Simulation of Scheduling Production System by Using Integrating Simulation Models with Artificial Neural Network Model

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ABSTRACT
Traditional methods of dealing with finding the relationship between the inputs data of simulation models and the outputs data fail or takes a long time to find this relationship. Artificial neural networks (ANNs) have the ability to learn complex relationships between inputs and outputs. Their use can greatly enhance simulation models and allow for more accurate representations of real life scenarios. This paper is concerned with the application of the mechanism of integrating simulation models with artificial neural network (ANN) model. This mechanism was tested by integrating simulation models of re-tubing heat exchangers line (RTHEL) with ANN model to schedule entering exchangers to inside re-tubing workshop. The result of applying this mechanism of integration in system (RTHEL) was in reducing completion time of re-tubing batches of heat exchangers by about (12.5%).

الخلاصة
النظريات التقليدية المستخدمة لأيجاد العلاقة بين البيانات الداخلة لنماذج المحاكاة والناتجة منها قد تفشل أو تأخذ وقت طويل لأيجاد هذه العلاقة. شبكات الخلايا العصبية الأصطناعية لها القابلية على التعلم لأيجاد أصعب العلاقات بين المدخلات والمخرجات (النواتج). أن أستخدام هذه الشبكات يحسن نماذج المحاكاة كثيراً وتسمح بتمثيل أدق لسيناريوهات العمل الحقيقية للأنظمة. يهتم هذا البحث بدراسة تطبيق آلية تكامل لنماذج المحاكاة بنموذج لشبكة خلايا عصبية أصطناعية. هذه الآلية أختبرت عن طريق تكامل نماذج المحاكاة لخط أعادة تأهيل المبادلات الحرارية مع نموذج لشبكة خلايا عصبية أصطناعية لجدولة دخول المبادلات الى داخل ورشة أعادة التأهيل. أن تطبيق آلية التكامل هذه على خط أعادة تأهيل المبادلات سوف يقلل من الوقت الكلي لأعادة تأهيل دفعات من المبادلات الحرارية بمقدار (١٢.٥%).

KEYWORDS
Integration; Simulation Models; Artificial Neural Network; Scheduling

INTRODUCTION
The risk of failing to complete activities and entire industrial projects on time is critical element of project management. Therefore, the decision making of scheduling is important to complete manufacturing the products on desired time. The importance of decision making in scheduling

production lines for complete all activities on time needs for an estimation tool for both engineers and managers.

Simulation offers a powerful tool to study, planning and improving simple and complex systems. In some cases of decision making by using simulation models, there is a difficulty to find the relationship between inputs data and outputs data. Therefore, intensive interest to use (ANNs) with simulation because; ANNs are effective tools capable of learning complex relationships between inputs data and outputs data **(G. Roberts 2004)**.

One method of integrating neural networks with simulation models is to simply use a separate program such as NeuralWorks **(NeuralWare 2006)** to develop a neural network, provide it with the desired inputs values, obtain the outputs and use outputs as parameters to the simulation program.

A generic approach for integrating simulation models with external systems such as neural networks is required. This approach should be able to encapsulate these external processes and provide standard access methods for exchanging information with the simulation models.

The objective of this paper is to develop a mechanism of integration discrete-event simulation (DES) models of RTHEL with ANN model to scheduling enters of heat exchangers to inside re-tubing workshop (find best array) with smallest completion time of re-tubing it.

SIMULATION MODELS

Building a simulation model can be a difficult and time-consuming task, it will be useful if decision maker could reuse a simulation model if possible and change it to solve a different problem or evaluate another option. Thus, it is desirable to have adoptable simulation models that are easy to change with little or no programming effort.

The RTHEL is one of primitive production lines; where it depends largely on performance, skills and experience mankind; and also for separation this line from automation. Therefore, there are two main reasons which cause a big varying in times of activities. The first reason is human factors and the second reason is the ancientness of machines and tools which they are using in this line. This leads to separate from recording times of all activities.

According to that, there is no history data for all activities times of this re-tubing line. For this situation (no history data exist), the suitable form to estimate the times of activities is (minimum, most likely and maximum values) **(Richard B. 2004)**. Therefore, in this work a use of PERT/CPM technique to estimate the times of activities from **eq. (1)**, concurs the critical path (C.P) and calculate the probability to meet the desired date from **eq. (2)** and **Table 1**.

$$ET = \frac{(T_a + 4T_m + T_b)}{6} \tag{1}$$

$$Z = \frac{(D - T_E)}{s_{cp}} \tag{2}$$

$$s_{cp} = \sum_{i=1}^{n} s \tag{3}$$

$$s = \frac{(T_b - T_a)}{6} \tag{4}$$

Where: ET = Expected Activity Time.
T_a = Optimistic Duration.
T_m = Most Likely Duration.
T_b = Pessimistic Duration.
σ = Standard Deviation of Activity Duration.
σ_{cp} = Standard Deviation of the Critical Path.
n = Activities Number of the Critical Path.
Z = Number of Standard Deviations (of a Standard Normal Distribution) that the Project, Due Date is from the Expected Completion Time.
D = Desired Completion Data for the Project.
T_E = Expected Completion Date for the Project.

Table 1: Standard Normal Cumulative Distribution (Mario F. Triola 2005)

Z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09
0.0	0.5000	0.5040	0.5080	0.5120	0.5160	0.5199	0.5239	0.5279	0.5319	0.5359
0.1	0.5398	0.5438	0.5478	0.5517	0.5557	0.5596	0.5636	0.5675	0.5714	0.5753
0.2	0.5793	0.5832	0.5871	0.5910	0.5948	0.5987	0.6026	0.6064	0.6103	0.6141
0.3	0.6179	0.6217	0.6255	0.6293	0.6331	0.6368	0.6406	0.6443	0.6480	0.6517
0.4	0.6554	0.6591	0.6628	0.6664	0.6700	0.6736	0.6772	0.6808	0.6844	0.6879
0.5	0.6915	0.6950	0.6985	0.7019	0.7054	0.7088	0.7123	0.7157	0.7190	0.7224
0.6	0.7257	0.7291	0.7324	0.7357	0.7389	0.7422	0.7454	0.7486	0.7517	0.7549
0.7	0.7580	0.7611	0.7642	0.7673	0.7704	0.7734	0.7764	0.7794	0.7823	0.7852
0.8	0.7881	0.7910	0.7939	0.7967	0.7995	0.8023	0.8051	0.8078	0.8106	0.8133
0.9	0.8159	0.8186	0.8212	0.8238	0.8264	0.8289	0.8315	0.8340	0.8365	0.8389
1.0	0.8413	0.8438	0.8461	0.8485	0.8508	0.8531	0.8554	0.8577	0.8599	0.8621
1.1	0.8643	0.8665	0.8686	0.8708	0.8729	0.8749	0.8770	0.8790	0.8810	0.8830
1.2	0.8849	0.8869	0.8888	0.8907	0.8925	0.8944	0.8962	0.8980	0.8997	0.9015
1.3	0.9032	0.9049	0.9066	0.9082	0.9099	0.9115	0.9131	0.9147	0.9162	0.9177
1.4	0.9192	0.9207	0.9222	0.9236	0.9251	0.9265	0.9279	0.9292	0.9306	0.9319
1.5	0.9332	0.9345	0.9357	0.9370	0.9382	.09394	0.9406	0.9418	0.9429	0.9441
1.6	0.9452	0.9463	0.9474	0.9484	0.9495	0.9505	0.9515	0.9525	0.9535	0.9545
1.7	0.9554	0.9564	0.9573	0.9582	0.9591	0.9599	0.9608	0.9616	0.9625	0.9633
1.8	0.9641	0.9649	0.9656	0.9664	0.9671	0.9678	0.9686	0.9693	0.9699	0.9706
1.9	0.9713	0.9719	0.9726	0.9732	0.9738	0.9744	0.9750	0.9756	0.9761	0.9767
2.0	0.9772	0.9778	0.9783	0.9788	0.9793	0.9798	0.9803	0.9808	0.9812	0.9817
2.1	0.9821	0.9826	0.9830	0.9834	0.9838	0.9842	0.9846	0.9850	0.9854	0.9857
2.2	0.9861	0.9864	0.9868	0.9871	0.9875	0.9878	0.9881	0.9884	0.9887	0.9890
2.3	0.9893	0.9896	0.9898	0.9901	0.9904	0.9906	0.9909	0.9911	0.9913	0.9916
2.4	0.9918	0.9920	0.9922	0.9925	0.9927	0.9929	0.9913	0.9932	0.9934	0.9936
2.5	0.9938	0.9940	0.9941	0.9943	0.9945	0.9946	0.9948	0.9949	0.9951	0.9952
2.6	0.9953	0.9955	0.9956	0.9957	0.9959	0.9960	0.9961	0.9962	0.9963	0.9964
2.7	0.9965	0.9966	0.9967	0.9968	0.9969	0.9970	0.9971	0.9972	0.9973	0.9974
2.8	0.9974	0.9975	0.9976	0.9977	0.9977	0.9978	0.9979	0.9979	0.9980	0.9981
2.9	0.9981	0.9982	0.9982	0.9983	0.9984	0.9984	0.9985	0.9985	0.9986	0.9986
3.0	0.9987	0.9987	0.9987	0.9988	0.9988	0.9989	0.9989	0.9989	0.9990	0.9990
3.1	0.9990	0.9991	0.9991	0.9991	0.9992	0.9992	0.9992	0.9992	0.9993	0.9993
3.2	0.9993	0.9993	0.9994	0.9994	0.9994	0.9994	0.9994	0.9995	0.9995	0.9995
3.3	0.9995	0.9995	0.9995	0.9996	0.9996	0.9996	0.9996	0.9996	0.9996	0.9997
3.4	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9997	0.9998

3.50 and up	0.9999									

Therefore, the use of the most familiar technique for building the DES models of RTHEL which is Network Technique; because this technique shows the interdependencies and relationships between events and activities. There are other reasons of using network technique for building model. First, the decision to use PERT/CPM technique is to estimate time of each activity and which activities are critical, where PERT is one of network's techniques. Second, network is easy to change with little or no programming effort and change it to solve a different problem. Third, network is a suitable model to DES, because network model can be make changes in it; when changing occur at discrete periods of time in system which network represents it.

Simulation models of RTHEL to re-tubing several types of heat exchangers are building and run by using *simulation software* which develops by using Visual Basic 6.0 language. **Fig. 1** show the main window of software, using this window the data is entered to *Master Database* of software or doing any change on this data. **Fig. 2** show the window of simulation models, using this window a simulation model of re-tubing one heat exchanger is built and run it to estimate completion time, concurs (C.P) and calculate the probability to meet the desired time. **Fig. 3** show the window which contain the draw of network (simulation model).

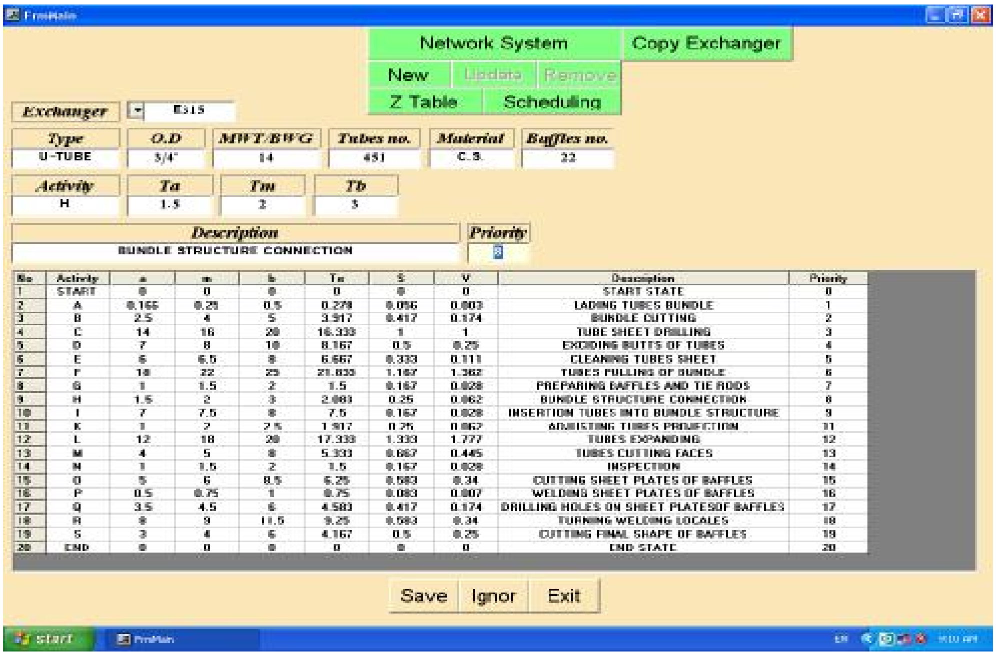

Fig. 1: The main window of simulation software

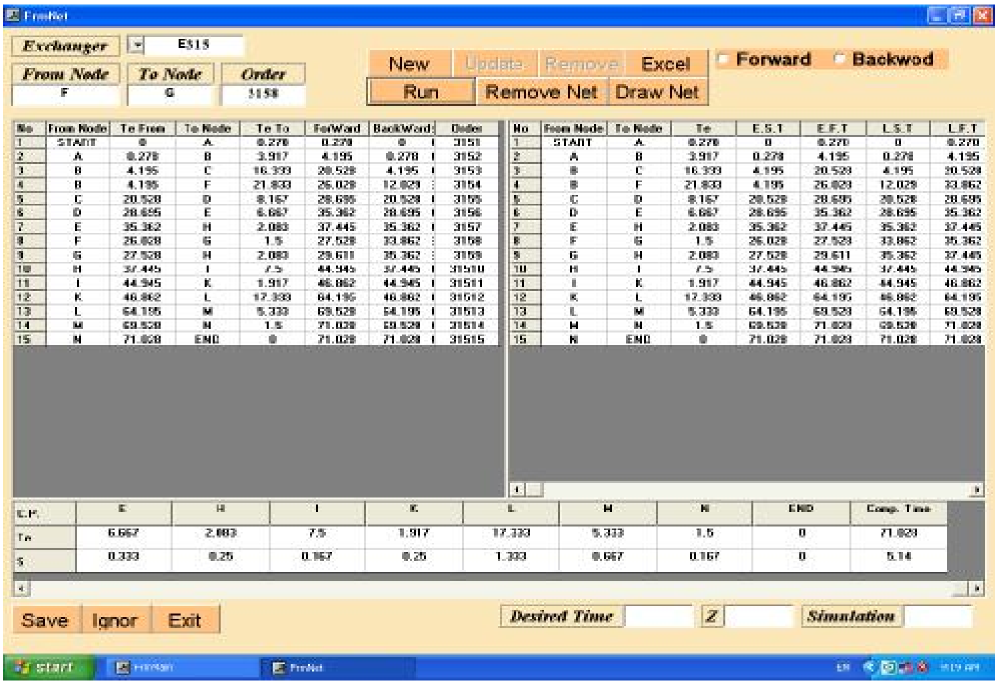

Fig. 2: The window of simulation models

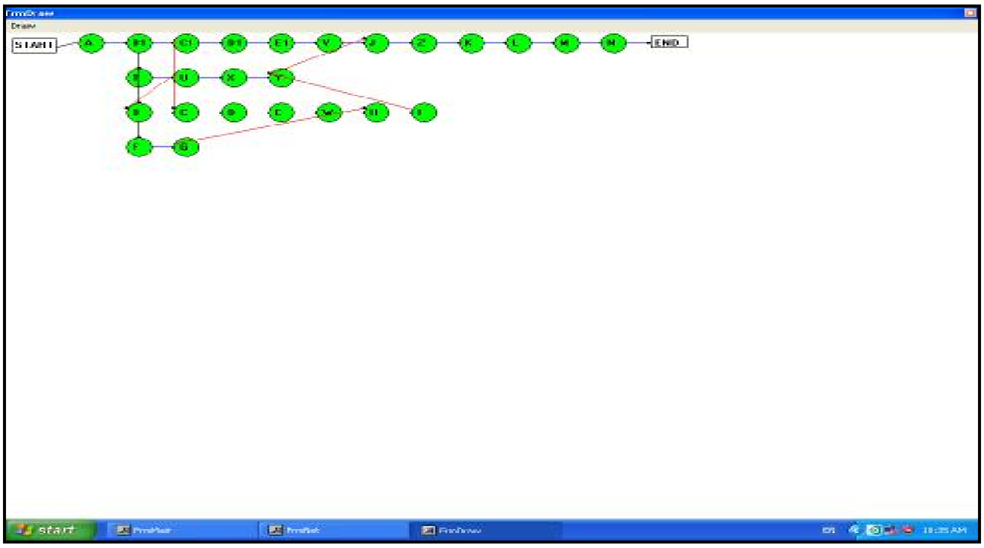

Fig. 3: The window drawing of simulation models

ARTIFICIAL NEURAL NETWORKS (ANNs)

The inspiration for artificial neural networks originated from the study of processes in the human brain. Neural networks are comprised of multiple simple element called artificial neurons **Fig. 4**, the network acquires knowledge through a learning process. The inter-neuron connection strengths known as synaptic weight are used to store the knowledge **(Haykin S. 1994)**. This learning ability of neural networks gives an advantage in solving complex problems whose analytic or numerical solutions are hard to obtain **(Rafiq MY. 2001)**. The scheduling production line is one of those problems.

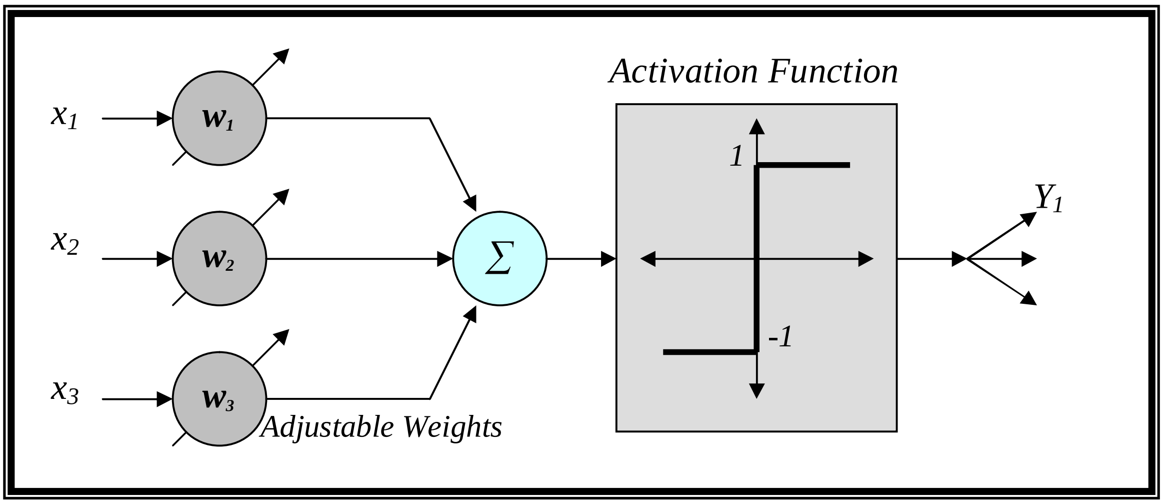

Fig. 4: Artificial neuron

The Design of Artificial Neural Network Model

The problem presented in this paper is based on optimum design and prediction utilizing a multi-layer feed-forward neural network (MLFFNN) architecture and new supervised learning algorithm.

The model has been developed in three phases; the modeling phase, the training phase and the testing phase. The modeling phase involves the analysis of data, the identification of time estimation parameters and the selection of the network architecture and of the internal rules. The training phase requires the preparation of the data and the adoption of the learning law for the training. The testing phase evaluates the prediction accuracy of the model.

The Modeling Phase

The modeling phase includes the design of the neural network architecture. It is a complex and dynamic process that requires the determination of the internal structure and rules (i.e., the number of hidden layers and the type of activation function). The model is designed according to the type of the data and the response required by the application.

The current model has been designed to include an input layer of (*p*) processing elements (neurons) corresponding to the (*p*) input parameters and an output layer of one processing element (neuron) as the target. One hidden layer of (*h*) processing elements was selected according the nature of problem **(D. T. Pham 2003)** as shown in **Fig. 5**.

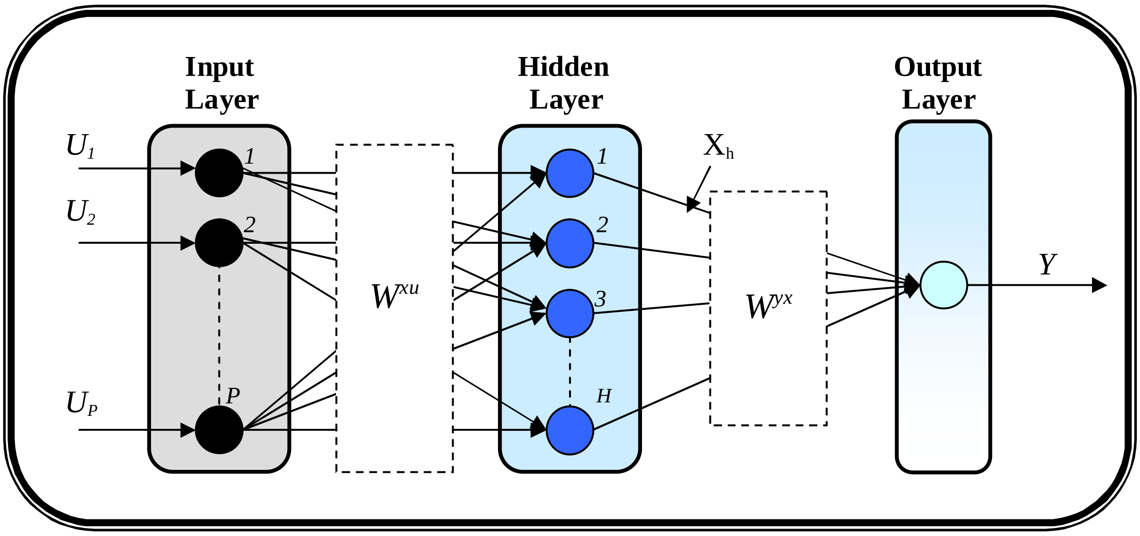

Fig. 5: The architecture of MLFFNN of problem in this work

Therefore, an effective number of processing elements is usually determined by trials for the hidden layers, since there is no rule to determine it **(Albino V. 1998)**, **(Setyawati BR 2002)**. In this work, the author finds equation can be determine the number of processing elements for the hidden layer of neural network of this work as shown in **eq. 5**.

$$h = p! \tag{5}$$

Where: h = Number of nodes in hidden layer.
p = Number of nodes in input layer.

A neuron basically computes the sum of their weighted inputs, subtracts its threshold from the sum, and transfers these results by a function. This can be explained mathematically as (Eq. (6)):

$$Y = f(net) \tag{6}$$

$$Net = \sum_{h=1}^{H} w_h x_p \tag{7}$$

Where: Y = Output of a neuron.
w_h =Weight associated with the input p.
h = Number of nodes in hidden layer = {1, 2 . . . . H}.
x_p = Input units.
f =Transformation function.

The neurons are interdependent on each other via weighted connections. These weights form the power of the influence between the neurons. All neurons are connected to the other neurons in the next layer.

The function of the hidden layer is to extract and remember the useful features and the sub features from the input patterns to predict the outcome of the network (values of the output layer) **(Rafiq MY. 2001)**. The characteristics of the activation function are important since it defines the behavior of the network model. An activation function is used because several impacts, if applied

additively, might cause these quantities (i.e., target values) to fall below the lower or rise above the upper bound.
The function adopted for the current completion time estimation problem was a linear function, given by **eq. 8**.

$$\text{Linear function} = c \times net \quad (8)$$

Where: c = neuron gain.

To learn this neural network, author decides to use supervised learning to learn MLFFNN of this work because; the inputs and the output of ANN are known. In general, there is a useful correspondence between the type of training that is appropriate and the type of problem. Additionally, there is a relationship between the number of learning epochs and the desired characteristics of the output **(D. T. Pham 2003).**

According the nature of problem of this work and the desired characteristics of the output, the ANN use to scheduling the entering of heat exchangers to inside workshop and find the best array from multi arrays, it is the same process to find minimum value from multi values. For this purpose, ANN need to one learning epoch to find the best array. Also, weights between input-hidden layers (W^{xu}) are fixed; and learning rate (η) and error goal (eg) are equal to zero because; there is no need to iterative training.

Therefore, author applies a new supervised learning algorithm to train the neural network. New supervised learning algorithms represent one of attempts to improving the learning speed of these learning algorithms for example; BP algorithm, which are still too slow to be applied in real-world applications even for a very simple problem.

The Training Phase

An important issue to be resolved when applying ANNs to a problem is to determine which training procedure to adopt. In this work a new supervised learning algorithm is applied to learn neural network. The steps which use to training the neural network in this work to find the best array with minimum value of completion time are explained as follows:

Step 1: Input units (x_p) (p = 1, 2 ….. P); receive input signal U_p.

$$x_p(k) = U_p(k) \quad (9)$$

Step 2: The interconnection weight (W_p^{xu}) of input-hidden layer have to be assumed (1) for each connection.

Step 3: Compute the outputs of hidden layer (X_h) by use the following equation:

$$X_h = \sum_{p=1}^{P} W_p^{xu} x_p \quad (10)$$

Where: X_h = outputs of nodes of hidden layer.
x_p = nodes of input layer.
p = Number of nodes in input layer = {1, 2 . . . . P}

W_p^{xu} = interconnection weight of input- hidden layer.

Step 4: The interconnection weight (W_h^{yx}) of hidden-output layer will be assumed as below:

- For the smallest value (W_h^{yx}) equal (1)
- For the other values (W_h^{yx}) equal (0)

Step 5: Compute the output of output layer (Y) by use the following equation:

$$Y = \sum_{h=1}^{H} W_h^{yx} X_h \tag{11}$$

Where: Y = output of output layer (output of network).
X_h = outputs of hidden layer.
h = Number of nodes in hidden layer = {1, 2 . . . . H}.
W_h^{yx} = interconnection weight of hidden-output layer.

THE INTEGRATION MECHANISM

The situation of analysis and decision making in fast paced, rapidly changing venues; such as job shop scheduling. In this situation, there is simply no time to perform multiple replications for the selected values of the decision variables. Also, some times it is difficult to solve some problems with traditional technique.

The problem of this work; which is scheduling the entrees of heat exchangers to inside re-tubing workshop, so as to finding the best array of entrance of the batch of heat exchangers to re-tubes it with smallest completion time of re-tubing. It is difficult to solve it through simulation models just and also it takes long time to get right decision. Therefore, it is necessary to integrate simulation models with other tool to solve this problem. Simulation models are integrated with ANN model because; ANN provides an effective tool for evaluating relationships between input data and result output.

Integrating simulation with other systems involves a careful analysis of the nature of the information that needs to be exchanged. Ideally, the integration mechanism should be generic enough to be used to link simulation models to ANN models as well as many other elements such as databases as shown in **Fig. 6**.

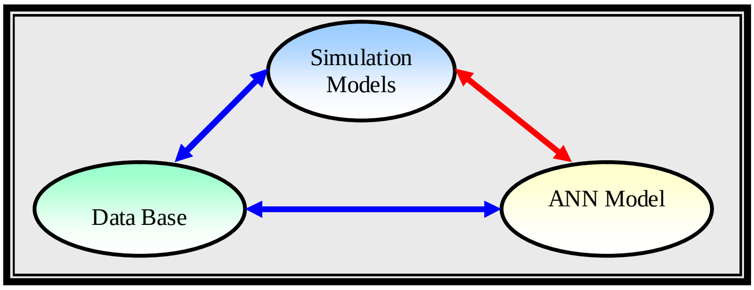

Fig. 6: Integrating Simulation with ANN and Databases

The mechanism of integrating simulation models with ANN model which is used in this work; is explain as follows:

1. The start begins with insertion of the order of manager RTHEL; which represent the batch of heat exchangers that wants to re-tubes it. This order takes as the inputs to ANN model.

2. The interconnections between nodes of input-hidden layers and hidden-output layers are fully connected.
3. There are two connections (one way) between hidden layer - master database of software and master database - simulation models.
4. There is a connection (two ways) between hidden layer and simulation models to transfer models for each node in hidden layer.
5. The nodes in hidden layer represent the probabilities of array. In each node, the simulation models are merging and then, compute the forward time (completion time).
6. There is a connection (one way) between output NN and simulation models to transfer the best array. Then, compute the backward time of this array to detect the critical path.

Fig. 7 shows the integration mechanism between simulation models and ANN model in simulation software and how the data of exchangers transfer between models.

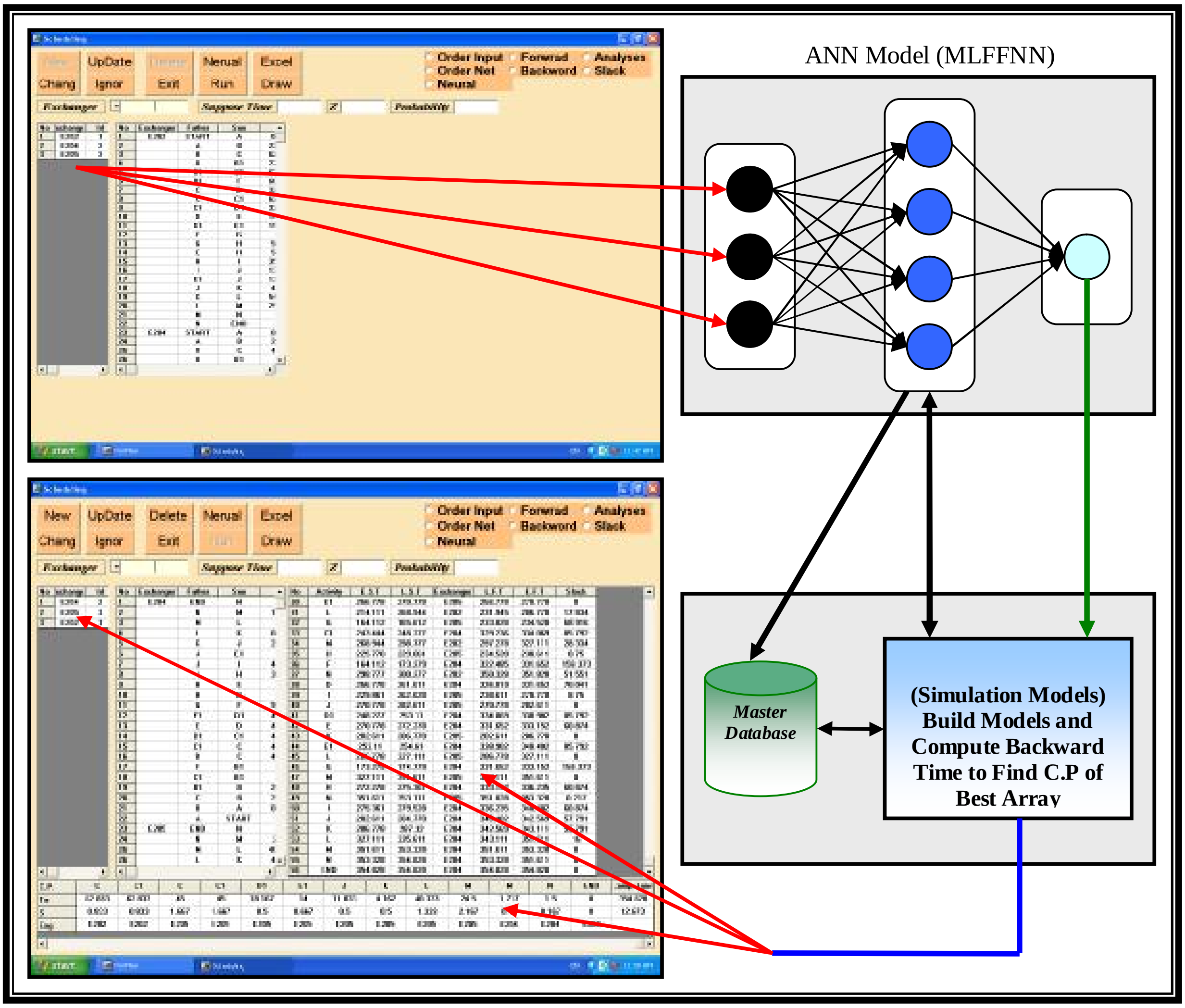

Fig. 7: The integration mechanism between simulation models and ANN model

The simulation software is designed to scheduling the entrees of heat exchangers, so as to find the best array to enter exchangers inside re-tubing workshop by using integrating simulation models with ANN model. Then, compute the completion time of this array and detects the critical path of this production process. Also, evaluate the probability to meet the desired completion time. **Fig. 8** show the window of scheduling, from this window it can find the best array of entering batch of heat exchangers by merging simulation models of these exchangers and run it to estimate completion time, concurs (C.P) and calculate the probability to meet the desired time. **Fig. 9** show the window which contains the table of ANN results. **Fig. 10** show the window which contain the draw of merging networks (merging simulation models).

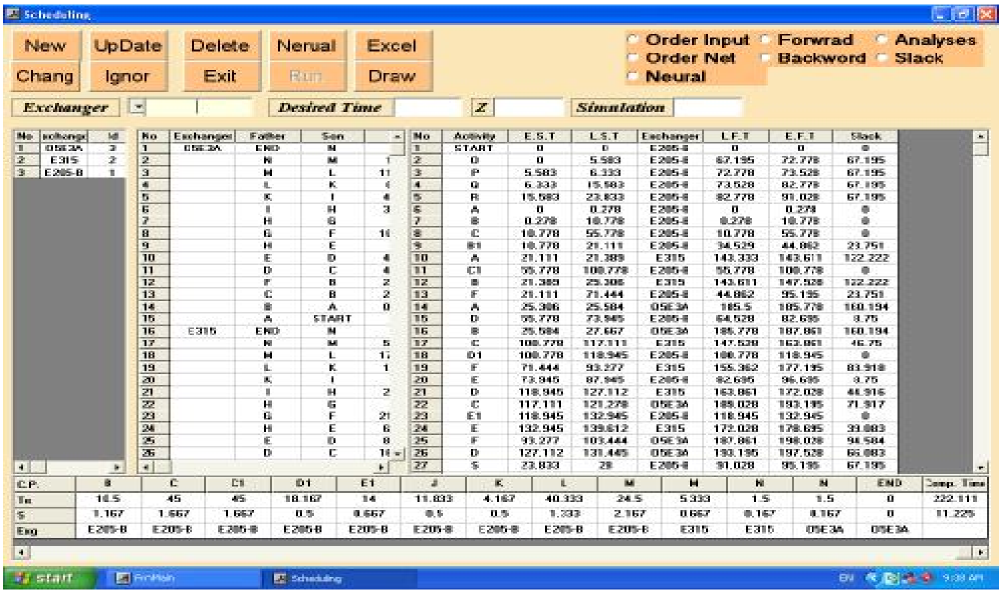

Fig. 8: The window of scheduling

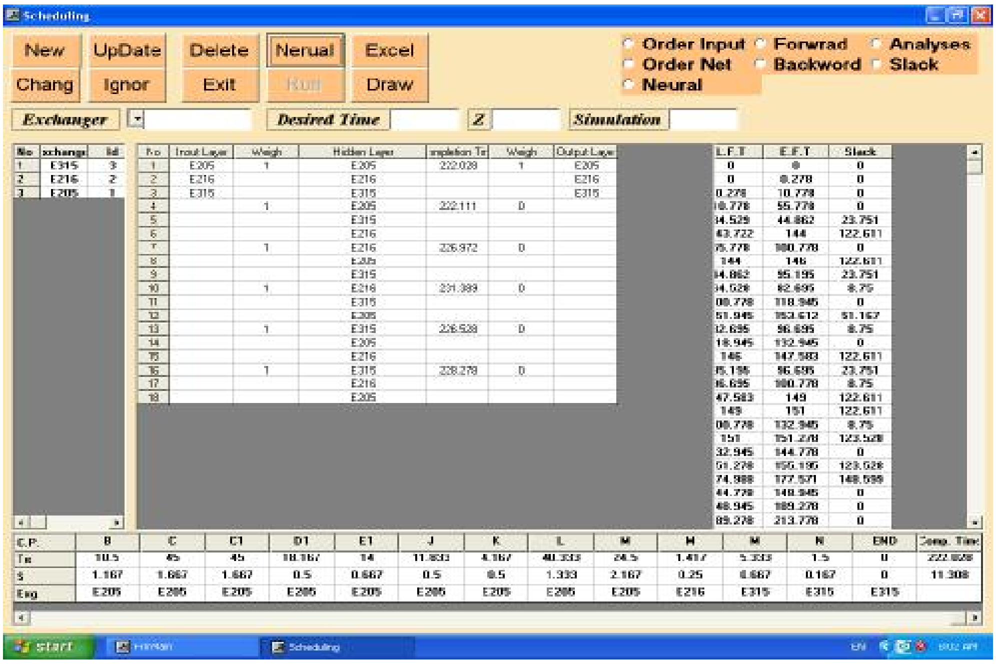

Fig. 9: The window of scheduling which contains the table of ANN results

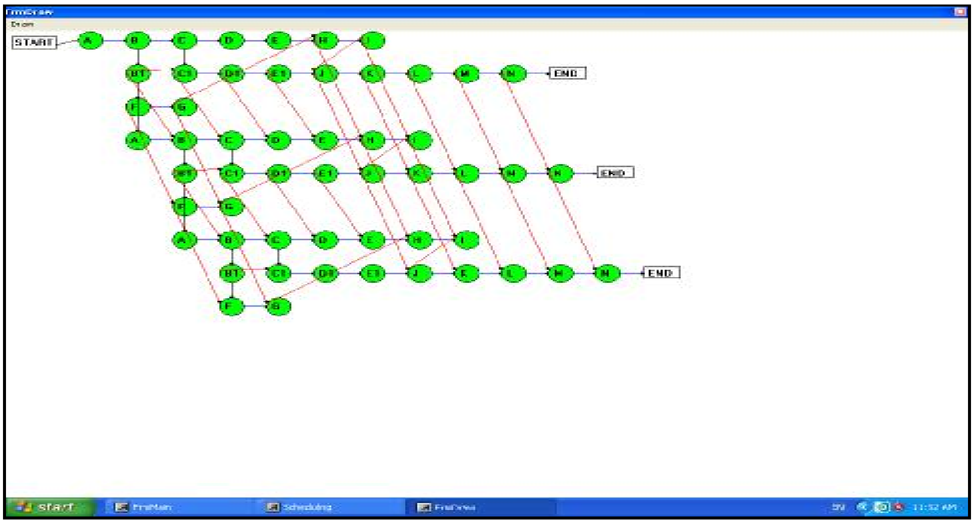

Fig. 10: The window drawing of merging simulation models

THE TESTING PHASE

After applying the integration mechanism, the output of this mechanism is tested by using validation technique called "*Validation Using Testing against Historical Data*". In this technique, author compared the results of simulation software with the actual data (historical data) of completion time for re-tubing some batches of heat exchangers as shown in **Table 2**.

Table 2: Results of simulation software and actual data of completion time for re-tubing some batches of heat exchangers

No. of Batch	Re-tubing Completion Time						
	Probability of Array						
	1	2	3	4	5	6	Actual
1st	**315.277**	**303.777**	**318.638**	**325.833**	**337.972**	**329.833**	**345.5**
2nd	**216.111**	**225.277**	**228.528**	**242.195**	**230.972**	**227.389**	**247**
3rd	**319.994**	**305.994**	**326.638**	**340.5**	**311.856**	**322.5**	**348**
4th	**219.028**	**228.278**	**233.972**	**247.389**	**226.528**	**238.278**	**252.5**

Then, it can be recognized from **Table 2** that the results of integration mechanism are close from the historical data of real system. This result leads that mechanism of integrating simulation models with ANN model is acceptable and it can represent the real system for finding best array.

RESULTS

The run of integration mechanism takes the shortest time to find the best array to entering the batches of heat exchangers to inside re-tubing workshop with its completion time and also concurs the (C.P) without any error in runs. The results of simulation software (simulation data) of completion time for re-tubing some batches of heat exchangers are summarized in **Table 3**, and then convert to **Fig. 11**.

Table 3: Simulation Data and Actual Data of Completion Time for Re-tubing some Batches of Heat Exchangers

Batch	Completion Time of Re-Tubing Batch of Heat Exchangers			
	First	Second	Third	Fourth
Actual Data	**345.5**	**247**	**348**	**252.5**
Simulation Data	**303.777**	**216.111**	**305.994**	**219.028**

From **Fig. 11**, it can be seen that completion time of re-tubing batch of heat exchangers has decreased about (12.5%) after applying the mechanism of integration simulation models of re-tubing heat exchangers with ANN model

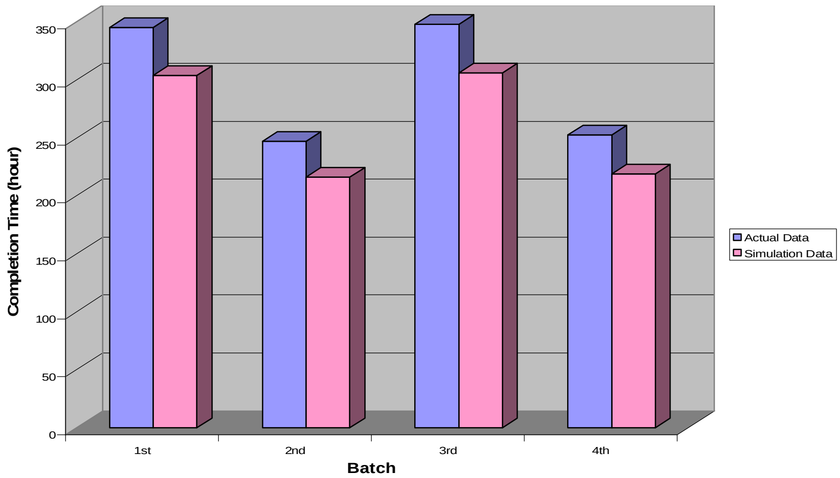

Fig. 11: Histogram of Completion Time for Re-tubing some Batches of Heat Exchangers

CONCLUSIONS

An approach has been presented to achieve the integration of simulation models with ANN model. The approach was designed to allow for future integration with other types of models as well.

Integration of the ANN model with re-tubing simulation models allows for more accurate representation of the real life operations as complex relationships between the heat exchangers needs to re-tubes it and the best array of entering these exchangers to inside re-tubing workshop.

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NOMENCLATURE

Symbol	Description
ANN	Artificial Neural Network
ANNs	Artificial Neural Networks
C.P	Critical Path
CPM	Critical Path Method
C	Neuron Gain
D	Desired Completion Data for the Project
DES	Discrete-Event Simulation
ET	Expected Activity Time
e.g	Error Goal
f	Transformation Function
h	Number of Nodes in Hidden Layer
n	Activities Number of the Critical Path
MLFFNN	Multi-Layer Feed-Forward Neural Network
PERT	Program Evaluation and Review Technique
p	Number of Nodes in Input Layer
RTHEL	Re-Tubing Heat Exchanger Line
Ta	Optimistic Duration
Tb	Pessimistic Duration
Tm	Most Likely Duration
T_E	Expected Completion Date for the Project
U	The External Inputs to the Neural Network
w	The weight of interconnection neuron
W^{xu}	Weighted Interconnection for Input-Hidden Layers
W^{yx}	Weighted Interconnection for Hidden-Output
x	Input units
X	The Output of Hidden Units

Y	The Output of Neural Network
Z	The Number of Standard Deviations (of a Standard Normal Distribution) that the Project Due Date is from the Expected Completion Time.
σ	Standard Deviation of Activity Duration
s_{cp}	Standard Deviation of the Critical Path
η	Learning Rate