A NEURAL NETWORK BASED ALGORITHM FOR ASSESSING RISK PRIORITY OF MEDICAL EQUIPMENTS

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ABSTRACT

This paper presents a robust algorithm for the assessment of risk priority for medical equipments based on the calculation of static and dynamic risk factors and Neural Networks (NNs). Four risk parameters have been calculated for a total of 345 different medical devices in two general hospitals in Baghdad. Static risk factor components (equipment function and physical risk) and dynamics risk components (maintenance requirements and risk points) were determined for the medical equipments under consideration. These risk components were used as an input to the feed forward NN trained with Back Propagation algorithm (BPNN). The accuracy of the network was found to be equal to 96% for the proposed system. Hence, this algorithm could serve as promising tool for risk factor assessment for the service departments in large hospitals in Iraq.

Index Terms— Risk factors, neural networks, back propagation algorithm, risk priority.

1. INTRODUCTION

Inherent in the definition of risk management is the implication that the hospital environment cannot be made risk-free. In fact, the nature of medical equipment to invasively or noninvasively perform diagnostic, therapeutic, corrective, or monitoring intervention on behalf of the patient implies that risk is present. Therefore, a standard of acceptable risk must be established that defines manageable risk in a real-time economic environment.

Risk factors that require management can be illustrated by the example of the "double-edge" sword concept of technology (see Figure 1). The front edge of the sword represents the cutting edge of technology and its beneficial characteristics: increased quality, greater availability of technology, timeliness of test results and treatment, and so on. The back edge of the sword represents those liabilities which must be addressed to effectively manage risk: the hidden costs, our technology , dependency incompatibility of equipment,.etc [1, 2].

Figure .1 Double-edged sword concept of risk management

For example, the purchase and installation of a major medical equipment item may only represent 20% of the lifetime cost of the equipment [3]. If the operational budget of a nursing floor does not include the other 80% of the equipment costs, the budget constraints may require cutbacks where they appear to minimally affect direct patient care. Preventive maintenance, software upgrades that address "glitches," or overhaul requirements may be seen as unaffordable luxuries. Gradual equipment deterioration without maintenance may bring the safety level below an acceptable level of manageable risk.

The NNs derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of input data into categories provided they are previously trained to do so. The accuracy of the classification depends on the efficiency of training. The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input [4].

One computer technique under investigation is based on artificial NNs[5], which may be regarded as tools for multivariate analysis that can be used to estimate disease risk. They are able to model complex nonlinear systems with significant variable interactions. Theoretical work

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suggests that neural networks may be able to consistently match or exceed the performance of traditional statistical methods [6]. Neural networks have been used effectively in several clinical studies, in areas including the evaluation of radiological studies [7], the diagnosis of acute illness [8], the prediction of intensive- care-unit length of stay [9], the diagnosis of appendicitis [10], the diagnosis of psychiatric disorders [11,12] and the diagnosis of acute pulmonary embolism [13]. In Urology, There is a good example of NN application to diagnose prostate cancer [14].

The purpose of this study is to develop a BPNN which will determine the risk priority based on the input components of static and dynamics risk factors. This network will act to help in the assessment of risk problems for medical devices for the large Iraqi hospitals.

2. RISK MANAGEMENT PROCESS

To apply risk management to the department of clinical engineering, one must understand the basic components of the risk management process. The process may be divided into the following five steps [15]:

1. Identify and analyze exposures.
2. Consider alternative risk treatments techniques.
3. Select the best technique to manage and treat the risk.
4. Implement the selected technique.
5. Monitor and improve the risk management program risk management program.

2.1 Risk Management Strategies

Reactive risk management is an outgrowth of the historical attitude in medical equipment management that risk is an anomaly that surfaces in the form of a failure. If the failure is analyzed and proper operational procedures, user in-services, and increased maintenance are supplied, the problem will disappear and personnel can return to their normal work. When the next failure occurs, the algorithm is repeated. If the same equipment fails, the algorithm is applied more intensely. This is a useful but not comprehensive component of risk management in the hospital. In fact, the traditional methods of predicting the reliability of electronic equipment from field failure data have not been very effective [1, 16].

The health care environment, as previously mentioned, inherently contains risk that must be maintained at a manageable level. A reactive tool cannot provide direction to a risk-management program, but it can provide feedback as to its efficiency.

Obviously, a more forward-looking tool is needed to take advantage of the failure codes and the plethora of equipment information available in a clinical engineering department. This proactive tool should use failure codes, historical information, the "expert" knowledge of the clinical engineer, and the baseline of an established "manageable risk" environment (perhaps not optimal but stable). The overall components and process flow for a proactive risk-management tool consists of a two-component static risk factor, a two-component dynamic risk factor, and a two different static risk and two "shaping" or feedback loops.

2.2 Static and Dynamics Risk Factors

The static risk factor classifies new equipment by a generic equipment type: defibrillator, electrocardiograph, pulse oximeter, etc. When an equipment is introduced into the equipment database, it is assigned to two different static risk categories as shown in Figure 2 [1,2]. The first is the equipment function that defines the application and environment in which the equipment item will operate. The degree of interaction with the patient is also taken into account. For example, a therapeutic device would have a higher risk assignment than a monitoring or diagnostic device. The second component of the static risk factor is the physical risk category. It defines the worst-cases scenario in the event of equipment malfunction.

The correlation between equipment function and physical risk on many items might make the two categories appear redundant. However, there are sufficient equipment types where such a case does not exist. A scale of 1–25 is assigned to each risk category. The larger number is assigned to devices demonstrating greater risk because of their function or the consequences of device failure. The 1–25 scale is an arbitrary assignment, since a validated scale of risk factors for medical equipment, as previously described, is nonexistent. The risk points assigned to the equipment from these two categories are algebraically summed and designated the static risk factor. This value remains with the equipment type and the individual items within that equipment type permanently. Only if the equipment is used in a clinically variant way or relocated to a functionally different environment would this assignment be reviewed and changed.

The dynamic components of the risk-management tool consists of two parts, as depicted in Figure 3 [1, 2]. The first is a maintenance requirement category that is divided into 25 equally spaced divisions, ranked by least (1) to greatest (25) average man hours per device per year. These divisions are scaled by the maintenance hours for the equipment type requiring the greatest amount of maintenance attention. The amount of non planned (repair) man hours from the previous 12 months of service reports is totaled for each equipment type. The second dynamic element assigns weighted risk points to individual equipment items for each unique risk occurrence. An occurrence is defined as when the device:

- Exceeds the American Hospital Association Useful Life Table for Medical Equipment or exceeds the historical Mean Time Before Failure (MTBF) for that manufacturer and model
- Causes injures to a patient or an employee
- Functionally fails or fails to pass a PM inspection
- Is returned for repair or returned for repair within 9 days of a previous repair occurrence
- Misses a planned maintenance inspection
- Is subjected to physical damage

- Is reported to have failed but the problem was determined to be a user operational error.

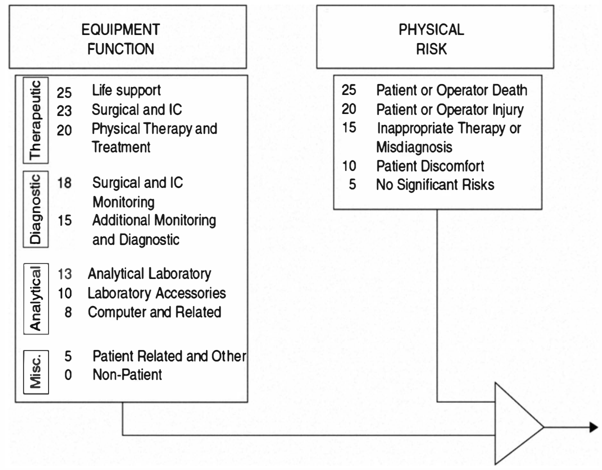

Figure 2. Static risk components

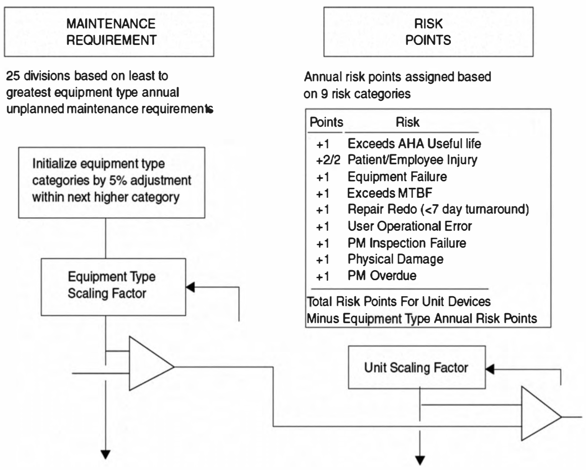

Figure 3. Dynamic risk components

3. THE BACK PROPAGATION ALGORITHM

Different network topologies with powerful learning strategies to solve nonlinear problems have been reported. For the present application, back propagation with momentum is used to train the feed forward neural network. The output units (y_k units) have weights w_{jk} and the hidden units have weights v_{ij} . During the training phase, each output neuron compares its computed activation y_k with its target value d_k to determine the associated error E for the pattern with that neuron, i.e.,

$$E = \sum_{k=1}^{m} (d_k - y_k)^2 \qquad (1)$$

Where m is the number of neurons

The ANN weights and biases are adjusted to minimize the least-square error. The minimization problem is solved by the gradient technique. This is achieved by BP of the error. When using momentum, the net is proceeding not in the direction of the gradient, but in the direction of a combination of the current gradient and the previous direction of weight correction. Convergence is sometimes faster if a momentum term is added to the weight update formula [17]. The summary of the BP algorithm applied in the present work can be described by the following steps:

1. ***Initialization*** Assuming no prior information is available, the synaptic weights and thresholds have picked to a random value.
2. ***Presentations of the training examples*** The network is presented with an epoch of training examples. For each example in the set, ordered in some fashion, the sequence of forward and backward computations described under points 3 and 4 is performed.
3. ***Forward computation***
4. ***Backward computation***
5. ***Iteration*** The forward and backward computations under points 3 and 4 are iterated by presenting new epochs of training examples to the network to reach the stopping criteria.

The BP algorithm is a supervised learning algorithm, which aims at reducing the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall mean square system error. The weight updating starts with the output layer, and progresses backwards. The weight update aims at maximizing the rate of error reduction, and hence, it is termed as 'gradient descent' algorithm. It is desirable that the training data set be large in size, and also uniformly spread throughout the class domains. In the absence of a large training data set, the available data may be used iteratively, until the error function is reduced to an optimum level. For quick and effective training, data are fed from all classes into a routine sequence, so that the right message about the class boundaries is communicated to the ANN [18, 19].

4. DATA COLLECTION

In this study, our survey covered two large general hospitals in Baghdad, namely the *Yarmook Teaching Hospital* and the *Specialized Surgeries Hospital*. A report is prepared which contains the coding of the static and dynamic risk components. These codes will be used in the calculation of the risk factor components. The period for collecting these reports was from September- 2008 to November-2008. A total of 345 reports for different medical equipments were collected from these hospitals with the help of the biomedical engineers in the service departments of these hospitals. A variety of medical equipments are included in our research starting from small to large, simple to complex and analytic to therapeutic equipments. These reports are analyzed and coded to calculate the following risk components:

1. **Equipments function.**
2. **Physical risk.**
3. **Maintenance requirements.**
4. **Risk points.**

The total number of cases for all reports in this study were divided into two groups. One group for the training process (290 cases), while the other for testing of the proposed network (55 cases). The MATLAB package version 7 was used to implement the software for the current work. A sample of the testing data for forty cases is shown in Table 1. A total set of (345) feature vectors each one with four risk components is prepared to be as an input to the proposed BPNN. Then the BPNN will give us the risk priorities based on the input data.

5. THE PROPOSED ALGORITHM

The NNs derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of input data into categories, provided they are previously trained to do so. The accuracy of the classification depends on the efficiency of training. The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input.

Three issues need to be settled in designing an ANN for a specific application:

• Topology of the network;
• Training algorithm;
• Neuron activation functions.

In our topology, the number of neurons in the input layer is fixed by the number of elements in the input feature vector. Therefore the input layer has 4 neurons for the ANN classifier. The output layer was determined by the number of classes desired. In our study, the risk priority stages are five, therefore, the output layer consists of three neurons. This will give us eight categories; the first five is used for the assessment of risk priority. The remaining three empty places are left and they are marked as null category. The number of hidden neurons was varied from 5 to 10 neurons. A best performance was achieved with the use of six neurons in the hidden layer. The general architecture of the proposed network is shown in Figure 4.

Before the training process is started, all the weights are initialized to small random numbers. This ensured that the classifier network was not saturated by large values of the weights. In this experiment, the training set was formed by choosing 55 data sets for the testing process.
The sigmoid function was used as the neural activation function. The most important reason for choosing the sigmoid as an activation function for our networks is that the sigmoid function f(x) is differentiable for all values of x, which allows the use of the powerful BP learning algorithm.

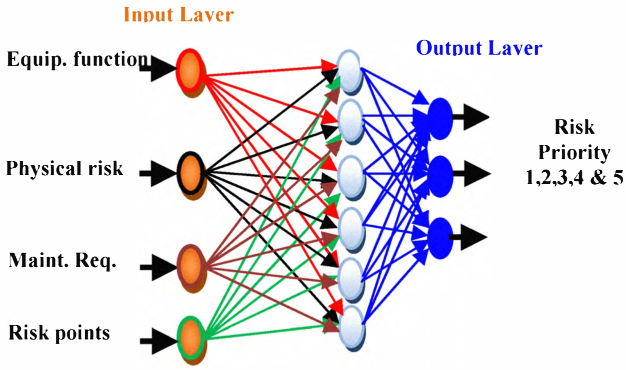

Figure 4. The general architecture of the proposed network

The network was trained with all of the (290) training data sets. These data sets were fed to the BPNN with four inputs and three output neurons.

The output of the network was as follows:
1. If the output of BPNN is (-1 -1 -1), this means that risk priority is 1 which is the minimum risk priority.
2. If the output of BPNN is (-1 -1 1), this means that risk priority is 2 which is a low risk priority.
3. If the output of BPNN is (-1 1 -1), this means that risk priority is 3 which is the moderate risk priority.
4. If the output of BPNN is (-1 1 1), this means that risk priority is 4 which is high risk priority.
5. If the output of BPNN is (1 -1 -1), this means that risk priority is 5 which is the maximum risk priority.

Other output are neglected and regarded as a null category. The training set is grouped into one matrix with dimension of (290x4). This matrix is fed to the input layer of BPNN.

After (100) epochs, the network reached a fixed performance and the training process completed. On the completion of the training process for all of the training data sets (290 cases), the last weights of the network were saved to be ready for the testing procedure. The training process took 7.3 seconds. The testing process is done for (55) data sets. These data sets were fed to the network and their output was recorded for calculating the accuracy of the network. The time of running the algorithm for the testing process was 2.3 seconds.

6. RESULTS AND DISCUSSION

The performance of the algorithm was evaluated by computing the percentage and accuracy of the network. The definition of accuracy of the proposed network is given by[20]:

$$\text{Accuracy} = \frac{\text{Correct identification}}{\text{Total no. of cases}} \times 100\% \qquad (2)$$

In our study, the use of BPNN has been proposed for risk priority assessment of the medical equipments from reports of risk factors by means of calculating the risk factors components (Equipments, function, physical risk, maintenance requirements and risk points). The obtained accuracy of the proposed network was found to be (96%). This is regarded as being very robust and the system is reliable.

In practice, the number of neurons in the hidden layer varies according to the specific recognition task and is determined by the complexity and amount of training data available. If too many neurons are used in the hidden layer, the network will tend to memorize the data instead of discovering the features. This will result in failing to classify new input data. The obtained accuracy of assessment for the BPNN and the required time to run the algorithm are shown in Table 2.

7. CONCLUSION

This paper suggested the implementation of a robust algorithm for risk priority assessment of medical equipments based on BPNN and risk factor components. A total of (345) reports were taken from two general hospitals in Baghdad. These reports were used for the calculation of the risk factor components. MATLAB package version 7 was used to implement the software in the current work. Four risk components (equipment function, physical risk, maintenance requirements and risk points) were calculated for the collected data sets. These risk components were carried out to generate training data for the BPNN and to assess risk priority.

The accuracy was calculated to evaluate the effectiveness of the proposed network. The obtained accuracy of the network was found to be 96%. We conclude that the proposed system gives fast and accurate risk assessment and acts as promising tool for assessing the risk factor in the service departments in large hospitals in Iraq.

Table 1. Sample of the data used for testing of BPNN

No.	**Device Name**	Equip. Function	Physical Risk	Maint. Reqs.	Risk Points	Risk Factor	Risk Priority
1	Carbon dioxide gas analyzer	13	15	5	0	33	2
2	Carbon monoxide gas analyzer	13	15	5	0	33	2
3	Oxygen gas analyzer	13	15	5	3	36	2
4	Monitoring spirometer	15	15	5	0	35	2
5	Gas pressure gauge	10	15	4	0	29	2
6	Anesthesia breathing circuit	25	20	10	0	55	3
7	Breathing gas mixer	25	20	10	0	55	3
8	Electro anesthesia apparatus	25	20	12	3	60	3
9	Nebulizer	20	15	5	0	40	2
10	Noninvasive blood pressure	10	15	9	3	37	2
11	Densitometer	15	15	3	6	39	2
12	Angiographic injector	10	5	6	6	27	2
13	Stethoscope	5	5	0	0	10	1
14	Cardiac monitor	18	15	11	8	52	3
15	Ultrasound	18	15	3	6	42	3
16	Electrocardiograph	18	20	3	12	53	3
17	Phonocardiograph	15	10	6	3	34	2
18	Pulse Oximeter	15	15	2	3	35	2
19	Intra-aortic balloon	25	25	17	14	81	5
20	External pacemaker	23	20	2	14	59	3
21	Implantable pacemaker	23	20	2	14	59	3
22	DC-defibrillator	23	25	5	14	67	4
23	Blood PCO2, PO2 test system	13	15	3	7	38	2
24	Total Cholesterol test system.	13	15	3	7	38	2
25	Creatine test system	13	15	3	8	39	2
26	Blood specimen collection device	13	15	3	8	39	2
27	Uric acid test system	13	15	2	8	38	2
28	spectrophotometer for clinical use	13	15	3	9	40	2

Table 2. The results of training the proposed network

	No. of cases	Accuracy of the network	Time
BPNN	**55**	**96%**	**2.3 S**

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