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Neural Networks as Radial-Interval Systems through Learning Function

Dr. R. Usha Rani[#1],
Associate Professor, CVR College of Engineering,Hyderabad.India.
teaching.usha@gmail.com

Abstract— This paper presents a novel dimension of neural networks through the approach of interval systems for great more forecasting activity. The artificial neural network (ANN) based models are the most popular ones for load forecasting and other applications. This approach is only a thought line that can enhance the fundamental requirement of all networks giving and incorporating the analytical and expertise knowledge in forecasting from the existential approaches. [1] Interval systems as an approach to approximate interval models by neural networks is proposed.

Keywords— *MLP, RBFNN, Interval Systems.*

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I. Introduction

An enormous upwelling of interest has grown inrecent years in application of neural networks to industrial processes. Their advantage isthat no complex mathematical formulation or quantitativecorrelation between inputs and outputs is required.[2] Many years' data are also not necessary. Theeffective performance of Neural networks[3,4,5] in thecontext of ill-defined processes has led to successfulapplication in forecasting procedures. As a consequence,pattern recognition [6], expert systems [7,8]and neural networks [9,17] have been proposed forelectric load forecasting. Expert system based methodscapture the expert knowledge into a comprehensivedatabase, which is then used for predicting the futureload. These models exploit knowledge of human expertsfor the development of rules for forecasting. However,transformation of an expert knowledge to a set ofmathematical rules is often a very difficult task. In this aspect a quantitative analysis termed knowledge can uplift our work of forecasting.

II. Related work

The literature study behind this is purely a analytical way of incorporating the inputs of multilayer perceptron into the defined structured method called interval systems. Radial basis functions networks are networks, which features the architecture of the instar –out star model and uses the hybrid unsupervised and supervised learning scheme, is the RBFN suggested by Moody and Darken [2].The RBFN is designed to perform input-output mapping trained by examples (x_k, d_k), k_ 1, 2,. . ., p. The RBFN is based on the concept of the locally tuned andoverlapping receptive field structure, studied in thecerebral cortex, the visual cortex, etc. Unlike thein star-out star model, in which the hidden nodes are oflinear winner-take-all-nodes type, the RBFN hiddennodes follow a normalized Gaussian activation function:

zq_gq(x)§Rq(x)Xlk_1
Rk(x) _exp[_jx_mqj2=2s2q]
Xlk_1exp[_jx_mkj2=2s2k]

Where x is the input vector. Thus, the hidden node qgives a maximum response to input vectors close to mq. Each hidden node q is said to have its own receptivefield Rq (x) in the input space, which is a region centredon mq with size proportional to sq , where mq and sq2are the mean (an m-dimensional vector) and variance ofthe qth Gaussian function, respectively. Gaussian functionsare a particular example of radial basis functions.

The output of the RBFN is simply the hidden nodeoutput weighted sum:

yi_ai_Xlq_1
wiqzq_ui_

whereai (_/) is the output activation function and ui is thethreshold value. Generally, ai(_/) is an identity function(i.e. the output node is a linear unit) and ui_/0.The present work adopts a systematic approach to theproblem of centre selection. Because a fixed centrecorresponds to a given regressed in a linear regressionmodel, the selection of RBF centres can be regarded as aproblem of subset selection. The orthogonal leastsquares method can be employed as a forward selectionprocedure, which constructs RBFN in a rational way.[14,15]

The process goes like choosing the appropriate RBF centres one byone from taken training data points until a satisfactorynetwork is obtained. Each selected centre minimizesthe increment to the desired output variance, thus illconditioned problems; the frequent happening can stop the recurrence. In contrast to most learning algorithms, whichcan only work if a fixed network structure is firstspecified, the orthogonal least squares algorithm is astructural identification technique, where the centresand estimates of the corresponding weights can besimultaneously determined in a very efficient manner during learning. Orthogonal least squares learningprocedure generally produces an RBF network smallerthan a randomly selected RBF network [3]. Due to itslinear computational procedure at the output layer, theRBFN is faster in training time compared to its BPcounterpart.A major drawback of this method is associated withthe input space dimensionality. For large numbers ofinputs units, the number of radial basis functionsrequired can become excessive. If too many centres areused, the large number of parameters available in theregression procedure will cause the network to be oversensitive to the details of the particular training set andresult in poor generalization performance (overfit). Avoid

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this problem, both the forward selection and zeroorderregularization techniques are proposed and appliedin [3] to construct parsimonious RBFN withimproved generalization properties.

A RBF network with *m* outputs and *nh*hidden nodes can be expressed as:

$$yi(t) = wio + \sum_{j=i}^{nh} wij\emptyset\left(\left\|v(t) - Cj(t)\right\|\right)$$

Where i=1,.....m.

where *wij*, *wi0* and *c (t) j* are the connection weights, bias connection weights and RBF centresrespectively, v(t) is the input vector to the RBF network composed of lagged input, lagged outputand lagged prediction error and f(·) is a non-linear basis function. (·) denotes a distance measurethat is normally taken to be the Euclidean norm.[18]Since neural networks are highly non-linear, even a linear system has to be approximated usingthe non-linear neural network model. However, modelling a linear system using a non-linear model can never be better than using a linear model. Considering this argument, the RBF network withadditional linear input connections is used. The proposed network allows the network inputs to beconnected directly to the output node viaweighted connections to form a linear model in parallelwith the non-linear standard RBF model The new RBF network with m outputs, n inputs, nh hidden nodes and nl linear input

$$yi(t) = wio + \sum_{j=1}^{nt} \square \;\; \square\square \;\; \square\alpha + \sum_{j=i}^{nh} wij\emptyset\left(\left\|v(t) - Cj(t)\right\|\right)$$

where the α‘s and vl’s are the weights and the input vector for the linear connections respectively.The input vector for the linear connections may consist of past inputs, outputs and noise lags. Sincel's appear to be linear within the network, the α's can be estimated using the same algorithm as forthe w’s.

III. INTERVAL SYSTEMS

Moore defined interval arithmetic for rational functions composed of a finite number of the four basic arithmetic operations on intervals of finite real numbers.[11,12,]Corresponding to the situation with real numbers, operations on intervals with extended (including infinite) endpoints and division by intervals containing zero were not defined. [19,20]Originally, neither was raising an interval to an integer power. Sincethe original formulation, the integer and real power functions have been given interval extensions, but only for intervals contained within function’s natural domainof definition. The sets of values that finite interval operations are defined to contain are described as follows:

Let [a, b] denote a real, closed, compact interval constant.

That is, for example:
[a, b] = {x ∈ IR | a ≤ x ≤ b} , (1)

where IR, denotes the set of finite real numbers, {x | −∞< x < +∞}. Ifop ∈ {+,−,×,÷} denotes one of the four basic arithmetic operators (BAOs), where d < 0 or 0 < c in the case of division, because division by zero is not definedfor real numbers. The right-hand side of (2) defines the sets of values that intervalarithmetic operations on finite real intervals must contain. While computing narrowintervals is desirable, the only requirement is containment. The right-hand side of(2) is the set of values that the operation, [a, b] op[c, d] must contain. The termcontainment set is used to refer to the set of values that an interval result mustcontain.

Arithmetic operation monotonicity makes possible the following rules to computeendpoints of finite interval arithmetic operations:

[a, b] +[c, d] = [a +c, b +d] (3a)
[a, b] −[c, d] = [a −d, b − c] (3b)
[a, b] ×[c, d] = _ min (a ×c, a × d, b × c, b × d) ,
max (a × c, a × d, b ×c, b × d) _ (3c)
[a, b] ÷[c, d] = _ min (a ÷c, a ÷d, b ÷c, b ÷d) ,
max (a ÷ c, a ÷ d, b ÷ c, b ÷ d) _ (3d)

where, to exclude division by intervals containing zero, d < 0 or 0 < c. Directedrounding is used to guarantee containment when interval operations are implementedusing IEEE-754 floating-point operations. [4,5]Dependence even where there forms no rounding error, this may result in intervals that no way can treated as requirement. Therefore, it is not surprising if a nominally positive interval nearzero contains negative values.[16,17] Subsequently, if a nominally non-negative intervalresult contains negative values and is an argument of an operation or function witha non-negative domain, existing unclosed interval systems will raise an exception.

For example, consider the functionf (x) = _x(x − 1) +1, (4)Evaluated over the interval X = [−2, 2] using interval arithmetic, the value of X(X − 1) + 1 is [−5, 7]. No rounding errors have been made. Every arithmeticoperation is exact. The above result is an example of the dependence problem ininterval arithmetic. The expression X(X −1)+1 is evaluated as if it were instead,X(Y − 1) + 1, with the intervals, X and Y, just by coincidence having the samevalue. To connote the fact that the interval variables X and Y are not identical, but that2arithmetic operations on a pair of intervals, [a, b] and [c, d] must produce a newinterval, say _e, f _, such that_e, f _ ⊇ {x op y | x ∈ [a, b] and y ∈ [c, d]} , As long as interval expressions are defined in terms of real or extended-real operationsand functions, no escape exists from limitations on the domain of operationsand functions in the underlying point systems.

These limitations take two forms:In the real and extended real systems (hereafter point systems), functions areundefined outside their domain of definition.In point systems, a function maps points from its domain to points in its range.[12] Multi-valued relations are mappings of sets of points in the relation’s domain setonto sets of points in its range set.Intervals are compact sets of points. This permits the underlying systemfromwhichinterval arithmetic is derived to also be sets, not single points. The closedcentred based set as a system is

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defined, which gives the possibility of constructing the closed interval system. This tries to produce enclosures of sets in this or other possible closed centred based set systems. The “Simple” closed interval system, is implemented in the most significant practical consequence of programming with a closed intervalsystem is that without exception. The valid interval result is obtained through the interval operation and an intrinsic function, along with its interval operands. In a closedinterval system have no “exceptional events” with which to contend.This result is not limited to a subset of intrinsic functions or operations and functions.

System constructs that either accept or produce REAL type data itemshave exception-free interval versions. Therefore, without exception, anyinterval expression can be evaluated if it can be written as a code list, whether it isa function or a relation. The returned interval is guaranteed to be an enclosure ofthe set of all possible values of the expression over the argument intervals, irrespectiveof whether the code list includes branches, loops and subprogram calls, arrayreferences, or overwriting of a variable’s value by a new value. The set of all possibleexpression values is the containment set of an expression and is proved in, tobe the topological closure of the expression.

Interval systems have a number of advantages over the additional realnumber-based interval system. Two new items are worthy of the attention byclosed interval systems algorithm developers are: 1.how to derive containment sets of expressions both at singular points and at argumentsthat create indeterminate formsand 2. How to verify expression continuity when required.

This Interval arithmetic
The addition, subtraction and multiplication of two intervals [a,b] and [c,d] are respectively defined as
Addition: $[a,b]+[c,d]=[a+b,c+d]$
Subtraction: $[a,b]-[c,d]=[a-b,b-c]$
Multiplication: $[a,b][c,d] = [\min(ac,ad,bc,bd), \max(ac,ad,bc,bd)]$

This possibility of the interval values evaluated through these systems can enhance our output result of RBFNN such that the ratio of comparison factor for prediction can increase its measure of equality in terms of similarity check. Number neurons in the hidden layer also influences the performance of RBF NN.But with toomany nodes it will take a longer time to train and some times over fit to data even though we go along with interval systems.

IV.CONCLUSION

The advantage of RBF neural network is that it can be trained much faster than MLP neural network. IT can also give a better performance with minimum number of training data set to perform the successful training and this performance can greatly be influenced by taking the linear data set and as well the non linear data set in the form of interval systems values of evaluating their activation function and the hidden layer input values. Future objective can be testing the system with a standard database, to compare with other training algorithms. This approach of successful study of rbfnn through interval systems may drives towards the better prediction works.

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