Adaptive Probabilistic Neural Network-based Crane Type Selection System

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Abstract: Due to the central role of cranes in construction operations, specialists in the construction industries have cooperated in the development of structured methods and software for crane selection. Most of these software tools are for crane model selection, and integrated systems that handle both crane type and model selection are not readily available. This paper presents the crane type selection features of IntelliCranes, a prototype integrated crane selection tool that assists in both crane type and crane model selection based on a set of inputs describing the construction operation under consideration. By using historical data and advanced artificial intelligence computing tools such as artificial neural networks, IntelliCranes automates crane type selection. Crane type and crane model selection are seamlessly integrated in a comprehensive crane selection tool, and consistency in the selection of cranes for similar situations is increased.

DOI: 10.1061/(ASCE)0733-9364(2002)128:3(265)

CE Database keywords: Cranes; Neural networks; Construction sites; Lifting; Computer software; Selection.

Introduction to Crane Selection

Lifting and hoisting are important construction process tasks that require meticulous planning. Due to the diverse lifting and hoisting needs of the construction industry, many types of cranes have been designed and produced by crane manufacturers. Fig. 1 depicts an overview of existing types of cranes. Each type is designed to handle different types of lifting and hoisting requirements. On a typical construction project, the selection of the appropriate crane can have a significant influence on the time, cost, and safety of the construction operations.

Before an exact crane model/configuration can be selected from a crane manufacturer's or operator's database, it is important to select the type of crane (fixed top-slewing tower, mobile crawler-mounted lattice boom, etc.) to be used for the specific lifting or hoisting requirements of a construction site. Then, in the model selection phase, the exact model/configuration of the crane is selected. Fig. 2 depicts a schematic representation of the above-described crane selection process. The available types of cranes and input parameters pertaining to the construction project for which the crane is to be chosen provide the starting point. Heuristics and past experience are then used to select an appropriate type of crane. The type of crane chosen then serves as input for the crane model selection phase.

Due to the central role of cranes in construction operations, specialists in the crane rental and construction industries have cooperated in the development and use of structured methods and software tools for crane selection. However, it is not uncommon in these crane selection programs to query the user for a selection of the type of crane to be used. This is due to the fact that criteria, which are applied for crane type selection, are numerous, difficult to quantify, and subjective. Although research in this area has produced some fuzzy logic and expert system–based methods for crane type selection, no comprehensive and integrated systems are available.

This paper presents the crane type selection features of a prototype integrated crane selection tool, named IntelliCranes, that uses artificial neural networks (ANNs) to process the subjective information needed for crane type selection in a consistent manner. ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated (Chester 1993), or where the relationships between inputs and outputs are not sufficiently known. The very nature of artificial neural networks is to map from a space of input patterns to a space of output patterns. As such, ANNs are tools that can be used to determine causal models and inverse mappings, and are useful for performing the tasks of crane type selection.

This paper is organized as follows. The next section of this paper provides an overview of crane selection with particular emphasis placed on crane type selection. The third section provides an overview of IntelliCranes; the fourth and fifth sections give a general description of adaptive probabilistic neural networks (APNNs) and a description of the architecture of the APNN used in IntelliCranes, respectively. This is followed by a section that describes several case studies that were used for the validation of IntelliCranes. Finally, a last section provides findings and concluding remarks.

Crane Type Selection

The selection of the type of crane to be used for a particular construction project is not straightforward. While there are construction projects where site and job conditions mandate the type

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Note. Discussion open until November 1, 2002. Separate discussions must be submitted for individual papers. To extend the closing date by one month, a written request must be filed with the ASCE Managing Editor. The manuscript for this paper was submitted for review and possible publication on February 11, 2000; approved on August 3, 2001. This paper is part of the ***Journal of Construction Engineering and Management***, Vol. 128, No. 3, June 1, 2002. ©ASCE, ISSN 0733-9364/2002/3-265–273/$8.00+$.50 per page.

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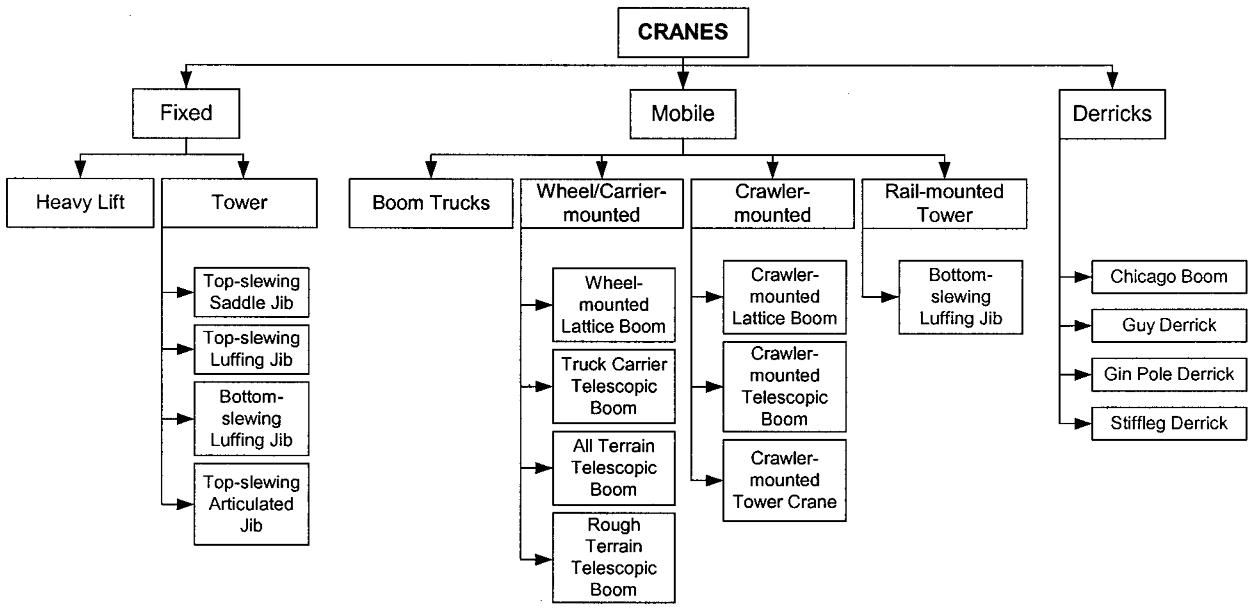

Fig. 1. Types of cranes

of crane to be used, a vast number of construction projects exist, in which both tower (fixed) and mobile cranes constitute practical solutions (Shapira and Glascock 1996). Further, the factors affecting the selection of a type of crane, such as the type of use, the duration of use, soil characteristics, and various site and construction properties, often involve information that is difficult to quantify or call for subjective judgment. The problem is compounded by the fact that the combination and compromise between all of the selection factors add complexity and fuzziness to the crane type selection process, and open it up for subjective judgment. The writers conducted a literature survey, interviewed experts, and determined a set of factors that are used in the crane type selection phase of IntelliCranes. These factors are as follows: (1) type of use; (2) duration on the site; (3) construction height; (4) site spaciousness or construction footprint; (5) terrain topography; (6) soil stability; (7) construction aspect ratio; (8) crane relocations on the site; and (9) site accessibility. The following subsections discuss the factors affecting crane type selection and their role in IntelliCranes' type selection features.

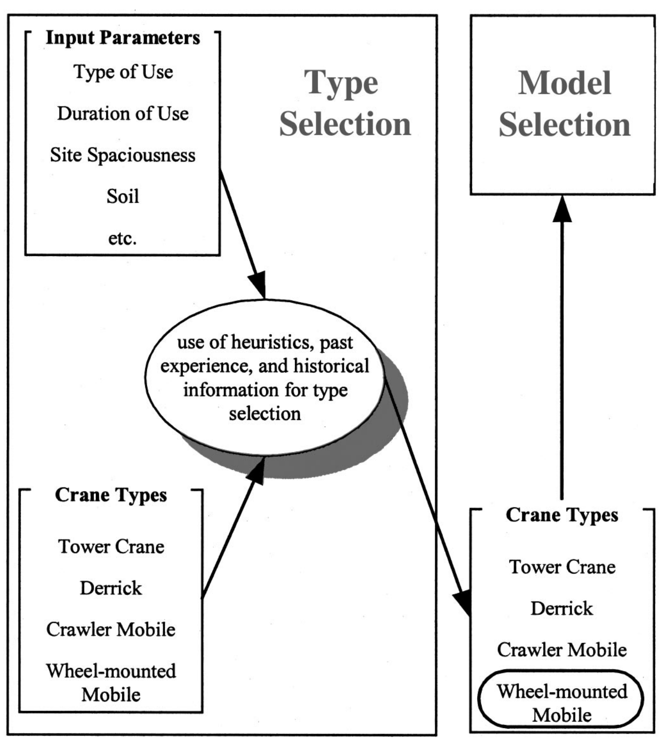

Fig. 2. Schematic representation of crane selection process

Type of Use

The type of work for which a crane is to be used can have a significant influence on the most appropriate type of crane. For instance, a tower crane (regarding its productivity) is more adequate for performing cyclic work for longer periods of time, as compared to a mobile crane. Once again, undefined limits and the variety of tasks a crane might be required to perform make choices of crane types difficult to compare and open room for subjective preferences. The type of use was selected as an input to the neural network for type selection.

Duration on Site

Due to the differences in setup and rental/operation costs of different types of cranes, even when of comparable capacity, the duration of the need for a crane(s) on a site can influence the cost of the cranage. Since other factors may take priority, this criterion may not always come to bear. Also, the varying differences in costs may turn an appropriate choice for a situation into an inappropriate one for the same situation in a different time or geographic setting. Thus, this criterion is intimately linked to cost data, and was selected as an input to the neural network for the selection of the type of crane.

Construction Height

The maximum height of the hook that is needed is a technical requirement that needs to be given consideration when calculating

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minimum boom lengths or selecting cranes from a database. It may also rule out the use of certain types of cranes. For example, in very tall buildings, the use of mobile cranes or even unbraced tower cranes may not be feasible. This parameter is thus not only needed to select crane models, but is also among those considered in the selection of the type of crane. As such, it was selected as an input variable for the neural network for type selection.

Site Spaciousness/Construction Footprint

The relation between the area of the construction and the site is of utmost importance. If a construction occupies the whole site, as is commonly seen in downtown sites, there is no space to set up mobile cranes or an external tower crane. Only an internal/climbing tower crane can be considered. Similarly, tower cranes are preferable in highly congested sites, since they arrive disassembled and need no space to move on the site. Mobile cranes are most practical in less congested sites. However, what is practical and what is not, just as what is congested and what is not, often remains a subjective decision. Nevertheless, the consideration of the site spaciousness in the type selection phase can, in cases such as a fully occupied site, eliminate certain options. This parameter is an input to the neural network for the crane type selection phase.

Slopes/Terrain Topography

The mobility of mobile cranes on a site or the need for a tower crane is conditioned by, among other factors, the terrain topography. While flat terrain allows the usage of mobile cranes, other more sloped sites may need the use of statically mounted tower cranes. The terrain topography needs to be considered in the crane type selection phase, and was included as an input to the neural network for crane type selection.

Soil/Foundation(s)

Soils can prompt the need for or prevent the use of a certain type of crane. Unsupportive soils call for crawler-mounted cranes or even tower cranes, which require specific foundations to be prepared for them. Similarly, if an interior climbing tower crane is used, the building's structure has to be supported or strengthened. During the selection of the type of crane to be used, the soils/necessary foundations for the crane should therefore be considered in conjunction with the inherent costs. This information is included as an input to the type selection neural network in IntelliCranes.

Construction Aspect Ratio

Information regarding the size, shape, and even construction process of a construction can be used in a number of ways. It can be utilized when determining the required number of a type of crane necessary to provide adequate coverage of a site. Consideration of this information in the selection of the crane type, however, may lead to the conclusion/realization that certain types of cranes may not be adequate. For instance, on vast low-rise buildings mobile cranes might at times operate from positions later enclosed by the buildings, thus eliminating the need for a tower crane that might otherwise have been required. Also, on very long and narrow constructions, one mobile crane may cover an area for which possibly two or more tower cranes would have been necessary.

Crane Relocations on Site

The number or frequency of on-site relocations of a crane can impact the adequacy of a type of crane. Wheel-mounted cranes need outriggers that have to be retracted and extended during each moving cycle. This procedure is usually more time-consuming than the relocation of a crawler-mounted mobile crane. Since this parameter affects the adequacy of a type of crane, it was included in the crane type selection phase and selected as input for the neural network.

Site Accessibility

The availability of a crane superbly suited to fulfill the requirements of a certain construction project is of little use if the crane cannot be brought to the construction site. Thus, the ease of access to the construction site is an important factor to be considered in the crane type selection phase.

The person selecting the type of crane to be used may base his or her selection not only on objective criteria and the factors described in the subsections above, but may also draw on past experiences and may be influenced by personal preferences and organizational traditions. While some research has been done in the field of crane type selection by Hanna and Kumar (1997) and Gray and Little (1985), user-friendly systems for this phase of crane selection are not readily available.

Personnel responsible for crane selections in the crane rental and construction industries would clearly benefit from a crane selection system such as IntelliCranes that can incorporate subjective input parameters necessary to perform crane type selections. Further, such a system should also integrate crane type and crane model selection into a comprehensive system.

Overview of IntelliCranes

IntelliCranes is composed of two major modules—a neural network–based crane type selection module and a knowledge-based expert system module for crane model selection. Other components are the user interface, a database with data on past crane selections used to test and train the type selection neural network, and a crane database with crane models from which the knowledge-based expert system can select. Fig. 3 provides an overview of the internal structure of IntelliCranes.

The user interface is used to update and modify the crane database, and to input the data necessary to perform the crane selections. The type selection module is used to select a type of crane for a particular construction project. The result of the consultation run is automatically exported as an input to the model selection module. The user can utilize this module to select the exact model and configuration of the crane to be used for a specified construction project. If desired, the user has the option to override the suggestion provided by the neural network for crane type selection. Fig. 4 provides a schematic representation of IntelliCranes' crane selection data processing.

IntelliCranes substitutes the multistage crane selection process depicted in Fig. 2 with a single integrated software program. As can be seen in Fig. 3, the IntelliCranes components relevant to crane type selection are (1) the user interface; (2) the type selections training data; and (3) the type selection module.

The user interface is used to provide database management and consultation input to the IntelliCranes system. It can be utilized by the user to manage and update the databases, and to input information pertaining to specific construction projects. This in-

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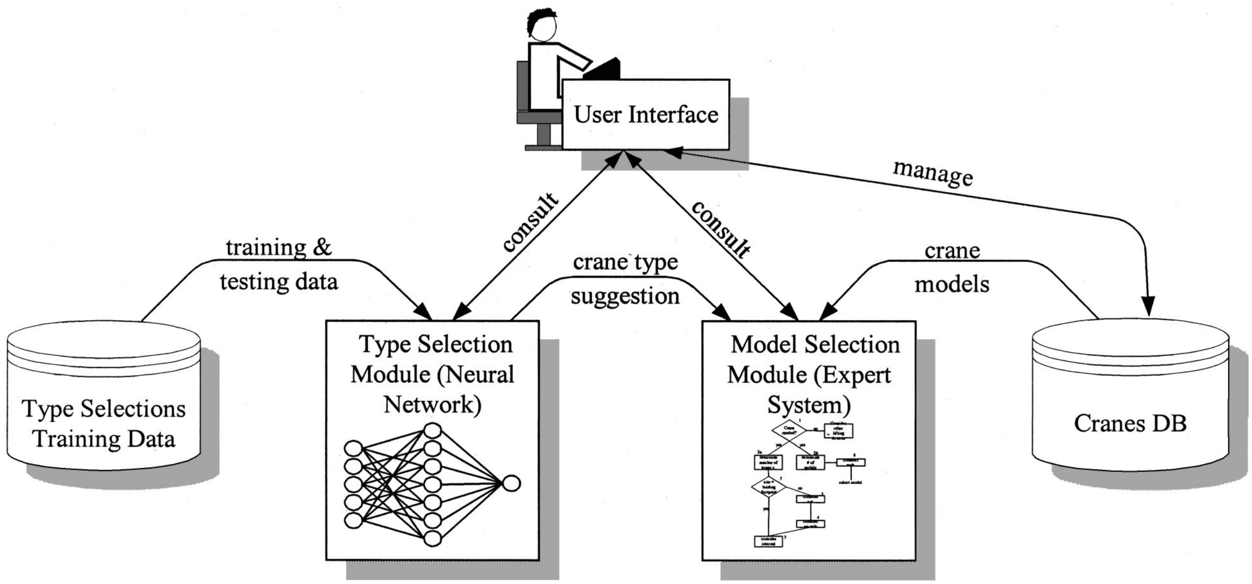

Fig. 3. Internal structure of IntelliCranes

formation given by the user is then used by the other IntelliCranes modules in the background to perform the crane selection for the given construction project.

The type selections training data database contains a series of examples of past crane type selections that were considered successful, i.e., where the crane was considered to have made positive contributions to the construction project. Data for each of the examples includes the type of use of the selected crane, the duration on the site, the construction height, the spaciousness of the site, the site's soil bearing capacity, the physical properties of the construction, the frequency of relocations on the site, site access, as well as the type of crane selected. These data were obtained from industry experts, and are based on actual crane type selections made by these experts. The data were used to train and test the neural network for crane type selection. Although the following functions were not implemented at this prototype stage of IntelliCranes, advanced users could expand these training data to train other neural networks to keep the type selection module updated, and would have the option of choosing between different neural networks for crane type selection.

The type selection module of IntelliCranes uses a trained and tested classification neural network to perform the task of selecting an appropriate type of crane for a construction project. The user is required to provide input data pertaining to the project for which the crane is to be selected. This input has the same format as the data contained in the type selections training data database.

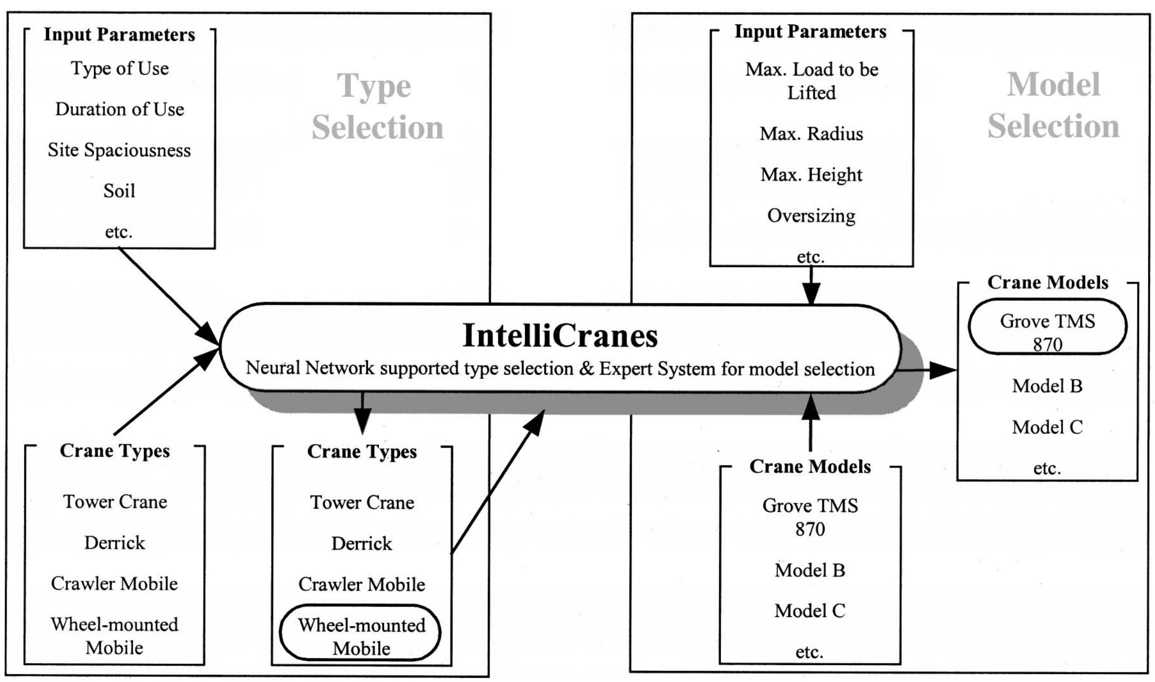

Fig. 4. Crane selection data processing in IntelliCranes

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The neural network then uses the input given by the user to select an appropriate type of crane for the construction project.

Limitations of IntelliCranes

The use of neural networks presupposes the availability of adequate and sufficient training cases data. The data on available crane selections were limited to eight crane types in IntelliCranes. For instance, only top-slewing saddle jib tower cranes could be considered at this prototype stage of IntelliCranes due to the limited amount of available cases in which other types of tower cranes were used. Also, relatively few training cases for crawler-mounted hydraulic boom cranes and carrier-mounted lattice boom cranes were available. This last limitation reduces IntelliCranes' accuracy when selecting these two types of cranes. Finally, another limitation is the fact that IntelliCranes in its present form does not allow one to simultaneously select more than one crane for a given construction site.

Adaptive Probabilistic Neural Networks

Neural computing is a relatively new field of artificial intelligence, which tries to mimic the structure and operation of biological neural systems, such as the human brain, by creating an ANN on a computer. ANNs are composed of simple interconnected elements called processing elements (PEs) or artificial neurons that act as microprocessors. Depending on the type of ANN, the PEs may be arranged in layers or clusters and may be connected to all other PEs or just to PEs in certain layers or clusters. According to its position within the ANN, a PE can be used to receive input data, perform calculations, or provide final output.

ANNs are modeling techniques that are especially useful to address problems where solutions are not clearly formulated (Chester 1993), or where the relationships between inputs and outputs are not sufficiently known. This is due to the ANNs' ability to learn by example. Patterns and relationships in the input and output data of historical example cases are recognized. This acquired ''knowledge'' can then be used by the ANN to predict unknown output values for a given set of input values. Alternatively, ANNs can also be used for classification. In this case, the artificial neural networks' output is a discrete category to which the item described by the input values belongs. An example of prediction would be financial forecasting, where an ANN could use current data to predict future stock prices. Similarly, a classification example would be medical diagnosis. Given a set of symptoms as input values, the ANN could determine what kind of pathology is at hand. For further general information on ANNs, especially with regard to their applications in civil engineering, the reader is referred to Lu et al. (2000), Faghri and Hua (1998), Garrett et al. (1997), Flood et al. (1994), and Specht (1991).

Many types of artificial neural networks exist—the most well known being the classical multilayer perceptron (MLP). However, not all networks are equally suited for a problem such as the crane type selection in IntelliCranes, which is a classification problem, as it could be stated that the neural network would classify construction sites/lifting tasks into categories best served by a specific type of crane. As such, the neural network used in IntelliCranes would need to be a classification network such as a PNN or a universal approximator such as a multilayer perceptron. Both PNNs and multilayer perceptrons were initially considered for IntelliCranes.

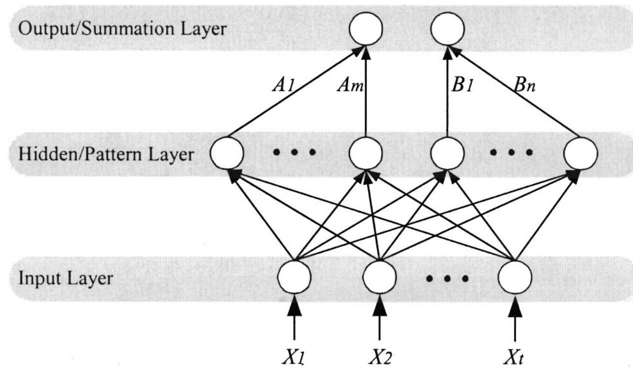

Fig. 5. Schematic representation of probabilistic neural network

After careful consideration and testing, it was decided to adopt a PNN for IntelliCranes. This was based on the fact that PNNs train quickly on small data sets (*NeuralWizard* 1999). Further, PNNs can model any nonlinear function using a single hidden/pattern layer with as many PEs as there are training cases. This eliminates guesswork and experimentation to determine the ideal number of hidden/pattern layers and the respective number of PEs (*Electronic* 1999). Other advantages include the capability to tolerate erroneous training examples, the adequacy of sparse training examples for PNN performance, and the adaptability of the complexity of the decision surfaces by choosing an appropriate smoothing factor (Chen 1996). Chen (1996) also discusses the superiority of PNNs and particularly APNNs to back-propagation neural networks, i.e., MLPs. Thus, it was decided that the type of ANN used in IntelliCranes would be an APNN. The disadvantages of PNNs, which are mainly related to the fact that PNNs must store and use all training vectors to classify new vectors as well as to the PNNs' tendency to need a large memory and computation time for a classification (proportional to the size of the training set), were determined not to be problematic in the case of IntelliCranes.

PNNs, developed originally by D. F. Specht (Specht 1988), are multilayer feedforward networks used to separate data into a specified number of output categories. PNNs typically employ one PE in the input layer for each input variable and one PE in the output/summation layer for each possible class/category. There must be as many PEs in the hidden/pattern layer as there are training patterns. Fig. 5 presents a schematic representation of a probabilistic neural network for classification of an input $\mathbf{X}$ in two classes/categories, A and B. The number of training examples with output in classes/categories A and B is m and n, respectively.

The PEs in the input layer are simple distribution units that provide the same input values to all PEs in the hidden/pattern layer (Chen 1996). These PEs form a dot product of the input vector $\mathbf{X}$ with a weight vector $\mathbf{w}_i$

$$Z_i = \mathbf{X} * \mathbf{w}_i \tag{1}$$

and subsequently perform a nonlinear operation on Z_i before outputting the result to a PE in the output/summation layer. Instead of a sigmoidal activation function commonly used for MLPs trained with back-propagation, the nonlinear operation used in PNNs is (Chen 1996)

$$\exp\left[\frac{(Z_i - 1)}{\sigma^2}\right] \tag{2}$$

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where σ = smoothing factor that determines how closely the probabilistic neural network matches its output to the data in the training examples. Since both $\mathbf{X}$ and $\mathbf{w}_i$ are normalized to the unit length, this is equivalent to using (Chen 1996)

$$\exp\left[\frac{-(\mathbf{w}_i-\mathbf{X})^t(\mathbf{w}_i-\mathbf{X})}{2\sigma^2}\right] \tag{3}$$

The hidden/pattern layer operates on the basis of competition; only PEs with the highest match to an input vector generate outputs. If an input does not relate well to any training example stored in the hidden/pattern layer, no output is generated (Data 1992). The PEs in the output/summation layer simply sum the inputs from the PEs in the hidden/pattern layer that belong to their class/category.

Alternatively, in other probabilistic neural network implementations, the PEs in the hidden/pattern layer subtract the stored input vector of a training example from the input vector and sum the squares of the differences to find the squared euclidean distance. This distance is the input to an exponential activation function that generates the PEs' output (Chen 1996).

PNNs use a supervised training set to develop distribution functions within the hidden/pattern layer (Data 1992), which has one PE for each training example. Each PE in the hidden/pattern layer of a PNN is trained once. The learning function simply selects the first untrained PE from the hidden/pattern layer and adjusts the weight vector $\mathbf{w}_i$ to be equal to the distinct weight vector of a training example in a certain class/category. The output of the newly trained PE is then connected to the appropriate output/summation element for that class/category (Bose and Liang 1996).

For PNN training, the single control factor that needs to be chosen is the smoothing factor σ. This factor determines how closely the PNN matches its output to the data in the training examples. Too small smoothing factors result in a very spiked output, which cannot generalize well, while too large smoothing factors eliminate (smooth out) detail. An appropriate value for the smoothing factor is usually easily chosen by experiment (*Electronic* 1999).

The original PNN uses a single smoothing factor σ for all classes/categories and a single pass of the training examples to train the network (Bose and Liang 1996). Modified approaches, such as the APNN, as used in IntelliCranes, employ a second phase in training to test a whole range of smoothing factors for each input variable, as this produces a network that works better on the test set (*NeuroShell* 1996; *NeuralWizard* 1999). Genetic algorithms, which are adaptive methods used to solve search and optimization problems, have been introduced to effectively enhance APNN training, i.e., to select smoothing factors (*NeuroShell* 1996). The above-described advantages of probabilistic neural networks in general and adaptive probabilistic neural networks in particular—especially the ability to train quickly on small data sets, the elimination of the need for guesswork and experimentation to determine the ideal number of hidden/pattern layers and the respective number of processing elements, the capability to tolerate erroneous training examples, and the adequacy of sparse training examples for PNN performance—were significant in the decision to use APNNs for IntelliCranes.

Architecture of Adaptive Probalistic Neural Networks used in IntelliCranes

The architecture of the APNN used in IntelliCranes has 340 processing elements in the hidden/pattern layer (equal to the number

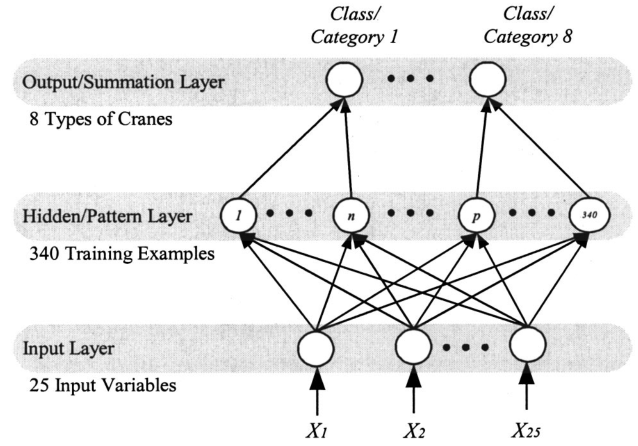

Fig. 6. Adaptive probabilistic neural network used in IntelliCranes

of training examples, i.e., 340). Of the example cases, 272 were used for actual training, while 68 were used for testing. The input layer contains 25 processing elements for the input variables, while the output/summation layer has eight, with each one representing one of the crane types. Ward Systems Group *NeuroShell 2* (1996) was used to implement the APNN for IntelliCranes. In future implementations of IntelliCranes, the user himself/herself will have the option of designing the architecture of the APNN. Fig. 6 depicts a schematic representation of the APNN used in IntelliCranes.

With the purpose of both determining the input variables to be included in the IntelliCranes neural network, e.g., the variables that influence crane type selection, and obtaining historical data on crane selections, a series of questionnaires and forms were circulated to construction companies operating in the Midwest. These were complemented by interviews conducted with experts in the field. The variables selected as input for the type selection module of IntelliCranes are described in detail in subsequent paragraphs.

All neural networks require numeric input, which implies that preprocessing and postprocessing stages are necessary to prepare data for input into a neural network and output for consumption. This obviously also reflects the implementation of files containing the historical data for training purposes. In IntelliCranes, the data are represented in the following fashion:

1. Type of use. A set of nine possible types of uses (concrete placing, formwork placing, steel erection, precast erection, rebar placement, equipment setting, materials handling, pick and carry, and heavy lift) was determined. Each is represented by a two-state variable that can take the values of 1 = true and 0 = false. For a given historical case, a 1 in the concrete placing column in the database with the training examples indicates that the crane was used for concrete placing. Similarly, a 0 indicates that the crane was not used for the respective purpose.
2. Duration on the site (days). The duration of the crane on the site is given in days; as such, it is a numerical value. However, numerical values have to be scaled into a range adequate for the neural network (*Electronic* 1999). In the design phase of the neural networks for IntelliCranes, a minimum value and a maximum value for the duration are established. The scaling function used is designated zero-to-one [0, 1]. Numbers contained in the training examples are scaled into the 0–1 range. The minimum value for the dura-

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Table 1. Sample Input for Type Selection Module

Input variable	User information	IntelliCranes input vector
Concrete placement	Yes	1
Formwork	Yes	1
Steel erection	Yes	1
Precast erection	No	0
Rebar placement	Yes	1
Equipment setting	No	0
Materials handling	Yes	1
Pick and carry	No	0
Heavy lift	No	0
Duration on site (days)	365	0.922
Construction height (ft)	100	0.208
No space	No	0
No space to move	Yes	1
Space to move	No	0
Unrestricted	No	0
No slope	No	0
Slopes	Yes	1
Good bearing capacity	No	0
Fair bearing capacity	Yes	1
Poor bearing capacity	No	0
Aspect ratio w/l	1.000	1.000
Often	No	0
Seldom	No	0
None	Yes	1
Restricted	Yes	1
Unrestricted	No	0

tion is set to 0, while the maximum value for the duration is set to 1. New numbers presented during consultation runs are cut off if they are above or below the numbers found in the training examples. Thus, if a crane is to be on the site longer than the APNN has been trained for, the APNN will use 1, i.e., the maximum duration it was trained for.

3. Construction height (ft). The construction height (0.3048 m) is given in feet. As with the duration of the crane on the site, its numerical value is then scaled.
4. Site spaciousness (no space, no space for crane movement, enough space for crane movement, and unrestricted spaciousness). The site spaciousness is represented by a multistate variable. To represent this information, *one-of-N* encoding is used. A number of two-state variables, equal to the number of possible states, are used to represent the multistate variable. One of the *N* two-state variables is set to 1 =true, while the others are set to 0=false. For example, no space={1,0,0,0}, no space for crane movement={0,1,0,0}, enough space for crane movement={0,0,1,0}, and so on.
5. Slopes (no slopes or slopes). A multistate variable with *one-of-N* encoding is used to represent this information.
6. Soil (good bearing capacity, fair bearing capacity, or poor bearing capacity). A multistate variable with *one-of-N* encoding is used to represent the data on soil bearing capacity.
7. Construction aspect ratio (w/l). Since this is a ratio of the shorter side divided by the longer side of the crane operating area, the numerical value will be between 0 and 1 (no scaling is necessary).
8. Relocations on the site (often, seldom, or never). A multistate variable with *one-of-N* encoding is used to represent the data on crane relocations on the site.
9. Site accessibility (restricted or unrestricted). A multistate variable with *one-of-N* encoding is used to represent these data.

Table 1 illustrates a complete input for the type selection module.

With regard to the output, eight major types of cranes were selected as possible output for the neural network–based type selection phase of IntelliCranes. These are (1) tower crane; (2) heavy lift crane; (3) crawler-mounted lattice boom crane; (4) crawler-mounted hydraulic boom crane; (5) carrier-mounted lattice boom crane; (6) carrier-mounted hydraulic boom crane; (7) all terrain crane; and (8) rough terrain crane. A multistate variable with *one-of-N* encoding is used to represent these output data.

The learning phase for the APNN in IntelliCranes used genetic algorithms to seek the best smoothing factors. Essentially, the genetic algorithm seeks to breed a population of individuals, each of which presents a potential solution to the problem. This potential solution is a set of smoothing factors that minimizes the mean-squared error of the test set (*NeuroShell* 1996). The population size, or breeding pool size, contained between 75 and 200 individuals, and the stopping criterion for the genetic algorithm was set to 20 generations without any improvement.

Case Studies for System Validation

To illustrate and validate the use of IntelliCranes, a number of crane type and model selections were performed and validated by a construction industry expert. The result of one of the crane type selections is described in the following paragraphs. Three similarly validated studies are presented in Table 2.

The first case study was the construction of the Fetzer Center Retreat in Kalamazoo Mich., in 1993/1994. The project earned the contractor, Miller-Davis Company of Kalamazoo, the 1995

Table 2. Data and Results of Three Case Studies

Item	Case study 2	Case study 3	Case study 4
Type of use	Steel erection	Materials handling	Steel erection
Duration on the site	83 days	Five days	61 days
Construction height	33.53 m (110 ft)	9.14 m (30 ft)	9.14 m (30 ft)
Site spaciousness	Space to move	Unrestricted	Unrestricted
Slopes	No slopes	No slopes	No slopes
Soil	Good bearing	Fair bearing	Good bearing
Aspect ratio (w/l)	1	1	0.2
Relocations on the site	Often	Often	Seldom
Site access	Unrestricted	Restricted	Restricted
Type of crane selected	Crawler lattice	Rough terrain	Carrier hydraulic

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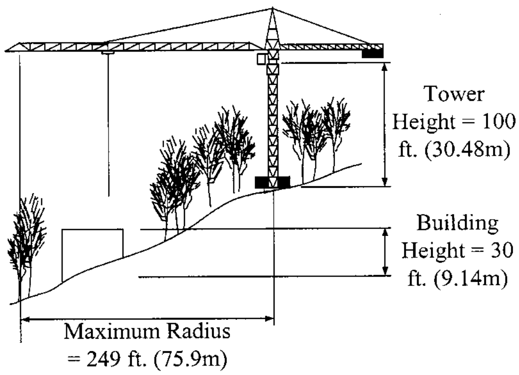

Fig. 7. Elevation of case study construction site

Associated General Contractors of America Build America Award. The project involved the construction of an arc-shaped building complex in a sloped and wooded area, as illustrated in Fig. 7. The crane was to be used on the site for approximately one year for concrete placing, formwork handling, steel erection, and rebar placement. The conditions dictated that the crane be positioned at some distance uphill. Also, the trees made it impractical for a crane to move on the site. Thus, a single crane had to cover the whole site, with the maximum radius being 75.9 m (249 ft). The maximum load to be lifted was 1,814.4 kg (4,000 lb), while the load placement height was, due to the slope present, actually lower than the crane's base. These and the remaining characteristics of this construction project are best deduced from Fig. 7. Figs. 8 and 9 depict the IntelliCranes input screens used to select a crane, both type and model. The model input screen is also the type selection output screen. As can be seen in Fig. 9, IntelliCranes selected a tower crane for this particular project. This coincides with the crane selected by the contractor, which was a Pecco tower crane with a load placement radius of 76.2 m (250 ft).

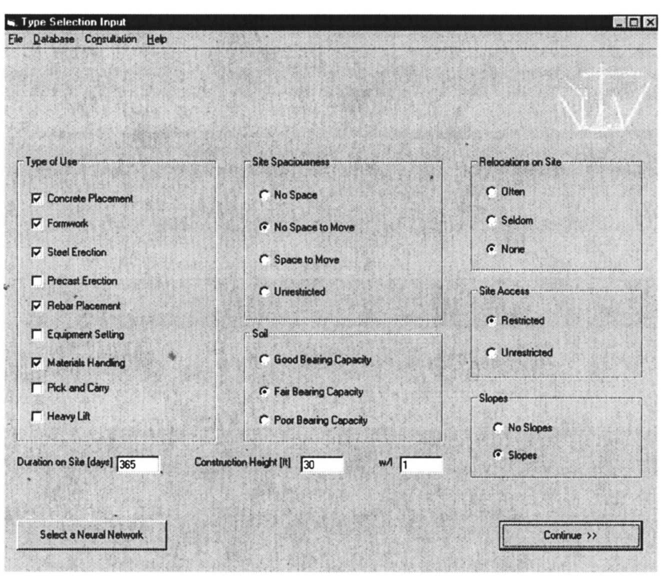

Fig. 8. Case study type selection input screen

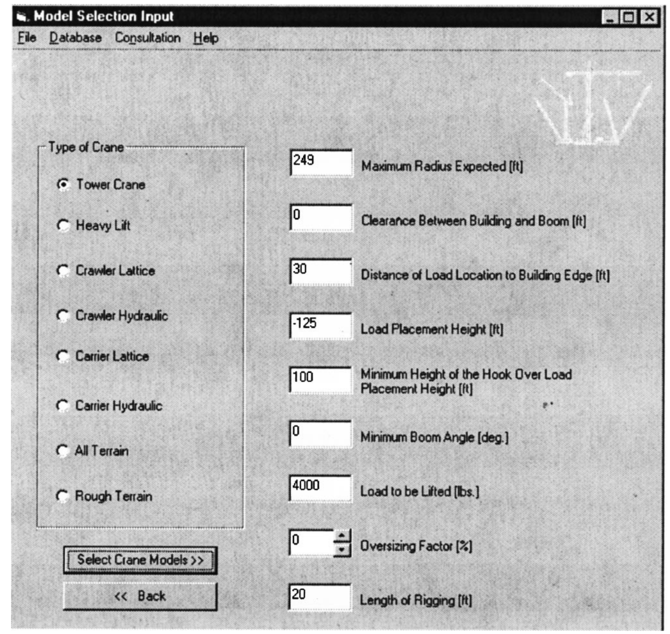

Fig. 9. Case study type selection output/model selection input screen

Findings and Conclusion

The above-described case studies, in concert with a large number of further consultation runs, revealed the capability of IntelliCranes to select appropriate cranes for a construction project. Overall, IntelliCranes' type selection module made 313 correct crane type selections and 27 erroneous ones—a success rate of 92.1%. Most errors were found to be in selections involving crawler-mounted hydraulic boom cranes and carrier-mounted lattice boom cranes. Although significant, it was found that this did not disprove the IntelliCranes concept, as these two types of cranes were the ones with the least amount of available data in the type selections training data database.

In many cases, IntelliCranes correctly changed its type selection due to the change of a single parameter. Similarly, type selections are changed if the specified construction height is too high for a particular crane type. For instance, if a certain height is reached, IntelliCranes selects an all terrain crane instead of a rough terrain crane, as the former typically has longer booms. Once again, if the specified heights are very high [>121.92 m (>400 ft)], only tower cranes are selected. Finally, repeated consultations of IntelliCranes reveal the tendency to select cranes with self-contained hydraulic booms over cranes with lattice booms for sites with restricted access/space, as these are easier to set up in such conditions.

IntelliCranes can be used to select appropriate cranes (both type and model) for a particular construction site/project. The cranes selected by IntelliCranes proved to be similar to the ones actually used in the case studies. This makes IntelliCranes an interesting and potentially useful tool, especially for less experienced construction industry personnel involved in crane selection. The user can easily and rapidly determine the influence that factors have on the selection of a certain type of crane. The potential of the use of artificial neural networks is demonstrated by the possibility, in IntelliCranes, to consider all factors that affect crane type selection in a consistent manner. This possibility or feature would be difficult to implement without the use of artificial neural networks.

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References

Bose, N. K., and Liang, P. (1996). *Neural network fundamentals with graphs, algorithms, and applications*, McGraw-Hill, New York.

Chen, C. H. (1996). *Fuzzy logic and neural network handbook*, C. H. Chen, ed., McGraw-Hill, New York.

Chester, M. (1993). *Neural networks—A tutorial*, Prentice-Hall, Englewood Cliffs, N.J.

Data & Analysis Center for Software (DACS). (1992). ‘‘*Artificial neural networks technology*.’’ Dept. of Defense, Rome, N.Y. ⟨http://www.dacs.dtic.mil/techs/neural/neuralToC.html⟩ (May 14, 1999).

Faghri, A., and Hua, J. (1998). ‘‘A neural network–based traffic control system for isolated intersections.’’ *Artificial neural networks for civil engineers: Advanced features and applications*, I. Flood and N. Kartam, eds., ASCE, Reston, Va., 35–52.

Flood, I., Kartam, N., and Tongthong, T. (1994). ‘‘The application of artificial neural networks to civil engineering.’’ *Proc., 1st Congress on Computing in Civil Engineering*, K. Khozeimeh, ed., ASCE, New York, 668–675.

Garrett, J. H., Gunaratnam, D. J., and Ivezic, N. (1997). ‘‘Introduction.’’ *Artificial neural networks for civil engineers: Fundamentals and applications*, N. Kartam, et al., eds., ASCE, New York, 1–18.

Gray, C., and Little, J. (1985). ‘‘A systematic approach to the selection of an appropriate crane for a construction site.’’ *Constr. Manage. Econom.*, E & FN Spon, London, 3, 121–144.

Hanna, A. S., and Kumar, V. S. S. (1997). ‘‘A fuzzy logic approach to selection of cranes.’’ *Working Paper*, Dept. of Civil and Environmental Engineering, Univ. of Wisconsin, Madison, Wis.

Lu, M., AbouRizk, S. M., and Hermann, U. H. (2000). ‘‘Estimating labor productivity using probability inference neural network.’’ *J. Comput. Civ. Eng.*, 14(4), 241–248.

NeuralWizard help topics. (1999). NeuroDimension, Inc., Gainesville, Fla.

Shapira, A., and Glascock, J. D. (1996). ‘‘Culture of using mobile cranes for building construction.’’ *J. Constr. Eng. Manage.*, 122(4), 298–307.

Specht, D. F. (1991). ‘‘A general regression neural network.’’ *IEEE Transactions on Neural Networks*, IEEE, Piscataway, N.J., 2(6), 568–576.

Specht, D. F. (1988). ‘‘Probabilistic neural networks for classification, mapping or associative memory.’’ *Proc., IEEE Int. Conf. on Neural Networks*, Piscataway, N.J., 1, 525–532.

Electronic manual for Trajan neural networks. (1999). Trajan Software, Ltd., Durham, U.K.

NeuroShell 2 user's manual, 4th Ed. (1996). Ward Systems Group, Frederick, Md.

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