run of the SDESA model replayed the actual segment installation processes (Figure 4.10). To further validate the simulation model, 100 Monte Carlo runs of the SDESA model were conducted, resulting in (1) the average total cycle duration of 103.61 hours −which is equivalent to 08:00 am in Day 5, and (2) the probability of completing the total cycle before the lunch break of Day 5 being about 60% − which was inferred from the cumulative distribution function (CDF) polygon for the total cycle time derived from simulation (Figure 4.11). In brief, the SDESA model under the base case scenario is validated as a close parallel of the actual site operations and provides a straightforward means for postulating and assessing alternative material inventory strategies.

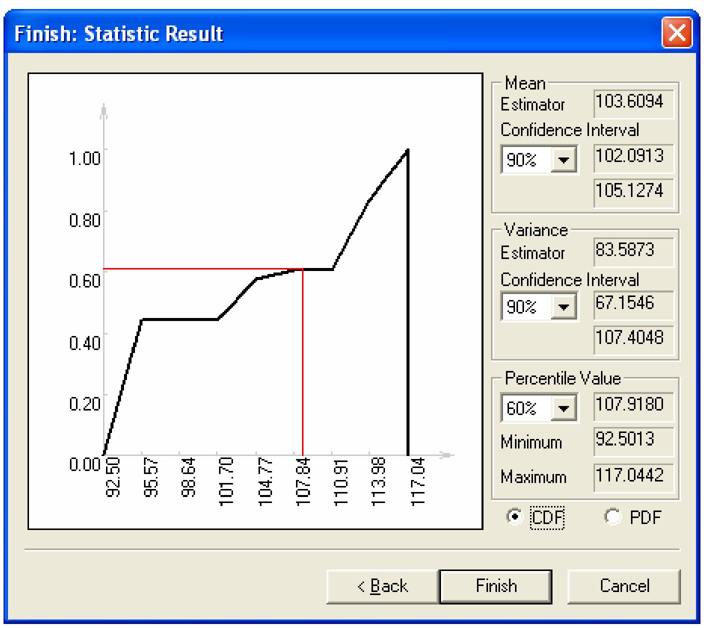

Figure 4.11: The CDF and Statistical Analysis of the Simulation Outputs: the Total Cycle Time for Erecting One Span of Viaduct

4.6. Experiment Design and Output Analysis

The objective of the simulation experiment design is to evaluate the sensitivity of the total cycle duration to the various segment storage strategies in regard to (1) the number of segments stored at the remote storage area, (2) the transit time from the remote storage area to the working span, and (3) the number of tractors rented.

Note, in order to simplify the experiment design, the following assumptions are made as advised by the site personnel: (1) all the segments of one span can be delivered in one batch before site erection operations starts; (2) in simulation, the precast segments stored at the temporary storage area are firstly hauled to the working span for installation, followed by hauling the segments stored at the remote storage area; and (3) to avoid double handling, the segments in the remote storage area will be hauled directly to the working span for installation and the temporary storage area will not serve as an intermediate buffer.

Twenty scenarios were postulated and simulated on computer, which are listed in Table 4.2. Each scenario is a unique configuration in terms of the number of segments stored at the remote storage area, the transit time from the remote storage area to the working span, and the number of tractors used. The mean and 80th percentile of the total cycle duration for each scenario collected from 100 Monte Carlo simulation runs are the main performance indices of the simulation. The column SME, an abbreviation for Segment Mobilization Effort, is defined as the product of (1) the number of segments remotely stored and (2) the haul time from the RSA to the working span, and represents the effort spent on segment transportation from the remote storage area.

Table 4.2: Summary of Input and Output Factors for Simulation Experiments

Scenario	No. of Delivery Batch	Rented Tractors	Remotely Stored Segments	Tractor Transit Time	Mean Cycle Duration (hr)	80th Percentile Cycle Duration (hr)	SME
1	1	2	0	N/A	103.61	113.63	0
2	1	2	4	0.33 hr (20 min)	105.38	114.12	1.32
3			7		106.02	114.11	2.00
4			10		106.00	114.32	2.31
5			14		106.61	114.28	3.00
6	1	2	4	0.50 hr (30 min)	108.47	114.78	3.30
7			7		111.51	116.27	3.50
8			10		113.26	116.44	4.62
9			14		114.15	116.56	5.00
10	1	2	4	0.75 hr (45 min)	112.72	116.53	5.25
11			7		115.70	116.87	7.00
12			10		116.47	117.17	7.50
13			14		116.61	117.12	10.50
14	1	3	10	0.50 hr (30 min)	104.89	114.09	5.00
15			14		105.78	113.99	7.00
16	1	3	4	0.75 hr (45 min)	108.38	114.51	3.00
17			7		109.36	114.72	5.25
18	2	2	0	N/A	116.74	117.19	0
19		2	14	0.75 hr	116.74	117.19	10.50
20		3	0	N/A	116.74	117.17	0

From Table 4.2, it can be observed that the overall trend in the first 13 scenarios (given two tractors are available for hauling segments) is that the mean cycle duration prolongs either as the number of segments at the remote storage area increases or as the remote storage area is placed farther away from the site. Scenario 13, in which all the fourteen segments are assumed to be stored at the remote storage area with the transit time being 45 min, extends the mean cycle time to 116.61 hours, 13 hours longer than the one in the base case (i.e. Scenario 1), in which all the segments are initially placed in the temporary storage area. Three tractors were provided in Scenario 14 to 17. Simulation results show that if one more tractor can be rented, the remote storage area can be located within 30 minutes journey time from the working span) without considerably cycle duration extension. The last 3 scenarios portray the operations with the two-batch-delivery of segments (the first batch of 7 segments are delivered on the night before the operations starts; and the second batch of 7 segments are delivered on the night of the first day). The simulation results show that two batches of delivery will lead to 116.74 hours of the mean cycle time independent of the number of tractor rented and the segment storage strategy. This indicates that (1) two batches of delivery will lead to the cycle-time overrun of one-span viaduct installation, and (2) even renting more tractors cannot shorten the total work hours for all storage settings.

To alleviate the congestion around the working span, a comprehensive analysis was launched to obtain more in-depth management insight from the simulation data. A surface plot is prepared for the first 13 scenarios in Figure 4.12. The surface plot correlates the mean cycle time with the number of segments remotely stored (denoted by the "SegNo.-T2" axis) and the haul time (denoted by the "Dist-T2" axis). It is observed that the slope against the "SegNo.-T2" dimension is not as steep as the one against the "Dist-T2" dimension. This indicates that the number of segments held in the remote storage area has less pronounced effect on prolonging the total cycle duration than the tractor haul time. Additionally, a threshold plane −intersecting the surface plot at the total cycle time of 109 hours (i.e. the end of lunch break on Day 5)− can be taken as the boundary that sets feasible scenarios apart from those infeasible ones: all the dots beneath the threshold plane can be regarded as feasible.

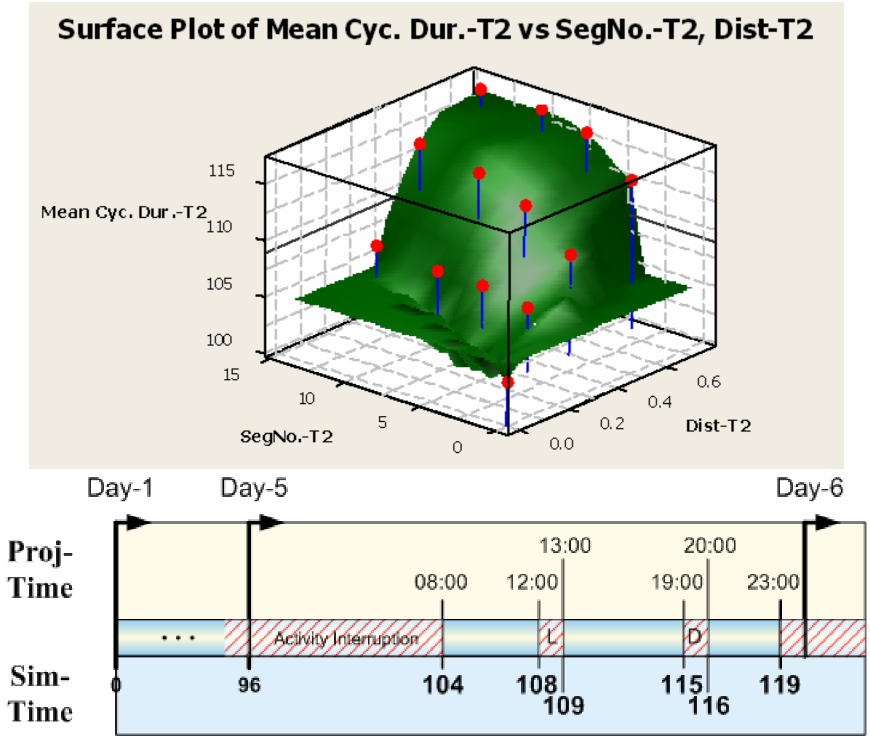

Figure 4.12: 3D-Surface Plot 3D-Surface Plot of the Mean Total Cycle Duration (Mean. Cyc. Dur.) against the Number of Segments Stored at the RSA (SegNo.) and Transit Time from the RSA to the Working Span (Dist.) (top); Time Line for Mapping Continuous Working Hours into Standard Time Format (bottom)

Figure 4.13 shows the contour plot for the mean of the total cycle time. The X-axis and the Y-axis of the contour chart are the “SegNo.-T2” and “Dist-T2” respectively, and different hatching patterns indicate different ranges of the total cycle time. In the contour plot for the mean total cycle duration, more than 70% of the area (Dist × SegNo) is hatched with the patterns “< 104” or “104-109”. In addition, if the haul duration between the RSA and the working span is less than 0.4 hour (24 min), it is highly possible that the total cycle time, on average, stays under the target of 109, even if all the 14 segments are remotely stored. On the other hand, if the number of segments stored in the RSA is less than 4, the chance of meeting the total cycle duration target is high, even if the segments are stored as far as 0.7 hours (42 min) away from the working span. Also note that once the number of segments stored in the RSA exceeds 4 while the haul distance exceeds 0.4 hour, it is highly likely that the total cycle ends beyond 109 hours but still within 119 hours, i.e. between dinner of Day

5 and the end of Day 5. The contour plot for the mean total cycle time also contains about 10% of the area hatched as "<104", revealing that the average total cycle duration could possibly fall within four working days (note the simulation time of 104 hours corresponds with 8:00 am on Day 5, i.e. the start of Day 5 or the end of Day 4). The information shown in the contour plot can be interpreted into two regards: (1) It is certain that the work cycle will finish after the lunch (>109 hours) but before the dinner break of Day 5 (<119 hours); (2) Over 5 segments stored at the RSA combined with longer than half an hour tractor-transit duration will extend the total cycle time over 116 hours (i.e. finish after the dinner of Day 5).

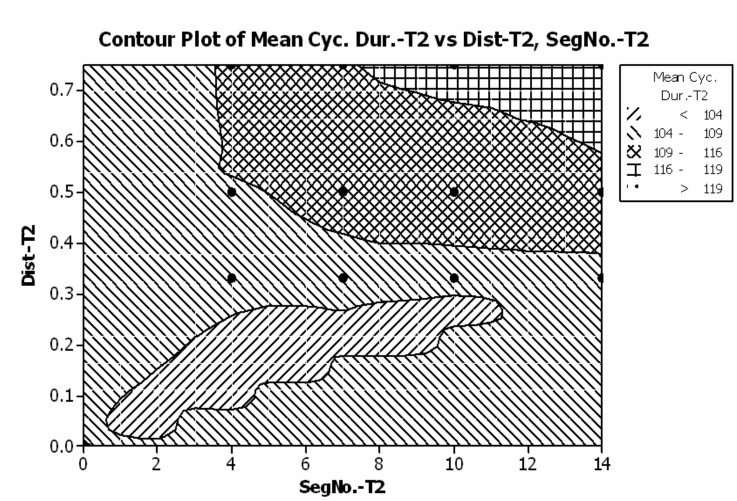

Figure 4.13: Contour Plots of the Mean Total Cycle Duration

The simulation results were summed up into simple, straightforward terms for passing on to the project team of the participating contractor, as follows:

When the temporary storage area near the working span is not adequate to accommodate all the fourteen segments, the site manager should locate a remote storage area within 25 min transit time (inclusive of any disruptions or delays caused by other ongoing site activities). Thus, the 4.5-day cycle time target can be achieved by renting two tractors, regardless of the number of segments stored at the remote storage area. In case the remote *storage area has to be placed beyond 30 min transit time but below 45 min due to practical constraints, it is recommended that the number of segments stored at the remote storage area be limited under four so as to hit the target cycle time; alternatively, one more tractor need be rented if more than four segments must be remotely stored.*

To process the simulation output via linear regression technique, an index represent the segment transportation effort from the remote storage area is defined. The Segment Mobilization Effort (SME) is defined as the product of the number of segments stored at the RSA and the journey duration required to haul one segment from RSA to the working span. The SME values for different cases of the first 13 scenarios (2 tractors rented) are listed in Table 4.2. The mean total cycle duration is correlated against the SME factor in Figure 7. The overall trend of the mean cycle duration is observed to be positively proportional to the SME, in spite of noted non-linear fluctuations. The relationship between the mean cycle duration and the factor SME is approximated by a dotted trend line (Figure 4.14) in order to generalize simulation knowledge and provide direct application of the simulation knowledge in the mean cycle duration estimation. Obviously the linear model is not a close fit of the complicated, non-linear relationships inherent in the problem. This justifies the use of ANN.

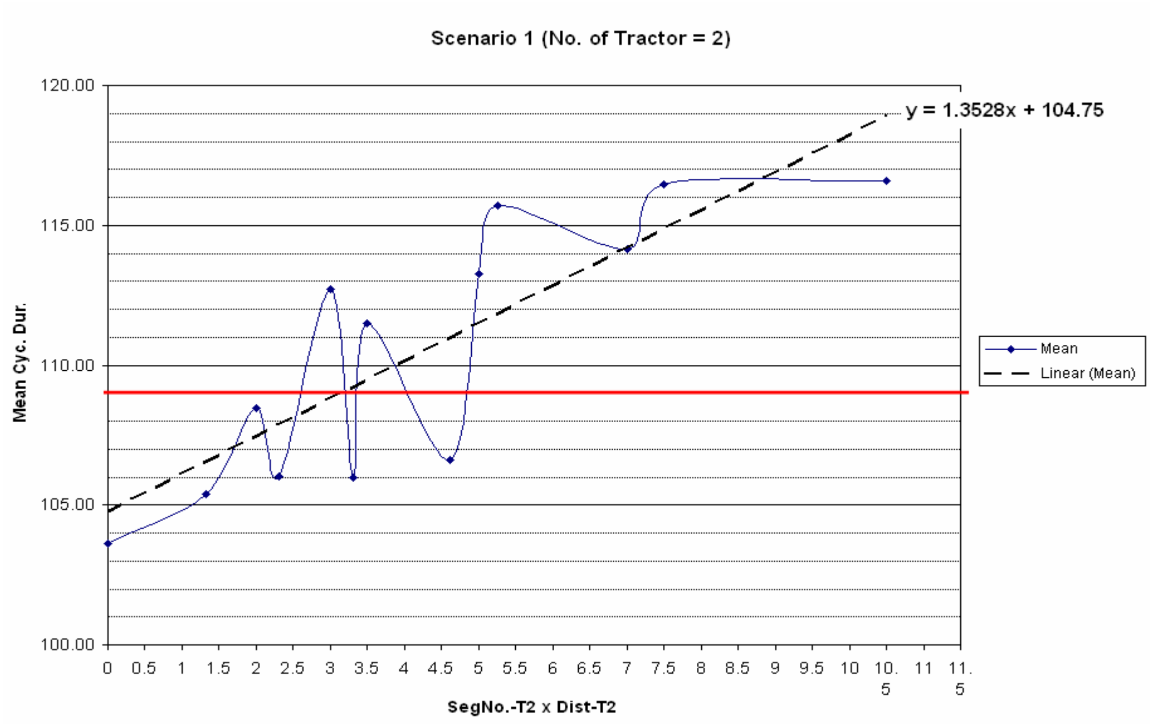

Figure 4.14: Chart of Mean Total Cycle Duration against the Segment Mobilization Effort (SME) with a dotted Trend Line

4.7. Apply ANN Method on this Case Study

In the previous section, the simulation experiment data was analyzed by conventional graphical analysis methods and useful management knowledge can be achieved. The knowledge as inferred from the simulation output records was summarized to facilitate the design of the optimum site storage area and tractor resource provision. In this section, the Artificial Neural Network (ANN) method was applied to build an ANN model which can approximate the input and output relationships of the simulation model. At the same time, it can evaluate the importance of each input factor and eventually help the site personnel identify those critical factors.

To build an ANN model, as stated in Chapter 3, the first step is to prepare the training data. 40 scenarios were prepared for the ANN model training. The 20 scenarios listed in Table 4.2 are part of the data prepared. Table 4.3 summarizes the relevant ranges and the data types for input factors and the output.

Table 4.3: Summary of the Input and Output Data Types and Ranges

Input Factors	Data Type	Min.	Max.	Range
No. of Tractors	Symbolic	2	3	1
Delivery Mode	Symbolic	1	2	1
% of Segments at RSA	Continuous	0%	100%	100%
Mean RSA Travel Duration (hr.)	Continuous	0	0.75	0.75
Output Factors	**Data Type**	**Min.**	**Max.**	**Range**
Mean Cycle Duration	Continuous	103.16	116.71	13.13

A single-hidden-layer back-propagation neural network (BPNN) with sigmoid activation functions was calibrated to map the relationships between the four input factors and the mean cycle time obtained from the simulation experiments. The 40 scenarios, or 40 records, were randomly divided into 3 subsets: a training set (24 cases), a testing set (10 cases), and a validation set (6 cases). The datasets were then fed into the SensitivityNN program for the ANN model training. By trial and error, the number of hidden nodes, the learning rate, the momentum, and the training iteration number are determined as given in Table 4.4.

Table 4.4: The Configuration of the Best Data Splits

Items	Optimum Values
No. of Hidden Nodes	14
Learning Rate	0.8
Momentum Rate	0.4
Training Iterations	15841

ANN's prediction accuracies on the Training, Test, & Validation datasets were plotted in the scatter plots (Figure 4.15). The results indicate that the ANN's outputs were highly correlated with the simulation outputs by the correlation coefficients (R, stated next to the title of each scatter plot in Figure 4.15) are all close to 1 in three sets of records. Thus, the ANN model is capable to approximate the simulation model by capturing its input-output relationships.

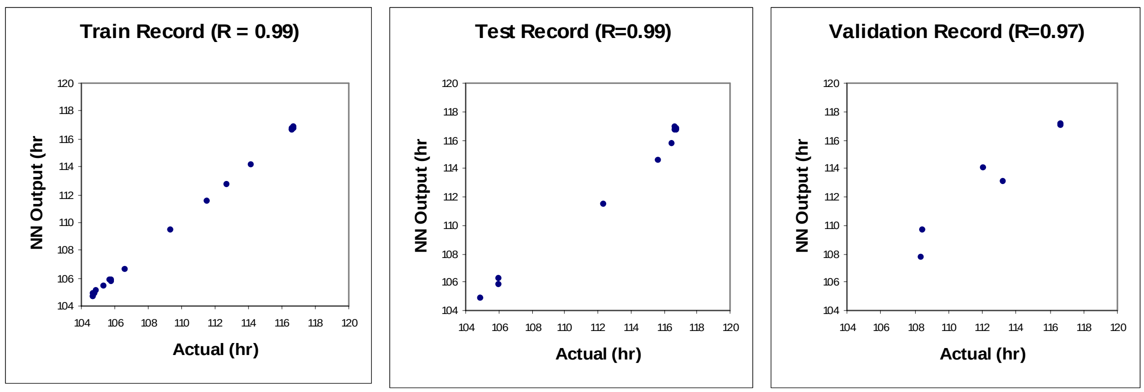

Figure 4.15: Actual Outputs versus Model Outputs of the Training set, Testing set, and Validation set in Approximating the Mean of Total Cycle Duration

The significance of each input factor upon the model output on the trained ANN model was determined as the partial derivative-based sensitivity measures suggested by Lu et al. (2005). Figure 4.16 shows the sensitivity measures of the four input factors. The bars in the chart represents the mean relative sensitivity measures, which are defined as the adjusted partial derivatives with respect to a change of 10% of the relevant range for a continuous input factor or the step value for a symbolic or discrete input factor. The relative sensitivity measures are intended to eliminate distortions on the absolute measures due to differences that exist between input factors in terms of input ranges, unit of measure, and data types. Note the step values for the first two factors (No. of tractor & Delivery mode) are both equal to 1. Factor 3 (% of segments at RSA) ranges from 0% to 100% in the data set, and Factor 4 (Mean Remote Storage Area Travel Duration) ranges from 0 to 0.75 hour.

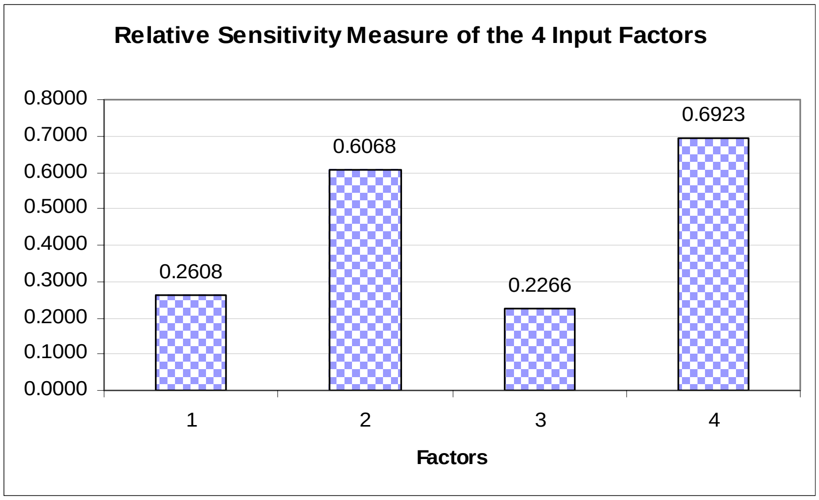

Figure 4.16: Sensitivity Measures for Input Factors of the Trained Neural Networks

As shown in Figure 4.16, the ranking of four input factors by relative sensitivity indicates that ***Factor 4***: *the duration required to haul a segment from the Remote Storage Area (RSA)* and ***Factor 2****: the delivery mode* exert a larger impact on the total cycle duration (a sensitivity measure of 0.6923, and 0.6068 respectively). ***Factor 1***: *the number of tractors rented* and ***Factor 3***: *the number of segments stored at the RSA* are relatively less sensitive, with sensitivity measure being 0.2608 and 0.2266 respectively. The results are compatible with the simulation experiment analysis results obtained in the previous section, which states that the construction duration is relatively more sensitive to delivery mode and the distance between the RSA and the working span.

Effective approximation of the simulation model and sound sensitivity analysis results demonstrate that the proposed ANN-Simulation integration method can successfully facilitate the knowledge discovering process in construction engineering.

4.8. Chapter Summary

In this chapter, a case study for the effectiveness improvement of the materials handling system in a precast viaduct construction project was presented. The simulation modeling and the integration of Artificial Neural Networks (ANN) to simulation are elaborated step by step. The implementation of the proposed ANN-simulation integration method shows that construction simulation can provide practicing engineers with supportive operations insight and effective decision support. And the proposed ANN-simulation integration method can speed up and simplify the knowledge discovery process from simulation for site operations management. The simple application procedure of the proposed ANN-simulation integration allows junior engineers without much experience to make informative and sound construction management decisions.

5. CONCLUSIONS

5.1. Summary of this Research

Although construction simulation has demonstrated a high potential of assisting construction practitioners in making sound decisions, the difficulty in simulation modeling and translating simulation outputs into practical knowledge has hindered the promotion of construction simulation, leaving site management stranded in making decisions by intuition and experience. In an attempt to simplify the modeling process, much research has been conducted on reducing the modeling effort and shortening the learning curve. However, practical applications of the simulation modeling methodologies proposed in the past are still very limited. This research has proposed a systematical modeling procedure by representing the site situation with a simulation model in an intuitive and natural manner. The proposed simulation methodology provides modelers with great flexibility and robustness, while simplifying notations in modeling.

By integrating Artificial Neural Networks (ANN) with simulation, the proposed AI-integrated construction simulation method facilitates the knowledge discovering process from simulation modeling. Enabled by the learning capability of ANN, a simulated system can be approximated by ANN and knowledge from simulation can be decoded into practical management insight via the ANN sensitivity analysis.

5.2. Research Contributions

The research contributions are not only limited to the formalization of the ANN-simulation integration methodology. Demonstrating the practical value of the proposed approach via the implementation in a real project is another important contribution to promoting the application of both simulation and artificial intelligence in construction engineering. The following summarizes the contributions of this research in regard to: (1) formalizing the construction simulation modeling method based on Simplified Discrete-Event Simulation Approach (SDESA) and (2) facilitating the knowledge discovery from simulation by ANN integration.

5.2.1. Contributions to Construction Simulation Method

Shortening the Learning Curve and Reducing the Application Effort

Viewing the construction operations system as a material handling system, the proposed simulation modeling dissembles the construction operations into workflows and maps a real site operations system into a SDESA model by following simple steps. The proposed modeling procedure guides construction practitioners to identify workflows within a construction operation system and naturally couple the site layout planning to the process model. The formalized modeling procedure not only shortens their learning curve of simulation modeling but also reduces the time and effort for applying SDESA.

Coupling Site Layout Planning with Simulation Modeling

The proposed modeling procedure highlights the movement of material and resources, assisting modelers to couple the site layout planning with the construction process modeling. The proposed modeling by SDESA places activities on predefined key locations on a virtual site layout plan. When dynamic simulation runs, the SDESA executive program traces the movements of material and resources; automatically generates and records the resource transit time. Finally, the interactions between resources, activities, and site locations are describe and captured by the simulation model in a simple and natural manner.

5.2.2. Contributions to Integrating Artificial Neural Networks to Construction Simulation

Mining Knowledge from Construction Simulation

Translating simulation outputs into more intuitive and understandable charts or equations can cost enormous analysis time and effort even for experienced modelers or analysts. This research proposed an ANN-simulation integration approach to mine knowledge from simulation. The simulation outputs are analyzed by an ANN model until the simulated system response can be accurately approximated by the trained ANN model. The learning ability of ANN allows non-simulation specialists to share the benefits from construction simulation. Moreover, through the integration of ANN with simulation, the sophisticated and tedious sensitivity analysis can be alleviated by ANN. The ANN sensitivity analysis explores the trained ANN model and determines the significance of each input factor.

5.3. Future Research Directions

1) Simulation Modeling Simplification

The systematized modeling procedure proposed in this research has set a good foundation for automated simulation modeling. The standard procedure is already capable to assist modelers to convert an observed real operations system into a SDESA simulation model. It is highly possible that simulation modeling can be further simplified in the near future. A tool (e.g. a natural language cognation program or digital picture or video conversion methods) can be researched in capturing operations information about the construction process and then generating the simulation model.

2) From One-Dimension Simulation Entity to Three-Dimension Simulation Entity

The coupling of site layout planning with a process simulation model as proposed in this research ties activities to one to two stationary key location points. Also the resource entities and flow entities are only represented by dimensionless icons in the existing SDESA simulation platform. It is suggested to extend the functionality to include the resource dimension definition and resource collision detection. These extensions in simulation functionality will enrich the appeal and function of simulation. It is anticipated that in the near future, the construction simulation will step into a new era and the benefits simulation brings to the construction engineering and management will be enormous.

5.4. Closure

In summary, the proposed AI-integrated construction simulation modeling methodology offers a new perspective of construction simulation. By the proposed modeling procedure, modelers can now explicitly consider the site layout configuration during modeling the construction process. The integration of Artificial Neural Networks (ANN) with operations simulation allows users to map and explore the significance of each input factor. With the proposed methodology, construction practitioners can be more proactive in addressing construction management challenges by taking advantage of computers, as the study and application of simulation have already been made simpler and better structures. The future work is suggested to extend the work in this research. It is hoped that the suggestions can give support to the future development of simulation for the construction industry. This research and following work will pave the way for promoting simulation in the construction industry and improving its productivity and competitiveness.

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Appendix

#	Year	Title	Authors	Journal/Procd.
1	1991	Neural Networks as Tools in Construction	Osama Moselhi; Tarek Hegazy; Paul Fazio	J. CEM
2	1994	Neural Networks in Civil Engineering. I: Principles and Understanding	Ian Flood; Nabil Kartam	J. Comp. CE
3	1994	Neural Networks in Civil Engineering. II: Systems and Application	Ian Flood; Nabil Kartam	J. Comp. CE
4	1994	Estimating Construction Productivity: Neural-Network-Based Approach	Li-Chung Chao; M. J. Skibniewski	J. Comp. CE
5	1995	An Artificial Neural Network Approach to Discrete-Event Simulation	Ian Flood; Kenneth Worley	AI for EDAM
6	1997	Neural Network Model for Estimating Construction Productivity	Jason Portas; S. M. AbouRizk	J. CEM
7	1998	Neural Network Model for Parametric Cost Estimation of Highway Projects	Tarek Hegazy; Amr Ayed	J. CEM
8	1998	Artificial Neural Network Approach for Pavement Maintenance	A. M. Alsugair; A. A. Al-Qudrah	J. Comp. CE
9	1998	Construction Labor Productivity Modeling with Neural Networks	Rifat Sonmez; J. E. Rowings	J. CEM
10	1998	Integrating Neural Network with Special Purpose Simulation	Dany Hajjar; S. M. AbouRizk; Kevin Mather	WSC
11	1999	Subsurface Characterization Using Artificial Neural Network and GIS	S. Gangopadhyay; T. R. Gautam; A. D. Gupta	J. Comp. CE
12	1999	Comparison of Case-Based Reasoning and Artificial Neural Networks	David Arditi; O. B. Tokdemir	J. Comp. CE
13	1999	ANN-Based Mark-up Estimation System with Self-Explanatory Capacities	H. Li L. Y. Shen P. E. D. Love	J. CEM
14	2000	Construction Simulation Using Parallel Computing Environments	Nabil Kartam; Ian Flood	Auto. in Constr.
15	2000	Classification of Defects in Sewer Pipes Using Neural Networks	O. Moselhi T. Shehab-Elden	J. Infrastr. Systms.
16	2001	Sensitivity Analysis of Neural Networks in Spool Fabrication Productivity Studies	Ming Lu; S. M. AbouRizk; U. H. Hermann	J. Comp. CE
17	2001	Neural Networks for Predicting Properties of Concretes with Admixtures	W. P. S. Dias; S. P. Pooliyadda	Constr. & Buildg. Materials
18	2001	Development of the Approximate Analytical Model for the Stub-girder using Neural Networks	Seung Chang Lee; Sung Kwon Park; Byung Hai Lee	Computers. & Structures
19	2001	Preliminary Design System for Concrete Box Girder Bridges	Z. Zhao W. He S. C. Fan	J. Comp. CE
20	2001	Estimating Labor Production Rates for Industrial Construction Activities	S. AbouRizk P. Knowles U. R. Hermann	J. CEM

#	Year	Title	Authors	Journal/Procd.
21	2001	Application of Neural Network Model to Forecast Short-Term Pavement Crack Condition: Florida Case Study	Z. Lou M. Gunaratne J. J. Lu B Dietrich	J. Infrastr. Systms.
22	2002	Neural Network Embedded Monte Carlo Approach for Water Quality Modeling under Input Information Uncertainty	R. Zou W. S. Lung H. Guo	J. Comp. CE
23	2002	Predictions of Design Parameters in Civil Engineering Problems Using SLNN with a Single Hidden RBF Neuron	S. Rajasekaran; R. Amalraj	Computers. & Structures
24	2002	Artificial Neural Networks Model for Predicting Excavator Productivity	C. M. Tam; T. K. L. Tong; Sharon L. Tse	Engrg., Constr. & Arch. Mangmt.
25	2003	The use of GA-ANNs in the Modeling of Compressive Strength of Cement Mortar	Sedat Akkurt; Serhan Ozdemir; Gokmen Tayfur; Burak Akyol	Cement & Concrete Research
26	2004	Use of BPNN for Landslide Monitoring: a Case Study in the Higher Himalaya	K. M. Neaupane; S. H. Achet	Engrg. Geology
27	2004	RBF neural Networks for the Prediction of Building Interference Effects	Aishe Zhang; Ling Zhang	Computers. & Structures
28	2005	Pile Construction Productivity Assessment	Tarek M. Zayed ; Daniel W. Halpin	J. CEM
29	2006	Neural Networks for Estimating the Productivity of Concreting Activities	A. S. Ezeldin; L. M. Sharara	J. CEM (TecNote.)
30	2006	Applying Undistorted Neural Network Sensitivity Analysis in Iris Plant Classification & Construction Productivity Prediction	Ming Lu; Daniel S. Yeung; Wing W. Y. Ng	Soft Computing

Keys of the Journal & Proceeding abbreviation:

- **AI for EDAM:** Artificial Intelligence for Engineering Design, Analysis and Manufacturing (Cambridge University Press)
- **Auto. in Constr.:** Automation in Construction (Elsevier Science)
- **Cement & Concrete Research:** Cement & Concrete Research (Elsevier Science)
- **Computers. & Structures:** Computer and Structures (Elsevier Science)
- **Constr. & Buildg. Materials:** Construction and Building Materials (Elsevier Science)
- **Engrg., Constr. & Arch. Mangmt.:** Engineering, Construction and Management (Blackwell Science)
- **J. CEM :** Journal of Construction Engineering and Management (ASCE)
- **J. Comp.** CE: Journal of Computing in Civil Engineering (ASCE)
- **J. Infrastr. Systms:** Journal of Infrastructure Systems (ASCE)
- **Soft Computing:** Soft Computing (IEEE)
- **WSC:** Proceeding of the Winter Simulation Conference (WSC. Organization / IEEE)

1	1991	**Neural Networks as Tools in Construction**	Osama Moselhi; Tarek Hegazy; Paul Fazio	J. CEM (ASCE)

Paper Summary:
Being an introduction of ANN for the practitioners and researchers in construction field, this paper gives fundamental information about ANN. The usages, basic mechanisms, characteristics, and some common terminologies of ANN were introduced. A brief comparison between some common ANN paradigms was also delivered in a table. A simple BPNN application was used to demonstrate the design, training, and recalling of the NN. Some potential ANN applications were suggested at the end of the paper.

Applications:
1) Optimum markup estimation under different bid situations

Data Collection:
- Literatures (3 papers)

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 3 nodes (no. of competitors, estimated mean bidding price, s.d. of bidding prices)
-Hidden: 6 nodes in 1 layer (Discrete [0,1] function)
-Output: 3 nodes (optimum markup stayed in the 3 literatures respectively)

2	1994	**Neural Networks in Civil Engineering. I: Principles and Understanding**	Ian Flood; Nabil Kartam	J. Comp. CE (ASCE)

Paper Summary:
This is another ANN introduction paper for construction engineers and researchers. Beyond the usages and potential applications of ANN, this paper came across the principle and theory behind ANN to novices. The training and recall mechanism of ANN were explained from the mathematical perspective through illustrative figures. ANN architectures and the corresponding learning parameters were also presented.

Applications:
1) Determining whether a cantilever will damaged by bending moment induced by two simple point loads

Data Collection:
- Hand calculation

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 2 nodes (loading at the free-end and middle of the cantilever respectively)
-Hidden: 3 nodes in 1 layer (sigmoid function)
-Output: 1 node (failure or not)

3	1994	**Neural Networks in Civil Engineering. II: Systems and Application**	Ian Flood; Nabil Kartam	J. Comp. CE (ASCE)

Paper Summary:

This is a companion paper to the previous one (2). In this paper, the basic characteristics of neural networks and the variety of systems available were identified. The significance of these characteristics in solving different classes of problems is considered. The authors suggested that modularized NN can be linked together (serially or in parallel) and form to deal with different types of problems. Suggestion was make on using ANN to perform the construction simulation which is conventionally done by Monte-Carlo discrete-event approach.

Applications:

Conceptual usage of ANN on construction simulation

ANN Architectures:

N/A

4	1994	**Estimating Construction Productivity: Neural-Network-Based Approach**	Li-Chung Chao; M. J. Skibniewski	J. Comp. CE (ASCE)

Paper Summary:

This paper shows an ANN application on excavator productivity estimation. The training data of the ANN was collected from a simulation program (CYCLONE) in an excavation and hauling operation (i.e. simple earth moving operation). It is noted that the duration of the excavation activity in the simulation model was the output of another ANN module which was trained by the data collected by the observations of a robotic desktop excavator.

Applications:

1) Predict the excavation cycle time due to the excavator's arm motions and soil condition
2) Predict the Productivity of a excavator in a earth moving operations system

Data Collection:

1) Observed from a robotic desktop excavator
2) Simulation model of the earth moving operations system

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1) Excavation cycle time estimation
-Input: 4 nodes (arm swing angle, horizontal reach, vertical position, and soil type)
-Hidden: 16 nodes in 1 layer (sigmoid function)
-Output: 1 node (excavation cycle time)

2a) Productivity of an excavator w/o reposition
-Input: 5 nodes (mean & s.d. of excavation cycle time, mean & s.d. of truck activity time, no. of truck)
-Hidden: 15 nodes in 1 layer (sigmoid function)
-Output: 2 nodes (mean & s.d. of excavator's Productivity)

2b) Productivity of an excavator with reposition
-Input: 8 nodes (5 same as (2a), probability, mean, & s.d. of excavator's reposition)
-Hidden: 48 nodes in 1 layer (sigmoid function)
-Output: same as (2a)

5	1995	**An Artificial Neural Network Approach to Discrete-Event Simulation**	Ian Flood; Kenneth Worley	AI for EDAM (Cambridge U. Pr)

Paper Summary:

This paper (related to paper 2 & 3) present an ANN based approach for construction simulation aiming to speed up the simulation process by parallel processing. Modularized NN were assembled to form a construction model. Similar to a recurring function the output of the NN (future state of the simulation) was looped back to the NN as its input (the preceding simulation state). A simple earth moving example was used to demonstrate their proposed research approach. However, the training neural network based simulation model was relied on a conventional discrete-event simulation model (ICONS).

Applications:

1) Using NN to approximate the dumping time interval of a typical earth-moving system with different no. of scraper provided

Data Collection:

- A simulation model established in a commercial package called ICONS

ANN Paradigm adopted:

- Radial Gaussian NN

ANN Architectures:

2 NN modules were linked together to do the simulation approximation:

M1) Scraper haul duration generator

-Input: 3 nodes (mean, s.d. of hauling duration, & an assigned random seed)

-Hidden: 100 nodes in 1 layer (Radial Gaussian)

-Output: 1 node (scraper haul duration)

M2) Core simulation approximating NN

-Input: 6~10 nodes (no. of dozer, dozer return dur., scraper hauling dur., other input is for feedback of the NN itself)

-Hidden: 300 nodes in 1 layer (Radial Gaussian)

-Output: 1 node (dump time interval)

6	1997	**Neural Network Model for Estimating Construction Productivity**	Jason Portas; S. M. AbouRizk	J. CEM (ASCE)

Paper Summary:

This research applied the ANN technique on construction productivity estimation. The training data was collected by the interviews of construction practitioners with standard questionnaire. Th output of the ANN is separated into 12 productivity levels, instead of the single point estimation. It is shown that incorrect prediction rate can be reduced using this classification output approach.

Applications:

1) Construction productivity estimation

Data Collection:

- Questionnaire

ANN Paradigm adopted:

- BPNN

Commercial packages adopted:

- Neuralworks Professional II Plus
- Visual Basic
- Neurowindows library of NN
-

ANN Architectures:

-Input: 55 nodes (half of the factors are about the site activity & environment and the rest about the project management)

-Hidden: 30 nodes in 1 layer (sigmoid function)

-Output: 12 nodes (12 levels of construction productivity)

7	1998	**Neural Network Model for Parametric Cost Estimation of Highway Projects**	Tarek Hegazy; Amr Ayed	J. CEM (ASCE)

Paper Summary:
This paper uses ANN to perform parametric cost estimation for highway projects. 18 actual cases of highway projects in Canada were used as the source of training data. The authors use an Excel spreadsheet to setup the ANN model and 3 different techniques (BP delta-rule; Excel internal optimizer; & GA optimizer) were compared in optimizing the ANN weights. In this case study, Excel internal optimizer outperformed the traditional BP-delta-rule in this case and was the best among the others.

Applications:
1) parametric cost estimation for highway projects

Data Collection:
- 18 actual cases of highway projects in Canada

ANN Paradigm adopted:
- BPNN

Commercial packages adopted:
- NeuroShell2 for BP-delta-rule
- MS Excel & its internal solver
- GeneHunter 1995 for GA optimization

ANN Architectures:
-Input: 10 nodes (identified project factors which affect the highway construction cost)
-Hidden: 5 nodes in 1 layer (sigmoid function)
-Output: 1 node (highway construction cost)

8	1998	**Artificial Neural Network Approach for Pavement Maintenance**	A. M. Alsugair; A. A. Al-Qudrah	J. Comp. CE (ASCE)

Paper Summary:
This paper presents an ANN application on pavement maintenance for selecting the optimum repair action for defected pavement. The training data was collected by visual inspection for the road network together with consulting the human experts.

Applications:
1) Pavement maintenance and repair action decision

Data Collection:
- visual inspection & expert consultancy

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 12 nodes (12 types of observable road distresses)
-Hidden: 28 nodes in 1 layer (sigmoid function)
-Output: 5 nodes (5 maintenance and repair options: thin overlay, thick overlay, strengthening, localized maintenance, & do nothing)

9	1998	**Construction Labor Productivity Modeling with Neural Networks**	Rifat Sonmez; J. E. Rowings	J. CEM (ASCE)

Paper Summary:

This paper use the data set collected from 8 building projects in Iowa to estimate the labor productivity. The productivity of three common site activities: (1) concrete pouring, (2) formworking, & (3) troweling were studied. Before the ANN training, the parsimonious model technique was used to eliminate unnecessary input features. Finally, simple factor sensitivity analysis was performed.

Applications:

1) Construction labor productivity modeling

Data Collection:

- 8 building project in Iowa from 1992 ~ 1994

ANN Paradigm adopted:

- BPNN

ANN Architectures:

2 NN were formed for each kind of activity. The first & second NN use (2n+1) & {(0.5n+1) or (n+1)} respectively as the no. of hidden nodes where n is the no. of input nodes.

<u>Concrete Pouring :</u>
-Input: 5 nodes (from parsimonious model)
-Hidden: 13 & 4 nodes in 1 layer
-Output: 1 node (production rate)
<u>Formworking :</u>
-Input: 2 nodes (from parsimonious model)
-Hidden: 5 & 3 nodes in 1 layer
-Output: 1 node (production rate)
<u>Troweling :</u>
-Input: 2 nodes (from parsimonious model)
-Hidden: 5 & 3 nodes in 1 layer
-Output: 1 node (production rate)

10	1998	**Integrating Neural Network with Special Purpose Simulation**	Dany Hajjar; S. M. AbouRizk; Kevin Mather	WSC

Paper Summary:

This paper presents an attempt of integrating ANN to simulation. An ANN model is first trained to approximate the excavation duration for different types of soil. The trained ANN is then linked dynamically to the virtual GIS system which generation soil data when excavators moving around during simulation. A typical earth moving example was used to illustrate, in broad-brush, the proposed approach.

Applications:

1) Prediction of excavation productivity

Data Collection:

- An informal survey of project personnel

ANN Paradigm adopted:

- BPNN
-

ANN Architectures:

-Input: 13 nodes (7 about soil condition, 6 about the working condition of the excavator)
-Hidden: 4 nodes in 1 layer (sigmoid function)
-Output: 1 node (predicted productivity)

<table>
<tr><td>11</td><td>1999</td><td>Subsurface Characterization Using Artificial Neural Network and GIS</td><td>S. Gangopadhyay;
T. R. Gautam;
A. D. Gupta</td><td>J. Comp. CE
(ASCE)</td></tr>
<tr><td colspan="5">Paper Summary:
This paper proposes a method for characterizing the subsurface using ANN & GIS. Training data are collected from the distribution of aquifer materials from monitoring well litho-logic logs. The predicted subsurface profile generated by the trained ANN was then compared with available geological sections underlying the Bangkok city for ANN validation.</td></tr>
<tr><td colspan="3">Applications:
1) Subsurface Characterization (estimating the underground soil strata profile)
Data Collection:
• Litho-logic logs form 60 monitoring wells
ANN Paradigm adopted:
• BPNN</td><td colspan="2">ANN Architectures:
-Input: 14 nodes (Coordinate X, Y, soil property of the well in 12 different levels)
-Hidden: 5 nodes in 1 layer (sigmoid function)
-Output: 3 nodes (decision of the soil type: clay, sand, or other material)</td></tr>
</table>

<table>
<tr><td>12</td><td>1999</td><td>Comparison of Case-Based Reasoning and Artificial Neural Networks</td><td>David Arditi;
O. B. Tokdemir</td><td>J. Comp. CE
(ASCE)</td></tr>
<tr><td colspan="5">Paper Summary:
Two different techniques ANN & case-based reasoning (CBR) were compared in construction litigation outcome prediction. A simple BPNN was setup for the comparison by a commercial package, called Brainmaker. The authors concluded that CBR is more suitable for predicting construction litigation outcome.</td></tr>
<tr><td colspan="3">Applications:
1) Predict construction litigation outcome by input features about the cases
Data Collection:
• Appellate court records from WESTLAW (a computer-assisted on-line legal research service)
ANN Paradigm adopted:
• BPNN</td><td colspan="2">ANN Architectures:
-Input: 45 x 2 = 90 nodes (45 features about the cases, e.g. whether CPM records are available?)
-Hidden: NO MENTIONED (sigmoid function)
-Output: 6 nodes (each one stands for one kind of predicted outcome)</td></tr>
</table>

13	1999	**ANN-Based Mark-up Estimation System with Self-Explanatory Capacities**	H. Li L. Y. Shen P. E. D. Love	CEM

Paper Summary:

The paper investigates the use of the KT-1 method for automatically extracting rules from a trained ANN. Using KT-1 method, the trained neural network is searched through layer by layer to seek confirming rule and/or disconfirming rule from hidden nodes or output nodes. However, it is obvious that the rule is impractical for large ANN and cannot guarantee informative explanations for all cases. Other rule extraction methods, such as (1) the decomposition approach, & (2) the pedagogical approach were introduced.

Applications:

1) Mark-up estimation

Data Collection:

- From 30 successful bidding examples of building projects from a local contractor

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1) Mark-up estimation
-Input: 10 nodes (Market, Competitors, Cash required, Overhead rate, Current workload, Labor availability, Project type, Size, Location, Complexity)
-Hidden: 3 nodes (represent Economic, Company, & Project respectively)
-Output: 1 node (Mark-up Percentage)

14	2000	**Construction Simulation Using Parallel Computing Environments**	Nabil Kartam; Ian Flood	Auto. in Constr.

Paper Summary:

This paper (related to paper 2, 3, & 5) introduces different methods to implement construction simulation. The conventional serial-algorithms (e.g. event list & activity scanning) was challenged to be memory consuming and low speed. The authors proposed the parallel-algorithms by using NN as an activity duration generator which estimates durations based on the work environment inputs. The NN estimated durations then input to a recursive NN which generates the next event time based on the last event time. However, the training data of the NN could inevitably provided by conventional serial-algorithms simulation model as the training and validating data can hardly be found in real operations.

Applications:

1) Mimic the simulation process of a typical earth-moving operations

Data Collection:

- Discrete-event simulation model (ICONS)

ANN Paradigm adopted:

- Radial-Gaussian Model

ANN Architectures:

1) Excavation duration estimation
-Not mentioned

2) Core simulation recursive NN
-Input: 7 nodes
-Hidden: 300 (Gaussian function)
-Output: 1 node (predicted excavation duration)

15	2000	**Classification of Defects in Sewer Pipes Using Neural Networks**	O. Moselhi T. Shehab-Elden	J. Infrastr. Systms.

Paper Summary:
This paper presents an automated system designed for detecting defects in underground sewer pipes and focuses primarily on the application of neural networks in the classification of those defects. This paper provides quite detail descriptions on the history, mechanism, and characteristics of ANN.

Applications:
1) detecting defects in underground sewer pipes

Data Collection:
- Images from CCTV recorder

ANN Paradigm adopted:
- BPNN

ANN Architectures:
1) Formworking
-Input: Many nodes (for the image converted matrix)
-Hidden: 32 nodes in 1 layer (several different functions were tried)
-Output: 1 node (defected or not)

16	2001	**Sensitivity Analysis of Neural Networks in Spool Fabrication Productivity Studies**	Ming Lu; S. M. AbouRizk; U. H. Hermann	J. Comp. CE (ASCE)

Paper Summary:
This paper presents a approach for the BPNN sensitivity analysis mapping the significance of each input to the ANN output. Methodology inspired from the regression analysis was developed such that the partial derivative was applied to explore the normalized input-output relationship. The BPNN and the proposed sensitivity analysis technique were demonstrated by the case study of pipe spool fabrication productivity estimation.

Applications:
1) productivity estimation of pipe spool fabrication

Data Collection:
- Company's various transaction systems (e.g. labor cost or material tracking system) and questionnaires

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 19 nodes (features about the job, material, and labor arrangement)
-Hidden: 19 nodes (sigmoid function)
-Output: 1 node (labor hour per pipe spool unit)

17	2001	**Neural Networks for Predicting Properties of Concretes with Admixtures**	W. P. S. Dias; S. P. Pooliyadda	Constr. & Buildg. Materials

Paper Summary:
This paper presents an ANN application on concrete strength prediction based on different prescriptions of admixture. An exponential multiple regression model was compared with the ANN. Sensitivity analysis was performed by graphical method.

Applications:

1) Predicting the strength and slump of concrete

Data Collection:

- 3 batching plants

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1) For Ready-Mixed Concrete (RMC)
-Input: 4 nodes (cement/water, total mix/water, coarse/fine agg., & retardant/cement ratio)
-Hidden: NO MENTIONED
-Output: 2 nodes (slump and strength)

2) For High Strength Concrete (HSC)
-Input: 5 nodes (cement+silica/water, total mix/water, coarse/fine agg., plasticizer/total, & silica-fume /cement ratio)
-Hidden: NO MENTIONED
-Output: 2 nodes (slump and strength)

18	2001	**Development of the Approximate Analytical Model for the Stub-girder using Neural Networks**	Seung Chang Lee; Sung Kwon Park; Byung Hai Lee	Computers. & Structures

Paper Summary:
This paper describes an ANN application on stub-girder system structural analysis. Fairly comprehensive information, from the architecture to the training & testing procedure, about ANN was given in the paper. Three ANN models, including two girder systems with point load and one with uniform distributed load, were setup for demonstration.

Applications:

1) structure analysis of simple stub-girder system

Data Collection:

- Finite element analysis software package LUSAS

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1) point load case -1
-Input: 3 nodes (stub length, first open length, second open length)
-Hidden: 4 nodes (sigmoid function)
-Output: 1 node (maximum deflection)

2) point load case -2
-Input: 3 nodes (concrete slab strength, stub strength, main girder strength)
-Hidden: 4 nodes (sigmoid function)
-Output: 1 node (maximum deflection)

3) Uniform distributed load case
-Input: 7 nodes (loading, length, spacing, depth, & width of stub, depth of girder)
-Hidden: 11 nodes (sigmoid function)
-Output: 4 nodes (maximum deflection, bending moment, shear stress, axial force)

19	2001	**Preliminary Design System for Concrete Box Girder Bridges**	Z. Zhao W. He S. C. Fan	J. Comp. CE (ASCE)

Paper Summary:
A neural network-based design system for concrete box girder bridges is presented in this paper. The system employs two knowledge extraction techniques (1) the RBFNN to derive design knowledge of the parameters having a clear input and output mapping; and (2) the fuzzy approach to provide feasible types of cross sections and longitudinal sections. The knowledge acquisition model described in this paper was actually the factor sensitivity analysis technique.

Applications:
1) Preliminary design of concrete box girder bridges

Data Collection:
- From 256 concrete box girder bridges built in various countries

ANN Paradigm adopted:
- BPNN & RBFNN

ANN Architectures:
-Input: 9 nodes
-Hidden: 13 - 14 nodes
-Output: 9 nodes

20	2001	**Estimating Labor Production Rates for Industrial Construction Activities**	S. AbouRizk P. Knowles U. R. Hermann	CEM

Paper Summary:
This paper presents an ANN application on labor production estimation for industrial construction tasks such as welding and pipe installation. A two-stage ANN was used for the prediction. The first-stage ANN classes the data into typical and non-typical, while the second-stage ANN performs the productivity estimation. The research shows that the training and testing error of an ANN model can be reduced if data can be clustered properly.

Applications:
1) Labor production rates prediction

Data Collection:
- From 27 industrial construction projects

ANN Paradigm adopted:
- BPNN

ANN Architectures:
1st stage
-Input: 6 nodes (mainly work conditions)
-Hidden: 10 nodes in 2 groups in 1 layer (Kohonen layer)
-Output: 2 nodes (typical and non-typical)

2nd stage
-Input: 6 nodes (mainly work conditions)
-Hidden: 35 nodes in 1 layer
-Output: 14 node (13 classes and 1 point prediction)

21	2001	**Application of Neural Network Model to Forecast Short-Term Pavement Crack Condition: Florida Case Study**	Z. Lou M. Gunaratne J. J. Lu B Dietrich	J. Infrastr. Systms.

Paper Summary:

This paper presents the BPNN application on forecasting the short-term time variation of crack index (CI) of Florida's highway network. The BPNN models can learn the historical crack progression trend from the CI database and accurately forecasting future CI values. It is worthy to note that the neural network model concerned was designed in a time-series approach that the crack index prediction of the last iteration will be the input of the next iteration.

Applications:

1) Forecast the short-term time variation of crack index for Florida's highway network

Data Collection:

- From the pavement performance database in the Florida Department of Transportation (20 years, 139421 historical CI survey data)

ANN Paradigm adopted:

- BPNN

ANN Architectures:

-Input: 7 nodes (including one CI(t): CI value from previous turn)
-Hidden: 12 nodes
-Output: 1 node (CI(t+1))

22	2002	**Neural Network Embedded Monte Carlo Approach for Water Quality Modeling under Input Information Uncertainty**	R. Zou W. S. Lung H. Guo	J. Comp. CE (ASCE)

Paper Summary:

This research used the Monte Carlo randomness simulate the uncertainly in water quality modeling and the statistical distributed data is used as data set for training and testing of an ANN. The target output of the data set was provided by conventional numerical calculation. The ANN mapped the calculation input and output so that users can bypass the complicated calculation steps.

Applications:

1) Water quality modeling

Data Collection:

- Numerical model: Total Phosphorus Model

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1st stage
-Input: 3 nodes (settling velocity, recycling velocity, burial velocity)
-Hidden: 6 nodes in 1 layer
-Output: 1 node (Total phosphorus)

23	2002	**Predictions of Design Parameters in Civil Engineering Problems Using SLNN with a Single Hidden RBF Neuron**	S. Rajasekaran; R. Amalraj	Computers. & Structures

Paper Summary:
This paper introduced the single hidden neuron Radial Basis Function (RBFNN) in solving civil engineering problems. Although the authors did not sufficiently explain what is RBFNN, the training procedure (i.e. searching of the center and effective width of the hidden node) of a RBFNN was illustrated clearly. After the training and validation, the RBFNN can even be converted into an instantly applicable equation which helps to understand the problem.

Applications:
1) Classification of soils
2) Determination of compressive strength and workability of concrete
3) Ultimate shear strength of RC beam prediction

Data Collection:
1) Not given
2) Not given
3) Previous research by Sanad & Saka (2001)

ANN Paradigm adopted:
- RBF

Commercial packages adopted:
- Matlab

ANN Architectures:
1) Classification of soils
-Input: 6 nodes (soil color, gravel%, sand%, fine particles%, Liquid limit, Plastic limit)
-Hidden: 1 nodes
-Output: 1 nodes (soil type)

2) Determination of compressive strength and workability of concrete
-Input: 5 nodes (Sand/Cement, Coarse agg/Cement, Water/Cement, Silica Fume%, Plasticizer%)
-Hidden: 1 node
-Output: (a) 1 node (Concrete strength)
(b) 1 node (Workability)

3) Ultimate shear strength of RC beam prediction
-Input: 9 nodes (not mentioned)
-Hidden: 1 node
-Output: 1 node (ultimate shear strength)

24	2002	**Artificial Neural Networks Model for Predicting Excavator Productivity**	C. M. Tam; T. K. L. Tong; Sharon L. Tse	Engrg., Constr. & Arch. Mangmt.

Paper Summary:
This paper applied ANN on excavator productivity prediction. The hidden layer adopted 3 different types of threshold (activation) functions, and sigmoid function was adopted at the output layer. However, how this special setting affect the ANN model was missing in the paper.

Applications:
1) Prediction of excavation productivity

Data Collection:
- Data of excavation scenarios from Edward & Holt (2000)

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 4 nodes (digging depth, swing angle, machine capacity, operation environment)
-Hidden: 9 nodes in 1 layer (3 x Gaussian, 3 x Gaussian Complement, 3 x tanh)
-Output: 1 sigmoid function output node (predicted excavation cycle time)

25	2003	**The use of GA-ANNs in the Modeling of Compressive Strength of Cement Mortar**	Sedat Akkurt; Serhan Ozdemir; Gokmen Tayfur; Burak Akyol	Cement & Concrete Research

Paper Summary:
This paper presents an ANN application on cement mortar strength prediction. Genetic Algorithms (GA) was used to sort the training and testing data. Cement mortar compressive strength against different input factors were plotted for sensitivity analysis.

Applications:
1) cement mortar compressive strength prediction

Data Collection:
- Data from a cement plant in Turkey

ANN Paradigm adopted:
- BPNN

ANN Architectures:
-Input: 20 nodes (15 about mortar ingredient, 2 about the set time, 2 about the particle size, 1 about the size of the compression surface)
-Hidden: 20 nodes in 1 layer (sigmoid function)
-Output: 1 node (predicted compressive strength)

26	2004	**Use of BPNN for Landslide Monitoring: a Case Study in the Higher Himalaya**	K. M. Neaupane; S. H. Achet	Engrg. Geology

Paper Summary:
This research applied ANN for landslide monitoring in Himalaya. A 2-hidden-layer BPNN was adopted in this case study.

Applications:
1) Predict land movement by the raining and geotechnical data

Data Collection:
- Published technical report by the Water Induced Disaster Prevent Technical Center in Nepal

ANN Paradigm adopted:
- BPNN

Commercial packages adopted:
- Matlab

ANN Architectures:
-Input: 6 nodes (Antecedent rainfall, rainfall intensity, infiltration coefficient, shear strength, groundwater level, slope steepness)
-Hidden-I: 5 nodes in 1 layer (sigmoid function)
-Hidden-II: 9 nodes in 1 layer (both node no. in layer I&II were by trial-and-error)
-Output: 1 node (predicted slope movement)

27	2004	**RBF neural Networks for the Prediction of Building Interference Effects**	Aishe Zhang; Ling Zhang	Computers. & Structures

Paper Summary:
This paper presents the application of RBFNN on estimating the resultant wind force on a building under the interference by a nearby building. This paper provides a good introduction to RBF novices because the geometrical meaning of the RBF and the basic training procedures were all articulated in it.

Applications:
1) Estimate the resultant wind force on a building under the interference by a nearby building

Data Collection:
- Data from some previous literatures

ANN Paradigm adopted:
- RBF

ANN Architectures:
-Input: 4 nodes (Relative orientation of the two buildings in X-Y plane, height ratio, ground roughness)
-Hidden: 8 nodes (trial from 4~25)
-Output: 1 node (Interference Factor)

28	2005	**Pile Construction Productivity Assessment**	Tarek M. Zayed ; Daniel W. Halpin	J. CEM (ASCE)

Paper Summary:
This paper presents an ANN application on pile construction productivity assessment. As up to 10 output features were expected, the authors breakdown one ANN into two for the ease of training.

Applications:
1) Pile construction productivity assessment

Data Collection:
- Questionnaires to contractors

ANN Paradigm adopted:
- BPNN

Commercial packages adopted:
- Matlab

ANN Architectures:
1) 1st ANN
-Input: 7 nodes (3 about the soil, 4 about the piling method)
-Hidden: 20 nodes in 1 layer (sigmoid function)
-Output: 5 node (drilling time, cage time, funnel time, tremie time, pouring time)

2) 2nd ANN
-Input: 7 nodes (3 about the soil, 4 about the piling method)
-Hidden: 50 nodes in 1 layer (sigmoid function)
-Output: 5 node (Adjust axis time, moving time, overall productivity, drilling cost, total cost)

<table>
<tr><td>29</td><td>2006</td><td>Neural Networks for Estimating the Productivity of Concreting Activities</td><td>A. S. Ezeldin;
L. M. Sharara</td><td>J. CEM /
TecNote.
(ASCE)</td></tr>
<tr><td colspan="5">

Paper Summary:

This paper presents an ANN application on productivity estimation for concreting related activities, including formworking, steel fixing, and concrete pouring (in three different ANN models). The source data was collected from questionnaire was separated and used for the training of the three ANN models.

</td></tr>
<tr><td colspan="5">

Applications:

1) Productivity estimation for 3 types of concreting related activities

Data Collection:

- Questionnaires

ANN Paradigm adopted:

- BPNN

ANN Architectures:

1) Formworking
-Input: 12 nodes (selected from the 20 common features about the project and work environment)
-Hidden: 22 nodes in 1 layer (sigmoid function)
-Output: 1 node (predicted productivity)

2) Steel fixing
-Input: 10 nodes (selected from the 20 common features about the project and work environment)
-Hidden: 15 nodes in 1 layer (sigmoid function)
-Output: 1 node (predicted productivity)

3) Concrete pouring
-Input: 11 nodes (selected from the 20 common features about the project and work environment)
-Hidden: 51 nodes in 1 layer (sigmoid function)
-Output: 1 node (predicted productivity)

</td></tr>
</table>

<table>
<tr><td>30</td><td>2006</td><td>Applying Undistorted Neural Network Sensitivity Analysis in Iris Plant Classification & Construction Productivity Prediction</td><td>Ming Lu;
Daniel S. Yeung;
Wing W. Y. Ng</td><td>Soft Computing</td></tr>
<tr><td colspan="5">Paper Summary:
This paper presents an ANN application on iris plant classification and construction productivity prediction. The ANN was applied to the iris plant classification which was trained by a standard dataset in order to validate the proposed sensitivity analysis methodology and the concreting productivity prediction in Hong Kong respectively. The source data about the concreting productivity was collected from the quality control records of five building construction projects in Hong Kong. The proposed approach helped the authors to identified the significant factors to concreting productivity.</td></tr>
<tr><td colspan="3">Applications:
1) Iris plant classification
2) Construction productivity prediction
Data Collection:
1) UCI-IRIS dataset from the UCI Machine Learning Repository
2) quality control records from five building construction projects in Hong Kong
ANN Paradigm adopted:
• BPNN</td><td colspan="2">ANN Architectures:
1) Iris plant classification
-Input: 4 nodes (sepal length & width, petal length & width)
-Hidden: NO MENTIONED
-Output: 1 node (predicted class)

2) Construction productivity prediction
-Input: 5 nodes (Pour size, supply of concrete, slump, pour location, pouring formwork shape)
-Hidden: NO MENTIONED
-Output: 1 node (predicted productivity)</td></tr>
</table>