# BLOOD GLUCOSE PREDICTION FOR DIABETES THERAPY USING A RECURRENT ARTIFICIAL NEURAL NETWORK

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**ABSTRACT**

Expert short-term management of diabetes through good glycaemic control, is necessary to delay or even prevent serious degenerative complications developing in the long term, due to consistently high blood glucose levels (BGLs). Good glycaemic control may be achieved by predicting a future BGL based on past BGLs and past and anticipated diet, exercise schedule and insulin regime (the latter for insulin dependent diabetics). This predicted BGL may then be used in a computerised management system to achieve short-term normoglycaemia. This paper investigates the use of a recurrent artificial neural network for predicting BGL, and presents preliminary results for two insulin dependent diabetic females.

## 1 INTRODUCTION

Diabetes mellitus (DM) affects an estimated 3-4% of the world's population (half of whom are undiagnosed), making it one of the major chronic illnesses prevailing today. It is defined as "*a syndrome characterised by chronic hyperglycaemia and disturbances of carbohydrate, fat and protein metabolism, associated with absolute or relative deficiencies in insulin secretion and/or insulin action*" [1].

The internationally-accepted classification system for DM is Type 1 (insulin-dependent DM or IDDM) and Type 2 (non-insulin dependent DM or NIDDM). Expert short-term management of the condition through good glycaemic control, is necessary to delay or even prevent serious degenerative complications such as retinopathy, neuropathy and nephropathy developing in the long term, due to consistently high blood glucose levels (BGLs) [2]. Potentially life-threatening short-term complications can also occur due to both very low BGLs (hypoglycaemia), and very high BGLs (ketoacidosis).

A critical factor which affects BGL in a (Type 1) individual is insulin sensitivity/resistance, which is closely linked to body mass index (weight/height ratio). This tends to be stable within an individual but differs substantially between individuals. External factors which exert a variable influence on a (Type 1) individual's BGL in the short-term include diet, exercise and insulin regime, and these are employed, together with a past record of a patient's BGL, to determine appropriate therapy.

Unfortunately, the complex combination of the above factors, together with their short-term dependencies, can lead to prescribed therapies for Type 1 diabetics being sub-optimal. In addition, a considerable proportion of patients are insufficiently knowledgeable regarding their condition, and are therefore unable to alter their short-term therapy confidently, in response to changes in diet or exercise levels, which can again result in sub-optimal therapy. The serious consequences of sub-optimal therapy not only affect a patient's long-term well-being, but lead to a considerable drain on a country's national health resources. A more satisfactory situation would be for the patient to take greater control of his/her short-term therapy, guided by a powerful, yet affordable, computerised management system. Regular attendance at a diabetic clinic would, of course, still be mandatory for longer-term clinical examination, assessment and therapy, in accordance with the St. Vincent Declaration [3].

The longer-term aim of the present study is to investigate the feasibility of using artificial neural networks (ANNs) for educating and advising Type 1 diabetic patients regarding their optimum short-term therapy. Benefits to patients include (a) improved short-term (and hence long-term) therapy, (b) patients encouraged to employ more self-management in the short-term, (c) should help to prevent the occurrence of short-term complications such as hypoglycaemia and ketoacidosis, (d) patient-centred system would be dynamically tailored to the physiology, lifestyle and diabetes condition of the individual, (e) accurate and comprehensive BGL and therapy models, together with appropriate graphical user interface, should aid patient understanding of their condition, and prove useful for teaching purposes in diabetes clinics and medical centres. Finally, a production model with an integral BGL meter, could be inexpensive and user-friendly. It could also produce full analysis and breakdown of BGLs, diet, exercise and insulin regimen etc.

This paper reviews the various approaches which have been investigated for computer-based management of diabetes, including the associated problem of BGL prediction. The use of artificial neural networks (ANNs) for BGL prediction are then discussed, and preliminary results achieved for two diabetic females using a recurrent ANN are presented.

## 2 COMPUTER-BASED DECISION SUPPORT SYSTEMS

Over the past two decades, a number of systems for supporting decision making have been developed to assist diabetes clinicians and patients. Originally, paper-based algorithms were used. However, more recently, computer-based expert systems have been proposed [4]. These include rule-based approaches [5,6], algorithm approaches [7], mathematical models [8-10], adaptive control methods [11], time-series analysis [12,13], fuzzy logic [14], and causal networks [10, 15-19]

A major disadvantage with many of these approaches is that they attempt to model an intrinsically complex, highly non-linear, stochastic metabolic process. Also, the majority of them do not consider the consequences of an exercise schedule, a factor which critically affects BGL. However, their greatest disadvantage is that they can become very large, complex and unwieldy, due to the necessity of incorporating knowledge in the form of production rules, which cause problems in generalising the systems to a large number of individual diabetes pathologies.

In contrast, artificial neural networks (ANNs), which can generalise, have been used very successfully over the past seven years for a variety of pattern recognition and expert system applications [20]. ANNs, which are (loosely) analogous to the animal brain, are particularly useful in situations which involve the identification of highly non-linear and/or empirical systems. They require to be trained on sets of patterns which display typical features of the system, and once trained, can then generalise using a variety of other data. The knowledge acquired through training is embedded in the weight matrices of the ANN. Further, through a dynamic learning process, they can assimilate information on a continuous basis.

ANNs have been used successfully in diabetes management to predict its onset [21], and for insulin regime prescription [22].

## 3 ANN PREDICTION OF BGLs

A number of ANN paradigms have been investigated for solving prediction problems [20]. These include multilayer perceptrons, ADALINE, MADALINE, cascade correlation, generalised regression, radial basis functions, self-organising feature maps and recurrent networks.

The simple recurrent network introduced by Elman [23] was eventually selected for the present application, since it has demonstrated superior performance for prediction problems, with short term prediction accuracy's ranging from 70-90% [24].

The architecture of the Elman network used in the present application is illustrated in Figure 1.

The Elman network has delays in the feedback loops at the outputs of the recurrent layer, which enable previous time-step values to be used in the current time-step.

Training was performed using backpropagation incorporating momentum and an adaptive learning rate.

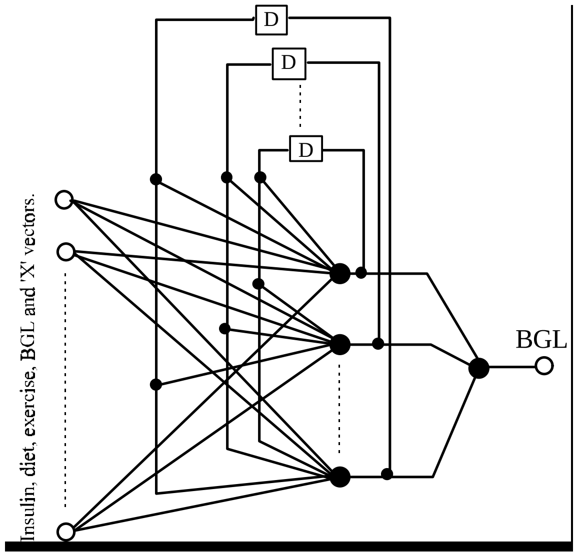


**Figure 1** Architecture of Elman recurrent ANN used for BGL prediction.

Two separate activation functions were employed; neurons in the recurrent layer used a tan-sigmoidal function, whereas neurons in the output layer used a linear function. Using a process of trial-and-error, it was found that 95 recurrent layer neurons gave the best results.

The input vectors consisted of the following parameters:

1. Insulin Vector Number of units of Types 1, 2 and 3 (long, short and intermediate acting), time of injection (absolute), injection site (0-no injection, 1-buttocks, 2-limbs, 3-stomach)
2. Diet Vector Total carbohydrates (gms) and time of meal (absolute).
3. Exercise Vector Duration (mins), mobility (0-3), strength (0-3), endurance (0-3) and time of exercise (absolute).
4. BGL Vector BGL (mmol/l), time of measurement (absolute) and prediction time (absolute).

5. 'X' Vector Stress/surgery/illness (no-0, yes-1) and pregnancy (no-0, yes-1).

The data used for training of the ANN, and also performance evaluation i.e. prediction, was relatively small (122 events in total). Hence, most of the data sets were used during training (97 events), with only a small number used to evaluate performance.

Training was carried out as follows. Starting from Day 1, each patient recorded their BGL at time *k*, and *k*+1. The ANN was then presented with any events of insulin, diet or exercise occurring between times *k* and *k*+1. The inputs were presented as indicated above, in the form of a **P**-matrix which included the value of BGL at time *k*. The ANN was then trained using the recorded value of BGL at time *k*+1. After this training period, the ANN was presented with the P-matrix for events covering times between *k*+1 and *k*+2, and the recorded value of BGL at time *k*+2 used to train the network. Hence, each time the network was trained, the output was the BGL of the following event-step. The number of epochs during training was typically 500, and the total amount of time for training was approximately 2 hours using a Pentium 166MHz PC (32MB RAM). Matlab and the ANN Toolbox were used to provide ANN functionality.

During performance evaluation, the network was presented with a **P**-matrix that it had not 'seen before', and one event-step predictions were determined. Performance was evaluated by comparing the predicted and actual BGL values, and performance was recorded as *satisfactory* when the difference was smaller than 1.5 mmol/l, and *poor* if the difference was greater than 1.5 mmol/l.

## 4 RESULTS

Two patients from the Diabetic Outpatient Department of Glasgow's Royal Infirmary were selected for this study.

Patient 1 was a 15 year old girl who had been diagnosed two years ago with Type 1 diabetes. Patient 2 was a 32 year old woman, four and a half months pregnant, who had also been diagnosed with Type 1 diabetes two years ago.

Both patients regularly monitored and recorded, in a diary, their BGLs, insulin regime, diet and exercise activity for a ten day period. Each input parameter was then converted into an appropriate value as described in Section 3, and entered into an MS Excel database. Calorific values of meals were sub-divided into energy, total carbohydrates, sugar carbohydrates, protein, fat, fibre and sodium. These values were calculated using a chart devised by the University of Glasgow Dietetics' Department.

In general, meals were taken at the times defined in the patient's diary. Insulin was injected 30 minutes before a meal. BGLs were monitored 10 minutes before insulin injections, and hence 40 minutes before the next meal. Exercise was generally taken 2 hours before the next meal.

The input data **P**-matrix was compiled which contained the insulin, diet and exercise vectors. Other input data included T, the target BGL value. An example of the transformation of data from the diary to a form acceptable to the ANN, is shown in Table 1.

| Time | Insulin/Diet/Exercise | BGL |
|---|---|---|
| 09.00 | | |
| 09.20 | Insulin: 46 units /intermediate/site 2 | 12.3 |
| 10.00 | Diet: carbohydrate 41gms | |
| 11.00 | Exercise: 15min 1/1/1 | |
| 11.20 | | 8.6 |

P=[0;0;46;09.30;2;0;0;0;0;0;41;1012.3;09.20;11.20;0;0]
T=[8.6]

**Table 1** Extract from diary (Patient 1 / Day 3) showing conversion to **P** matrix and T value.

Figures 2 and 3 show comparisons between actual BGL measurements and ANN predictions, for Patients 1 and 2, respectively. Most of the ANN predictions are very close to the measured values provided by the patient's BGL meters (difference of 1.5mmol/l or less).

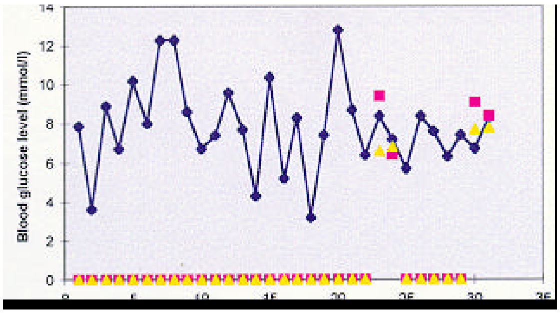


**Figure 2** Comparison between BGL measurements and ANN predicted values for Patient 1. Nomenclature:
◆ BGL meter measurements; ■ ANN predicted values.

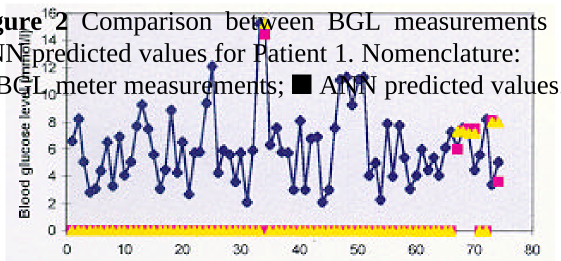


**Figure 3** Comparison between BGL measurements and ANN predicted values for Patient 2. Nomenclature:
◆ BGL meter measurements; ■ ANN predicted values.

## 5 CONCLUSIONS AND FUTURE PROPOSALS

The prediction of BGL in a non-invasive way, using ANNs, could be beneficial to diabetic patients if accurate predictions were assured. Invasive techniques cause pain and discomfort to diabetic patients. A successful ANN, even if it was used alongside BGL meters, would decrease the discomfort of diabetic patients, especially those who require frequent monitoring during the day. The data set used to train the network and test its performance was relatively small. This problem relates to the number of diabetic patients that were willing to co-operate for the study. A possible solution to this problem would be to use data from diabetic patients who had been admitted to hospital for a short period of time. There was also concern as to whether the patients were recording the contents of their meals accurately. Jensen et al [25] showed in a study that individuals often make mistakes when asked to evaluate their meal size and carbohydrate intake. The same study showed that patients start evaluating meals correctly, only when training is provided. These problems limit not only the quantity but also the quality of the data. However, given these problems, the ANN still shows considerable promise.

Future work will include (a) an investigation of an ANN-based diabetes therapy optimiser which will employ the ANN BGL predictor, (b) investigation of other ANN paradigms, with possible hybrid solutions, (c) implementation of the BGL predictor and therapy optimiser on a PC platform, together with a user-friendly graphical user interface, for education and training within diabetes clinics and medical centres, (d) development of an inexpensive, hand-held ANN diabetes therapy system for patients, which will incorporate a BGL monitoring device.

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