A Computer Based Software Tool for Assessing Plant Operatives' Productivity

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ABSTRACT | Developments in computer hardware and software have significantly influenced the accuracy of estimating and predicting construction productivity. To date, a plethora of unique computer software packages is readily available and these packages have helped to increase production and profitability whilst simultaneously reducing financial risk. This paper presents and describes the development of a new prototype Computer Based Software (CBS) human resource management tool, that can be used to assess a plant operative's potential productivity output. The CBS utilises information extracted from a range of factors and variables that exhibit a significant correlation between machine production and operator attributes (for example, management practices and site conditions).

KEYWORDS | Computer software, productivity, plant operative, off-highway plant and equipment

1 Introduction

Researchers have recognised that in order to improve the productivity of the construction process, increasing attention needs to be given to the factors that impact upon it, such as inept project management, human resource management and working conditions (Thomas et al., 1997; Thomas and Napolitan, 1995). By developing a comprehensive understanding of the factors (and the variables which in turn affect these factors that enhance or impair productivity performance), a more thorough understanding of productivity stimulants can be acquired (Kim, 1993). To date, many of the studies that have sought to enhance production rates in construction have predominantly focused upon the labour resource and its impact upon productivity gains or losses (Thomas 1999, 2000, 2001; Goodrum and Haas, 2003; Harrison et al., 2001). A plethora of factors and variables have been measured by these studies and labour productivity has indeed been shown to be a key indicator of construction productivity efficiency (Rojas and Aramvareekul, 2003). In conjunction with this body of work, a wide range of methods of measurement and computer software simulation tools has been developed (Motwani et al., 1995). Yet, Motwani et al. (1995) maintain that construction productivity is infamously difficulty to measure and control due to the highly unpredictable factors and variables (and random chance occurrences) involved in different construction projects. These unpredictable (or at least, difficult) factors and variables include equipment application, employee skills, employee placement, standards, physical environment, supervision and materials management (Snow and Alexander, 1992).

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Whilst no single definitive model exists to accurately measure and predict construction productivity performance, a variety of rudimentary computer simulation software tools (for productivity measurement) has been developed (Lee et al., 2004). This situation is particularly relevant to construction plant productivity measurement and specifically the impact of the plant operator (Cabahug et al., 2004; Oloke et al., 2004 and Yang, et al., 2004). To address this observed current deficiency this paper presents and describes the development of a prototype computer based neural network software system that can be used to classify a plant operative's productivity based upon factors such as management, motivation, education and training, stress and maintenance skills. Specifically, the work reports upon the process involved in the development of a Computer Based Intelligent Software (CBS) tool for classifying plant operatives' productivity. This process includes: creation of an artificial neural network model, development of a computer based software package and testing and validation of the software package.

2 Estimating productivity

While estimating overall construction productivity, Thomas and Kuprenas (2003) examined and monitored falsework productivity in bridge construction. This involved an analysis of labour hours and an assessment of factors such as location of bridge, design factors, construction equipment usage (i.e. cranes) and materials delivery. To estimate overall productivity they relied upon their earlier work which had developed a conceptual model to measure productivity of the design process and used a measure of cost efficiency to determine the production rates (Thomas, et al., 1999). Similarly, Herbsman and Ellis (1991) estimated construction productivity using technological and organisational factors including building specifications and design, project location and materials (technological) distribution/management, human resource and social (organisational) factors.

Management philosophies, such as lean production, have suggested that better productivity and cost performance can be achieved by improving the labour reliability flow (where good reliability flow aims to reduce labour absence, sick leave etc.) (Thomas et al., 2003). Ballard (1999) suggested that improving labour reliability would also consequently improve management performance since the latter relies upon the efforts of those employed to undertake physical construction activities. However, AbouRizk and Hermann (2002) pointed out that labour productivity is affected by design complexity, prevailing climatic conditions, site supervision and the skills, competence and experience of the labour resource.

Thomas (2001) estimated that construction labour efficiency is affected by deviations from on-site work activities and the scheduling relationship that exists between these activities (often termed workflow). Indeed, workflow, along with the schedule of work, has been identified as being a key influence on fluctuations in labour productivity (ibid). Notably, Mendelsohn (1998) identified that teamwork provides the key to improving construction project productivity, provided that each team member actively participates in the teamwork effort. This relies upon each team member satisfying their own individual motivators and gaining internal satisfaction.

Yet despite the volume of aforementioned research work undertaken, a method or software package for measuring the plant operator's impact upon construction productivity has so far eluded researchers in the field. Rather, broad rules of thumb and subjective assessments have been relied upon. For example, a plant utilisation rate of 80 percent is often quoted and operators are classified as being either good, average or poor without providing any guidance regards the criteria that differentiate between these classifications.

3 Developments in plant and equipment research

Despite previous years of under investment, the plant and equipment research community has witnessed a renaissance period during the past decade with a wide variety of work being undertaken by Universities, plant manufacturers and independent research consultants (Edwards, et al., 2003). Plant productivity in particular has attracted growing attention (Schecnayder and David, 2002). For example, Bhurisith and Touran (2002) developed an obsolescence cost model to examine the productivity of plant equipment and items over a 15 year period. The model demonstrated that construction plant and equipment productivity has increased principally because of rapid mechanical technological advancements.

Others have focused more upon the utilisation of blue skies technologies, for example, global satellite positioning systems, and the potential benefits in terms of improved production performance on construction sites (Jonasson, et al., 2002). The research by Jonasson et al. (2002) provided an advanced guidance system with which to monitor equipment operational activities in order to better control equipment productivity. More specifically, Chao and Skibniewski (1994) conducted experimental research which used a computer simulation software package linked to an Artificial Neural Network (ANN) system, to predict the productivity of a tracked hydraulic excavator. This research was based on a computer simulation model of the excavation process (including excavate, slew, dump and so forth) and it confirmed two main factors that impact upon an excavator's productivity; namely, job condition and operational elements. Job condition elements consist of the environment surroundings, for example, soil condition, specification of the excavator and excavation position, such as the vertical position of the cutting edge. Operational elements consist of extraneous activities not specifically linked to the excavation operation, for instance, poor scheduling of support vehicles. One example is an increase in the waiting time for dump trucks either because the wrong capacity has been specified or an inadequate number of dump trucks allocated.

The work conducted by Chao and Skibniewski (1994) was investigated further by Edwards and Holt (2000), who produced ESTIVATE to predict the production output of a tracked back-acter 360° excavator operating in the construction and opencast mining industries. ESTIVATE was based upon a multiple linear regression equation using the variables machine weight, digging depth and machine swing angle to calculate machine cycle time. Having reliably predicted cycle time, production output was then calculated using additional variables such as bucket capacity, bucket fill factor and soil condition. To improve the accuracy of ESTIVATE, Edwards and Griffiths (2000) developed a feed forward ANN approach to calculate excavator cycle time and production output. This model was independently validated several years later by Tam et al. (2002) who applied a similar ANN architecture to the original data set. The culmination of research conducted confirmed the reliability and robustness inherent within the ANN technique.

4 Intelligent computer applications

A wide range of computer software packages has been developed to simulate and estimate construction and plant productivity together with associated cost implications (Smith, 2002). These packages have significantly enhanced managerial efficiency when managing construction and civil engineering projects (AbouRizk et al., 2001). Computer based simulation software tools have provided more accurate cost estimations, thus allowing effective budgeting and financing of construction projects as well as increasing company profitability (Adeli and Wu, 1998). Decision support systems have also been developed using ANN as the basis (Lee et al., 2004; Harrison et al., 2001; Cheng and Ko, 2003). Other researchers have

employed computer based decision tree tools to analyse the impact of factors which influence productivity, including factors such as materials delivery schedules and changes to construction work activities to determine construction productivity losses (Lee et al., 2004). Similarly, a decision support system tool was utilised to assist managerial staff in improving performance and production rates (Harrison et al., 2001). A culmination of this previous work served to consolidate the work of Yang et al., (2003) who developed a decision support system to contribute towards the design of construction site layout and materials delivery to assist construction project managers.

The success of decision tree or support systems can largely be attributed to their inherent ability to organise information/data management systems to intake up-to-date information/data (Change and Tsai, 2003). However, the decision tree or support system has less capability to identify the factors which have strong correlations with output (productivity) (ibid). This inherent shortcoming has been overcome with the application of ANNs (Yang and Edwards, 2004)

Computer based ANN system applications are typically used to ascertain the relationship between factors and/or variables with a single output (in this instance, productivity) (AbouRizk et al., 2001). Wales and AbouRizk (1993) employed ANNs to estimate and simulate the influence of construction site condition on labour productivity. Portas and AbouRizk (1997) discussed an ANN model developed to predict formwork construction productivity which involved an analysis of the impact of construction activity on labour production rates. Similarly, Lu et al. (2000) developed a classification model to process factors including site location, construction activities, equipment and materials management and project durations, to predict construction production rate.

Goodrum and Haas (2002) cited the almost exponential rate of equipment technological development as one factor that may account for increasing construction

productivity. Five specific equipment factors, namely, energy, control, functional range, information processing and ergonomics were observed using multiple linear regression. The research revealed that equipment technology could substantially improve longer-term construction productivity.

Yet despite the extensive volume of research into plant and equipment science and the development of intelligent computer applications, these two distinct fields of research have not hitherto converged upon the plant operator and the many factors and variables that impact upon machine productivity. This is a particularly important issue when considering that mechanisation is perceived by many as a means by which site productivity can be improved.

5 Computer Software tool

The development of a computer based software tool for classifying the impact of a plant operator upon machine production rates followed an iterative four stage procedure. Each stage in this logical process sought to provide a basis upon which the next stage could be developed. These four stages were:

1. System architecture design and computer Graphical User Interface (GUI);
2. Generation of the ANN module component within the system;
3. Handling of the data flow within the system, to deal with both input and output data as well as the classification result; and
4. Validation and testing of the software tool.

5.1 System Architecture Design and Computer Graphical User Interface

The system was developed as a 'stand alone' executable software package and can therefore be installed onto, and operate on, any personal computer (PC) workstation. The software architecture consists of modules, including (refer to Figure 1):
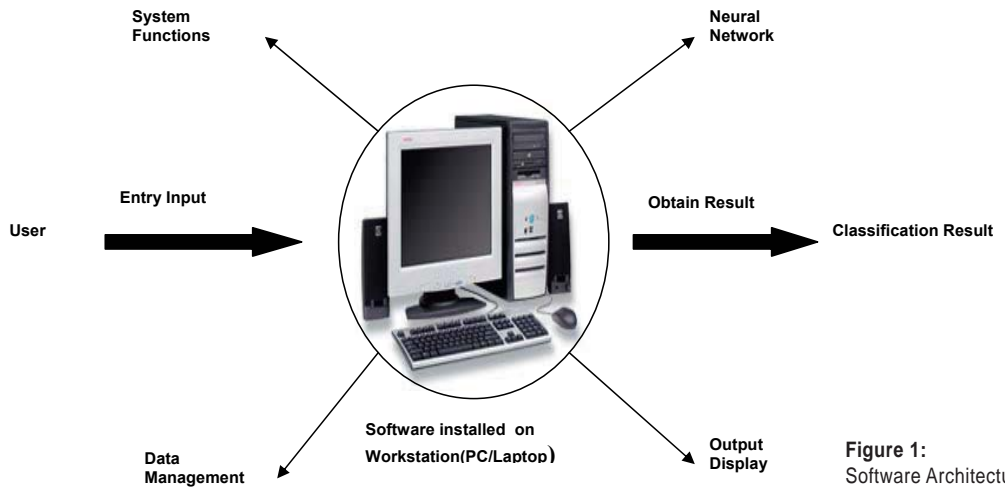
- System functions, for example, data input, help functions, start menu etc.;
- Data management functions including update of variables and transference of variables (factors) into the ANN model;
- ANN algorithmic functions including the processing of factors and variables and the production of a final classification result; and
- Output display.

To develop the Graphical User Interface (GUI) (a friendly interface between the user and the software), Visual Basic 6 (VB 6) was used as the preferred computer language because VB has a proven track record for producing user-friendly applications (Lee and Christensen, 1997). Figure 2 illustrates the Computer Use Interface for the system. There are three main functions, namely: i) main user menu, ii) information management and iii) display interface and classification (via the ANN). A range of sub-modules (functions) is available within each of the main functions and includes running a demo, data input, classification and so forth. The interface enables the software user to be guided through the process in a user-friendly environment, albeit future work will aim to ensure that the package complies with the Special Educational Needs and Disability Act 2001 (2001).

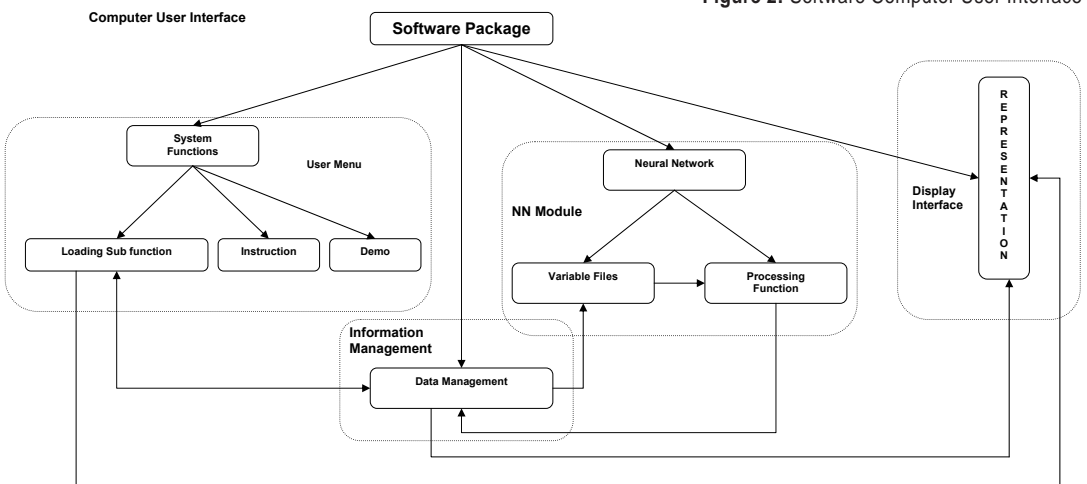**Figure 2:** Software Computer User Interface

Figure 3: User menu

Figure 4: Classification menu

5.1.1 Main User Menu

The user menu is the first screen to be presented to the user when accessing the system (Figure 3). The user menu consists of three options which provide access to sub functions for introducing the user to the software, running a demo and carrying out a classification (the loading function).

- The instructions for using the software provide a detailed review of the software tool, its potential applications, limitations and functionality. Where applicable, step-by-step instructions are provided to guide the uninitiated user through the system.

- Running a demo provides a useful tutorial feature to visually guide the user through the software's features, controls and functions.

- The loading function provides the interface between the database of classification factors and variables and the ANN modelling environment and therefore acts as a gateway to generating the classification result.

5.1.2 Information Management

The information management (IM) module works as an integrated function throughout the software tool. The first screen presented (Figure 4) allows the user to view an existing classification or carry out a new one. If the option to carry out a new classification is chosen, then a new screen is presented; the factor rating input screen (Figure 5). This screen enables the user to choose an

appropriate value in a scale for each individual variable or factor under consideration. Once the selections have been completed, the user can press the process button to proceed to the next stage. The system stores the values entered ready for generating the classification using the processing function. The processing function can automatically retrieve the variables from the input file and produce the classification result using an ANN generated by the NeuroSolution software package. All files are stored and retrieved in a TXT format. The TXT format is easy to maintain, and is more flexible than other formats such as XLS (MS Excel) or MDB (MS Access) (Lee and Christensen, 1997). Using the information management module, the user can extract the classification result from the ANN module and display it using the Display Interface (DI).

4.1.3 Display Interface (DI) and Classification

The designated DI is a user-friendly screen that ensures that the user has a clear view of the generated classification result. From the DI window, the user can readily observe the classification result, namely, good, average or poor production performance (Figure 6). Future developments may include a reports function option which would provide supporting evidence for the classification result. Such an option could reveal which variables are significant and the relative importance of these when compared to each other.
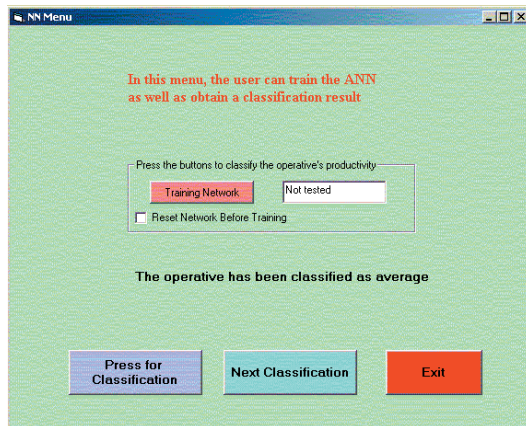
Figure 5: Input screen

Figure 6: Classification representations

4.2 Classification via Artificial Neural Network Module (ANN)

The ANN was employed as the core mathematical module within the system using the NeuroSolution software package developed by NeuroDimensions (Lynn, 2004). Within the ANN model, three different kinds of file are generated, namely the input file, attached file and output file (desired outcome file). The input file is used to receive the up-to-date variables entered. The attached file is stored in the PC's memory and consists of input variables; this type of file can be used to update variables as well as enter them into the processing function. The classification result (once generated) is then saved as an output (desired) file.

The ANN model topology was built using a Generalized Feed Forward (GFF) network, an extension of the Multiplayer Perceptron (MLP). Lynn (2002) pointed out that in theory, GFFs could solve any problem that MLPs could solve. Practically however, GFFs often solve the problem much more efficiently and adequately (Freeman and Sakura, 1991). The GFF system topology consisted of 174 input processing elements (PEs), one output PE and one hidden layer with an embedded probe configuration which reported upon the performance of the classification confusion matrix. The network was then trained using supervised learning algorithms (Lynn, 2002).

The ANN model transferred the input and output variables with Tanhaxon topology. The TanhAxon applies a bias and tanh function to each neuron in the layer which compresses the range of each neuron in the layer to between -1 and 1. Such nonlinearly elements provide a network with the ability to make soft decisions (Equation 1).

$$\int(x_i, w_i) = Tanh\left[x_i^{lin}\right]$$

Equation 1

where $x_i^{lin} = \beta x_i$ is the scale and offset activity inherited from the LinearAxon. x_i is an accumulation of input activity from other components, w_i is an internal weight.

4.2.1 Data Flow

Data flow is one of many key features in any software package and has to be both simple to comprehend and the software program, easy to use (Everett and Harghal, 1997). In the absence of an appropriate data flow, the software system becomes unduly cumbersome to operate and time consuming to implement. With this
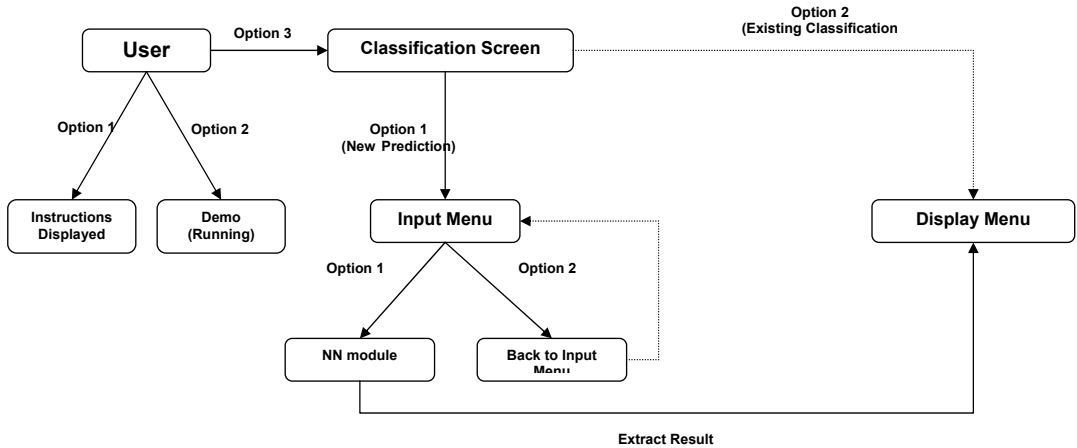
Figure 7: Data flow

in mind, data flow design for this software package was produced as a series of detailed schematics before finalising the design (Figure 7). With each design, five potential users were consulted with in order to ascertain the user friendliness and appropriateness of the software.

As shown in Figure 7, when running the software for the first time, the user menu is displayed. There are three options, created using an optional function in VB 6 code, and the user can choose any option to proceed further. However, users are able to return to the main User Menu anytime and perform other functions. Once the user has selected the loading function option, the program will leave the user main menu and enter the classification menu (Figure 4).

Within the classification menu, two options are available; to view an existing classification and create a new prediction. By using the existing option, the user is able to retrieve the last round of forecasting and review it if so required. For a new prediction, the data entry screen is loaded to allow the user to enter new variables and update the input file where necessary (Figure 5). Once variables have been entered into the system, the updated information is used to generate a result, which will be stored in the output file and is ready to be displayed in the DI.

The result(s) data (output 'desired' file) can be retrieved to the display interface using an extractive function, which is built using program code (VB 6). The user is always permitted to move forward or return back to any functions in the program and stop running or exit the program at anytime during operation. Whilst running the program, the updated file will automatically save any actions that are taken. This feature offers great benefits to the user who wants to protect new data entered from any unpredictable events that may prematurely close the program and lose valuable data (for example, power surges, computer crash etc.).

4.2.2 Test and Validation

Software testing essentially aims to find bugs in the application and fix them (de-bug) (Beizer, 2000). Beizer (2000) suggested that the process of testing involves an assessment of both the functional and structural components of the system developed. Functional tests examine the program from the users' perspective; inputs into the program and then the outputs are checked for conformance to a specified reference. Structural testing examines how the program is implemented in terms of programming, for example, style and design. The key to software testing is to try to find the myriad of failure modes within the system by using the application and every feature inherent within it (Cigital, 2004).

To test the software tool, each functional module (user menu, ANN model, information management and display interface) was rigorously tested using a variety of techniques. These techniques included: i) presenting the software tool to a sample (10 No.) of potential users who were then invited to report upon the user friendliness of the application; ii) examining how well the tool could predict production outputs; and iii) inviting software designers to comment upon the software's GUI with a view to making any possible improvements.

Only a few relatively minor failures were found and most of these were then corrected accordingly. For example:

- the extracting function was designed to retrieve a classification result from an array data and an error was generated due to misallocation of the data position.
- the graphical user interface was found to be too simplistic and although a complex design was not required, a more professionally presented package was desirable. Future work will aim to address this particular problem and such may involve employing a design consultant to conduct the works.

Software validation aims to assure product quality for application software, device software and software-automated operations (Lee and Christensen, 1997). Software validation can increase the usability and reliability of the device or application, resulting in decreased failure rates, fewer recalls and corrective actions, less risk to users and reduced liability to manufacturers (Software Solution, 2004). For this research, validation was conducted using the input data chosen from existing survey questions to ensure that the software reached the highest classification accuracy; in this instance 82 per cent accuracy was observed. Reasons for the high accuracy of prediction observed may be because the input data used was inherently reliable as it was collected via a real time excavation experiment on site (Yang and Edwards, 2003). ANN system shells built into software tools have

been proven (over various studies) to generate higher classification accuracy over and above traditional statistical techniques (Principe, et al., 2000).

6 Conclusion

The Computer Based Software tool for assessing plant operative productivity was developed using a combination of software and programming tools. Microsoft Visual Basic provided the GUI and interaction with the modelling environment, whilst NeuroSolutions by NeuroDimensions was utilised for its modelling and data processing capabilities. In combination, an effective toolkit was developed to help managerial personnel choose the optimum plant operatives (and/or determine inadequacies apparent within new employees). Namely, using a variety of significant factors and variables, the plant operator's anticipated productivity rate (good, average or poor) could be determined. A prototype package is already being used by a trial sample of plant and equipment operator training providers within the UK. Initial results suggest that the package can successfully identify 'weak' operators from a cohort of new recruits. However, future work is required to measure the validity of these early observations and accuracy of the classification result.

Despite the complex algorithms employed, the system design was user friendly and relatively straightforward to use. Admittedly, the prototype application is a relatively simple programming package and the GUI design does need to be improved further. Indeed, future versions of the tool will include a greater variety of features and functionality and will include help functions, edit functions etc.

An essential aspect of the work however relates to the ANN modelling topology which is currently determined by algorithms developed using data collected from field study trials. Using existing data, a classification accuracy of 82 percent was obtained but it is envisaged

that changes to the modelling approach, topology and network connectivity may enhance the classification accuracy of the software developed even further.

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