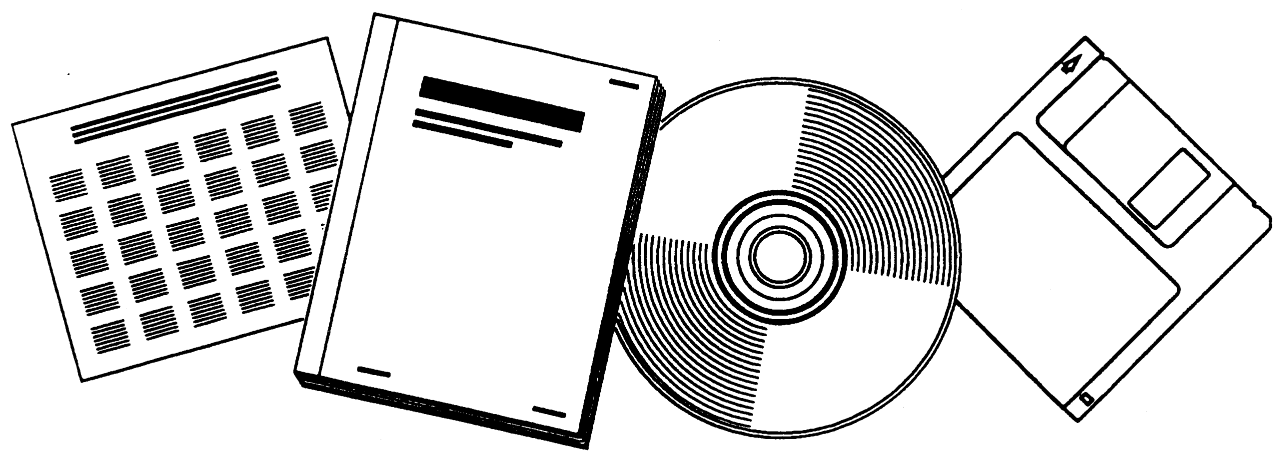
A NEURO-RELIABILITY-BASED APPROACH

KANSAS STATE UNIVERSITY
MANHATTAN, KS

MAY 97



U.S. DEPARTMENT OF COMMERCE
National Technical Information Service

Report No.:KS-97-3
Final Report

PB98-105521

MODELING THE DURABILITY OF AGGREGATE USED IN CONCRETE PAVEMENT CONSTRUCTION: A NEURO-RELIABILITY-BASED APPROACH

Yacoub M. Najjar
Imad A. Basheer
Kansas State University
Manhattan, Kansas

May 1997

MODELING THE DURABILITY OF AGGREGATE USED IN CONCRETE PAVEMENT CONSTRUCTION: A NEURO-RELIABILITY-BASED APPROACH

FINAL REPORT

To

Kansas Department of Transportation

Yacoub M. Najjar
Imad A. Basheer

Department of Civil Engineering
Kansas State University
Manhattan, Kansas 66506

May 1997

1. Report No. KS-97-3	2. PB98-105521	3. Recipient Catalog No.
4. Title and Subtitle Modeling the Durability of Aggregate Used In Concrete Pavement Construction A Neuro-Reliability-Based Approach		5. Report Date May 1997
		6. Performing Org. Code
7. Author(s) Yacoub M. Najjar and Imad A. Basheer		8. Performing Org. Report No.
9. Performing Organization Name and Address Kansas State University Department of Civil Engineering Manhattan, Kansas 66506		10. Work Unit No. (TRAIS)
		11. Contract or Grant No. (C-835)
12. Sponsoring Agency Name and Address Kansas Department of Transportation Docking State Office Bldg. Topeka, Kansas 66612		13. Type of Report and Period Covered Final Report June 1995 to May 1997
		14. Sponsoring Agency Code 106 RE-0093-01
15. Supplementary Notes		

16. **Abstract**

The resistance of aggregate as a building material to cyclic freezing and thawing constitutes a critical issue in design and construction of rigid pavements as well as other concrete structures. The susceptibility of aggregate to frost action is commonly assessed experimentally by subjecting small concrete beams containing the aggregate to repeated cycles of freezing and thawing. Such laboratory testing yields both the durability factor and and percent expansion which are the major indicators of aggregate durability. Due to the high cost and long time (3-5 months) involved in completion of a single test according to ASTM C-666 (Method B), models that relate durability to easily measured physical properties of the aggregate would be cost effective and highly desireable in pavement management studies.

In this report, backpropagation neural networks are developed from a large database containing data pertinent to 750 different experimental investigations on concrete durability. The database was acquired from the Kansas Department of Transportation (KDOT). The networks are designed to enable determination of the durability factor and percent expansion from five basic physical properties of the aggregate. The developed neural models were found to classify the aggregates with regard to their durability with a relatively high degree of accuracy. The experimental data and perdictions were used to produce reliability factors that indicate the probability that tested aggregate will meet specifications. In a second phase, the developed neural models were also validated against 778 new experimental durability data sets. The matrix was also found to truly represent the model characterization based on new experimental data. This indicates that the reliability matrix has stabilized.

17. Key Words	18. Distribution Statement
Aggregate durability, neural network model, concrete pavement, freeze and thaw, computer program, backpropagation.	No restrictions. This document is available to the public through the National Technical Information Service, Springfield, VA 22161

19. Security Classification (of this Report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	40	

Form DOT F 1700.7 (8-72)

ACKNOWLEDGEMENT

This report describes a study carried out for the Kansas Department of Transportation investigating durability of aggregate used in concrete for pavement construction. The authors would like to acknowledge the KDOT personnel who conducted the durability experiments and those who provided the data used by the authors in modeling aggregate durability. Special thanks go to Engineer Richard McReynolds for the efficient and continuous monitoring of the project and reviewing this manuscript.

NOTICE

The authors and the state of Kansas do not endorse products or manufacturers. Trade or manufacturers' names appear herein solely because they are considered essential to the objective of this report.

This information is available in alternative accessible formats. To obtain an alternative format, contact the Kansas Department of Transportation, Office of Public Information, 7th Floor, Docking State Office Building, Topeka, Kansas, 66612-1568, or phone (913) 296-3585 (Voice) (TDD).

DISCLAIMER

The contents of this report reflects the views of the authors who are responsible for the fact and accuracy of the data presented herein. The contents do not necessarily reflect the views or policies of the State of Kansas at the time of publication. This report does not constitute a standard, specification, or regulation.

TABLE OF CONTENTS

List of Figures iii
List of Tables iv
Abstract v
Conversion Factors vi

CHAPTER 1 : INTRODUCTION 1

CHAPTER 2 : EXPERIMENTAL TESTING AND EVALUATION 3

CHAPTER 3 : DATA AND VARIATION OF DURABILITY 6

CHAPTER 4: MODEL DEVELOPMENT AND ANALYSIS 12
4.1. MODELING METHODOLOGY -- NEURAL NETWORKS 12
4.2. MODEL DEVELOPMENT 13
4.3. MODEL ANALYSIS 16
4.3.1. DF-EXP Neural Network 16
4.3.2. DF Neural Network 17
4.3.3. EXP Neural Network 18

CHAPTER 5 : PREDICTION RELIABILITY 23
5.1. RELIABILITY BASED ON PHASE 1 23
5.2. RELIABILITY BASED ON PHASE 2 24
5.3. SOFTWARE DEVELOPMENT 25

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS 34

CHAPTER 7: BIBLIOGRAPHY 36

LIST OF FIGURES

Figure 2.1. Flowchart showing testing program for aggregate durability 5

Figure 3.1. Variation of durability factor (DF) and percent expansion (EXP) with various physical properties of aggregate 9

Figure 3.2. Relationship between DF and EXP. 11

Figure 4.1. Schematic of three-layers backpropagation neural networks 19

Figure 4.2. Classification accuracy of DF as predicted by the DF-NN model 20

Figure 5.1. Schematic of durability neural network model with reliability prediction . . . 26

LIST OF TABLES

Table 4.1 : Errors associated with prediction of DF and EXP using the various developed neural network models 21

Table 4.2: Accuracy of classification of the various developed neural network models 22

Table 5.1: The reliability of aggregate to meet DF or EXP specifications (using phase 1 data) 27

Table 5.2: The reliability that an aggregate will meet DF and EXP specifications (using phase 1 data) 28

Table 5.3: The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data of ledge type) 29

Table 5.4: The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data of production type) 30

Table 5.5: The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data) 31

Table 5.6: The reliability that an aggregate will meet DF and EXP specifications (using phase 1 and phase 2 data combined) 32

Table 5.7: The distribution of number of data sets (using phase 1 and phase 2 data) in reliability matrix 33

ABSTRACT

Resistance of aggregate as a building material to cyclic freezing and thawing constitutes a critical issue in design and construction of rigid pavements as well as other concrete structures. The durability of aggregate to frost action is commonly assessed experimentally by subjecting small concrete beams containing the aggregate to repeated cycles of freezing and thawing. Such laboratory testing yields both durability factor and percent expansion, both comprising major indicators of aggregate durability. Due to high cost and long time (3-5 months) involved in completion of a single test according to ASTM C-666 (Method B), models that relate durability to easily measured physical properties of the aggregate are highly effective and desirable in pavement management studies. In this report, backpropagation neural networks are developed from a large database containing data pertinent to 750 different experimental investigations on concrete durability. The database was acquired from the Kansas Department of Transportation (KDOT). The networks are designed to enable determination of durability factor and percent expansion from five basic physical properties of the aggregate. The developed neural models were found to classify the aggregates with regard to their durability with a relatively high degree of accuracy. The experimental data and predictions were used to produce reliability factors that determine the reliability of tested aggregate to meet specifications. In a second phase, the developed neural models were also validated against 778 new experimental durability data sets. The reliability matrix was also found to truly represent the model characterization based on new experimental data. This indicates that the reliability matrix has stabilized.

CONVERSION FACTORS

The following conversion factors are used to convert between English and SI units:

Length:

1 ft	=0.3408 m
1 ft	=30.48 cm
1 ft	=304.8 mm
1 in.	=0.0254 m
1 in.	=2.54 cm
1 in.	=25.4 mm
1 mile	=1.609 km

Area:

1 ft^2	=0.0929 m^2
1 ft^2	=929.03 cm^2
1 ft^2	=92903 mm^2
1 $in.^2$	=6.452×10^{-4} m^2
1 $in.^2$	=6.452 cm^2
1 $in.^2$	=645.2 mm^2

Stress:

1 lb/in^2 (1 psi)	=6.897 kN/m^2
1 lb/in^2 (1 psi)	=6.897 kPa
1 lb/in^2 (1 psi)	=0.0069 MPa

Temperature:

Temp. °F	=32.0 + 1.80×(°C)

CHAPTER 1

INTRODUCTION

Concrete pavements are the most widely used type of pavements and continue to constitute a high percentage of roadways worldwide. In 1990, a total length of concrete pavements of approximately 130,000 miles was estimated to cover a large area of the United States (Huang 1993). The dependence on concrete pavements is attributed to their low maintenance costs and their capacity to withstand high volumes and excessive loads of traffic. In regions where concrete pavements is exposed to freezing and thawing, the pavement service life is more likely to be affected significantly. Therefore, durability of concrete masses and particularly the composition of the concrete matrix is a primary concern in the design and construction of concrete pavements as well as other concrete structures.

One major component of concrete mixes for highway pavements is aggregate. In Kansas, D-cracking of concrete pavements containing limestone coarse aggregate is thought to be responsible for this mode of deterioration. Durability of limestone aggregate and the related characteristics of the aggregate are presumed to be influential factors in the observed D-cracking.

Commonly, the durability of concrete is measured by testing its resistance to rapid cycles of freezing and thawing (ASTM C 666-92). Aggregate suitability as a constituent in concrete mixes is checked by preparing concrete specimens (beams) of prespecified dimensions (approximate volume 0.60 ft^3) containing the aggregate under investigation. After curing for a certain period of time (up to 90 days), concrete beams are subjected to repeated cycles of freezing in air (or water) at 0 °F and thawing in water at +40 °F such that each cycle is completed in a three-hour period of time. After a prespecified set of freezing and thawing cycles (not exceeding 36), the specimen is tested for fundamental transverse frequency and change in length. The specimen's relative dynamic modulus of elasticity after c cycles of freezing and thawing is calculated as the ratio of squared values of fundamental transverse frequency at c cycles and 0 cycles. The specimen is continued in the test until it has been subjected to 300 cycles or until its relative dynamic modulus of elasticity reaches 60% of its initial value, whichever occurs first. Alternatively, if the change in length is recorded then 0.10% expansion of the sample may be used as the criterion for termination of the test. A complete freezing and thawing test may *typically* last for up to 4.5 weeks, depending on the aggregate and integrity of concrete mix, with a preliminary 3 months of curing, therefore, a total time of 4 to 5 months is needed to complete one test.

In this report, the durability of concrete is modelled by determining the durability factor based on experimentally determined physical characteristics of the aggregate used to prepare the beams. It is obvious that any prediction model will be beneficial to avoid the excessive testing time and the associated high costs. To the best of the authors' knowledge, little or no similar investigation and modeling effort is available in the literature. The experimental evaluation of the physical properties of aggregate are much less time consuming and involves considerably less amount of effort and cost as compared to freezing and thawing test. The physical properties of aggregate under consideration in this study includes modified freeze and thaw (soundness), absorption, specific gravity, and acid insoluble residue, requiring about 2 weeks, 12 hrs, 24 hrs, and 3 hrs, respectively, for completion for a typical limestone coarse aggregate. Neural network-based models are developed and compared for their accuracy in predicting the durability factors.

CHAPTER 2

EXPERIMENTAL TESTING AND EVALUATION

In this chapter, a brief description of the testing and evaluation protocols commonly used in KDOT's laboratory for testing durability of concrete specimens is presented. The purpose of this presentation is to provide a quick and an adequate amount of information of how the experimental testing is performed. Additional information can be obtained from the original sources of ASTM and AASHTO standards mentioned below.

Rocks of limestone are crushed to pass through 3/4" and retained on +3/8" sieves. Portion of the sieved aggregate are used to measure the following physical properties:

i. Specific gravity: saturated surface-dry density (GSSD) and oven-dry density (GDRY) using [AASHTO T-103 (x)].

ii. Absorption (ABS) using [AASHTO T-103 (x)].

iii. Modified soundness or modified freeze and thaw loss-ratio (FT) using [AASHTO T-103 (v)].

iv. Total acid insoluble residue (ACIDR) using [AASHTO T-103 (y)].

The remaining portion of the sieved aggregate is used to prepare three replicates of beams according to ASTM C-192 as follows:

1. *Mix Design:* Monarch Cement (Type II) with 25% aggregate (-3/4" to +1/2"), 25% aggregate (-1/2" to +3/8"), 50% FA-A, Y.C.F. of 601.6 lb/yd^3, w/c=0.4431 to 0.4784, air=5 to 7%, and slump of 1.5" to 2.5". These proportions total to an approximate volume of 0.60 ft^3.

2. *Curing:* samples are cured in moisture room for 67 days, air-dried for 21 days, and subsequently soaked in water for and additional 2 days. The total curing time=90 days.

3. *Record reference data:* the data recorded are the 90-day values of weight, dynamic modulus of elasticity, and length of sample at 40 °F.

4. *Rapid freezing and thawing:* this test is carried out according to ASTM C666-Procedure B (rapid freezing in air and thawing in water, temperature range= 0 °F to +40 °F). Test is terminated after 300 cycles or when sample achieve 60% of initial modulus (whichever occurs first). Otherwise, terminate beams when average expansion reaches 0.10%(do not compute any durability factor).

5. *Calculations:* upon completion of a test, the following are calculated: i) weight change, ii) percent expansion, iii) relative dynamic modulus of elasticity, and iv) durability factor.

For all types of concrete construction, according to KDOT specifications a coarse aggregate made of crushed limestone is designated as durable and resistant to freezing and thawing if the test results meet the following three conditions:

1. Durability Factor, DF$\geq$ 95.
2. Expansion, EXP(%)$\leq$ 0.025.
3. Modified freezing and thawing (Soundness), FT$\geq$ 0.85.

The KDOT testing protocol for a given aggregate is shown in Fig. 2.1.

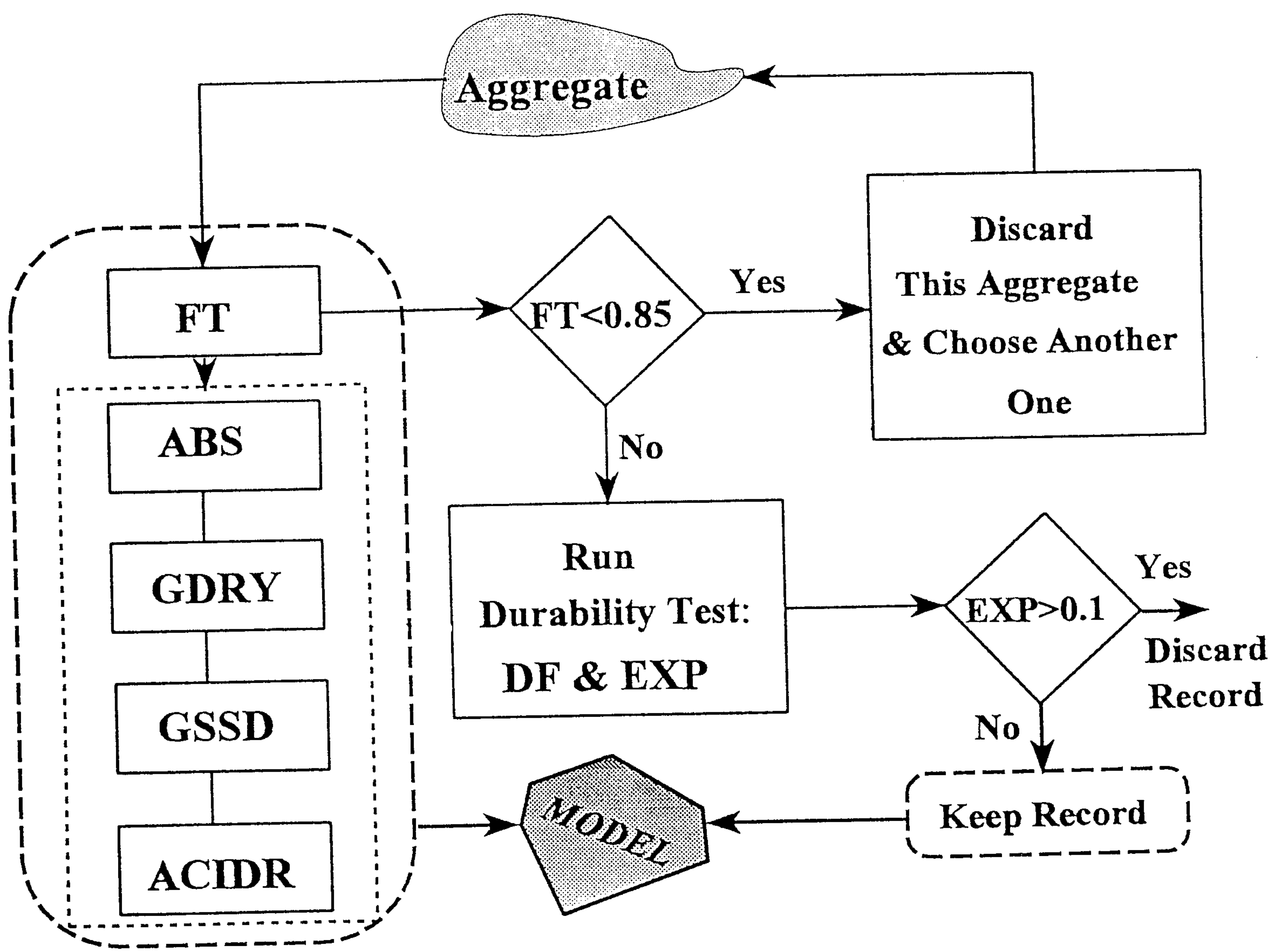


Figure 2.1. Flowchart showing testing program for aggregate durability

CHAPTER 3
DATA AND VARIATION OF DURABILITY

The Kansas Department of Transportation (KDOT) has been using crushed limestone in construction of rigid pavements for long period of time. Testing of limestone has produced a large database pertaining to experimental testing of aggregate durability. Typically, soundness of aggregate (modified freeze and thaw) is the first experimental indicator of the potential of a given aggregate to be further tested for durability factor using concrete beam specimens. No testing for durability factor (DF) is performed if the modified freezing and thawing (FT) of aggregate is below 0.85. Moreover, for those aggregate with FT$\geq$ 0.85, durability factor is not computed if expansion (EXP) of the concrete beams due to cyclic freezing and thawing exceeds 0.10%. A large database containing data from 1080 tests on aggregate and on durability factor of poured concrete beams was generated by collecting experimental data from various test records. After eliminating those tests where testing for DF was not appropriate and other cases where EXP $\geq$ 0.10 %, the database size reduced to a total of 750 data sets covering a wide variety of aggregate properties and testing conditions. The soundness (FT) of aggregates in the database ranged from 0.85 to 0.99; aggregate absorption (ABS) ranged from 0.18 to 9.94; specific gravity based on dry conditions (GDRY) ranged from 1.96 to 2.7; specific gravity based on saturated surface-dry conditions (GSSD) ranged from 2.14 to 2.72; and total acid insoluble residue (ACIDR) ranged from 0.62 to 37.34. The resulting durability factor, DF, for all tests in the database spans over a relatively wide range of 25 to 100, and the percent expansion, EXP, ranged from 0.0 to 0.1.

In an attempt to study the variation of both DF and EXP with the aggregate physical properties, variation plots are generated from the database containing 750 data sets which are displayed in Fig. 3.1 (a through j). Generally, these plots revealed no clear or distinct relationship to exist between any of the physical properties of aggregates and either DF or EXP. The observed independence of DF or EXP on any of the physical properties of aggregate may indicate a strong interrelation of the various physical properties that can not be ignored when studying the variability of DF or EXP. While this interrelation can be significant, one may clearly notice that no relationship exists between either DF or EXP and the modified freeze-thaw (FT) (Figs. 3.1-a and 3.1-b) when this parameter (i.e. FT) is considered alone. On the other hand, the data shown in Figs. 3.1-c and 3.1-d may indicate good relationship between absorption (ABS) and both DF and EXP. Despite the observed scatter in the variational plot one may notice a trend of increasing DF by increasing ABS. This trend is also verified by considering Fig. 3.1-d where a trend of decreasing EXP with increasing ABS can be seen. While such relationships are rather unusual, it is shown later that the developed neural models will provide a more realistic relationship since such models account for the variability in all parameters. In Figs. 3.1-e and 3.1-f the trend of decreasing DF and increasing EXP by increasing GDRY (and similarly of GSSD displayed in Figs. 3.1-g and 3.1-h) also presents an unrealistic behavior. However, such relationships between DF or EXP and one parameter can be anticipated when ignoring the effect of other parameters. Data from phase 1 were used to determine the relationship between DF and EXP. Figure 3.2 shows that decreasing trend between DF and EXP prevails, which is rather expected.

Regardless of the observations that might be drawn from the variational plots presented in Fig. 3.1, one can clearly postulate a strong dependence of all of the aggregate physical properties among each other. This obviously can necessitate the development of a model that combines the influence of the various aggregate properties for the purpose of prediction of both the durability factor and percent expansion of concrete beams. In Chapter 4, prediction models based on artificial neural networks are developed from the available database of experimental durability. Due to the considerable scatter in the data, statistical modeling is stipulated to be both non-viable and inadequate to explain the scatter and interdependence of the various parameters. Preliminary investigation of the conventional statistical correlation methods to model the present problem revealed that predictions by the developed regression equations is far from the corresponding experimental values. The several statistical models attempted in this study produced R^2 representing agreement between predicted and experimental values not exceeding 0.15. Hence, neural networks are used for modeling the DF and EXP of limestone aggregate in an attempt to reduce this discrepancy.

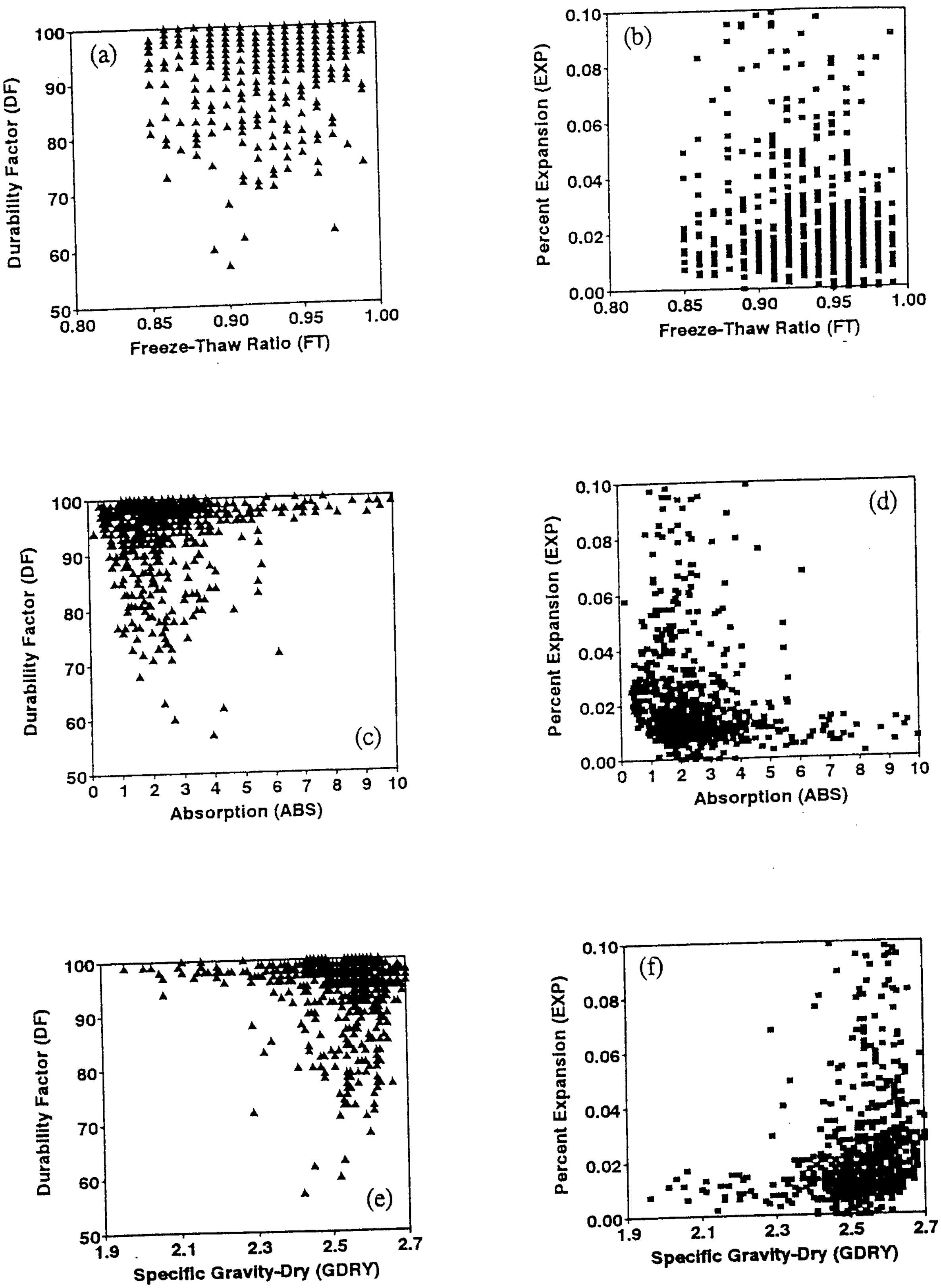


Figure 3.1. Variation of durability factor (DF) and percent expansion (EXP) with various physical properties of aggregate

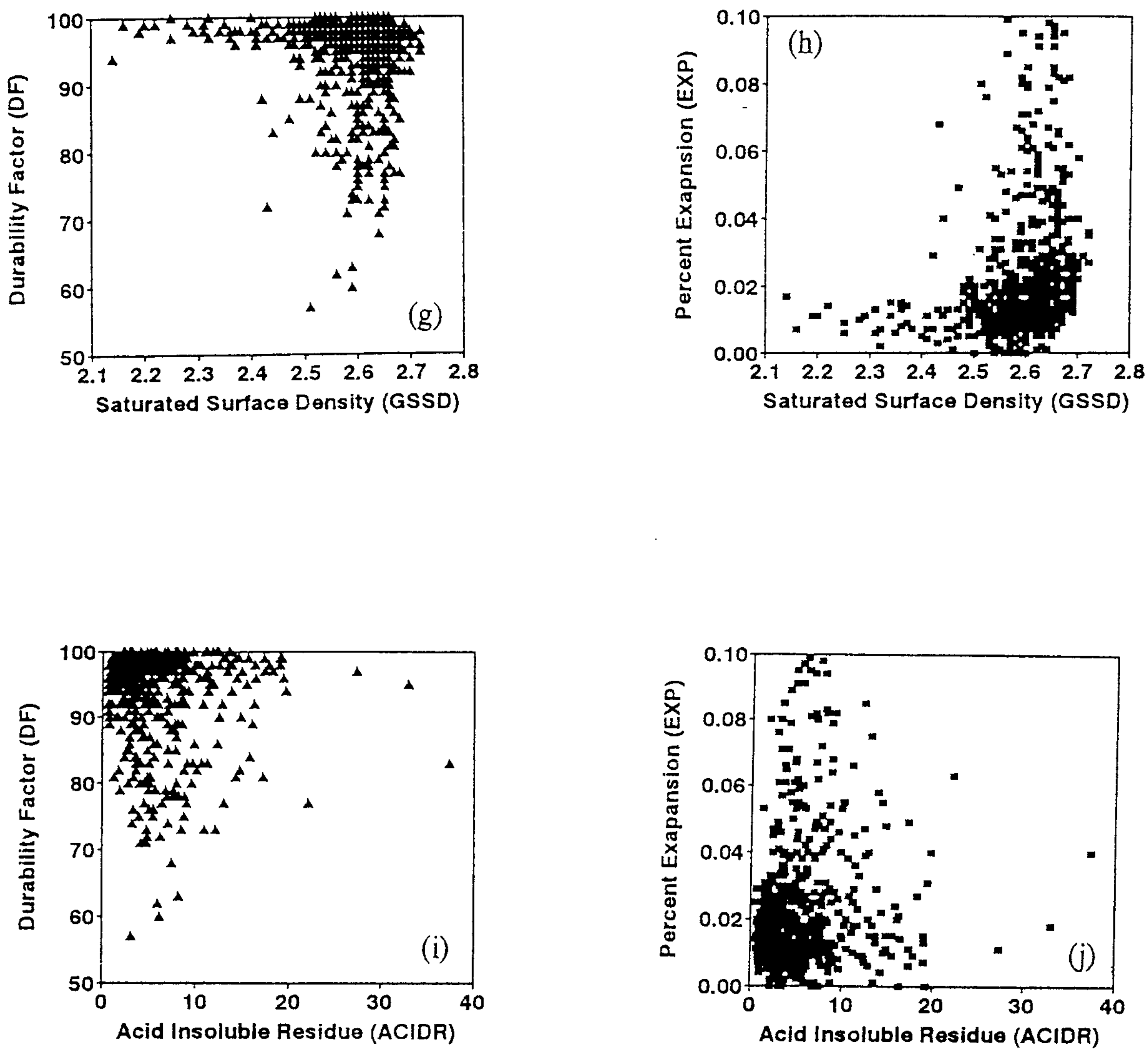


Figure 3.1. (Cont'd) Variation of durability factor (DF) and percent expansion (EXP) with various physical properties of aggregate

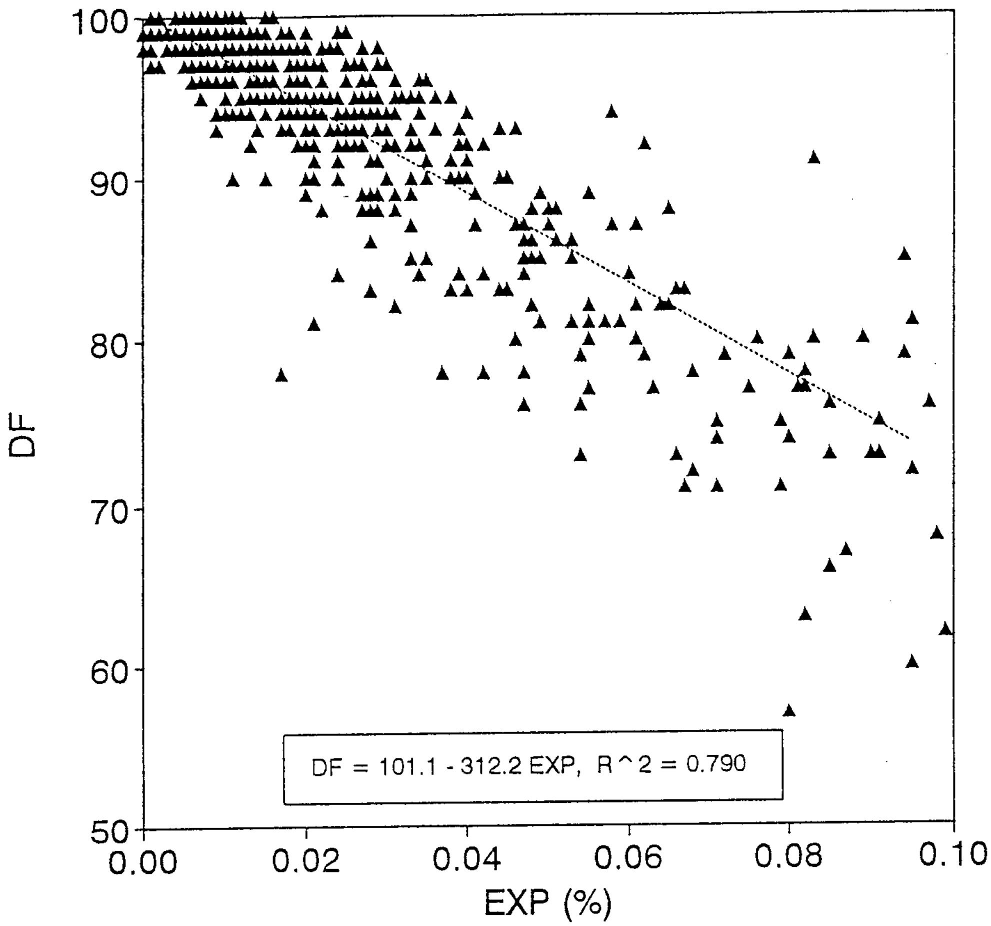


Figure 3.2. Relationship between DF and EXP.

CHAPTER 4

MODEL DEVELOPMENT AND ANALYSIS

4.1. MODELING METHODOLOGY-- NEURAL NETWORKS

In order to understand the development of the aggregate durability neural models, it is essential to briefly describe neural networks and discuss the methodology of neural computation. In this chapter, neural networks are discussed and various stages in development and design of neural models for predicting the durability factors and percent expansion of tested beams are presented.

Neural networks are simply defined as highly nodal structures copied after the nervous system of the mammalian cerebral, that when fed with appropriate data, can perform parallel computation in a fashion analogous to that of the brain. The nodal structure of an artificial neural network (NN) resembles a drastically oversimplified architecture of the biological structure of neurons in the nervous system. Although there are many variations of neural networks, the backpropagation neural network (BPNN) and its variants are currently the most widely used networks due to their apparent efficiency to model highly nonlinear problems and their flexibility to model a wide spectrum of applications in all research disciplines. BPNNs are multilayer structures constructed of three different types of layers. An input layer containing the input nodes receives information in form of signals from the external environment and process and forward them to a set of subsequent layers called hidden layers. The hidden layers receive the processed data and process and feed them forward towards an output layer where the solution of the problem is pursued. A schematic representation of multilayer BPNN is shown in Fig. 4.1. As can be seen from Fig. 4.1, all nodes in one layer are connected (by links with appropriate and adjustable weight) to all nodes in adjacent layers but no side connections are permitted in such a networking scheme. One node receives signals from a number of nodes and integrate the signals as a weighted average. This weighted sum is simply the sum of all signals multiplied by their respective weights. The integrated signal at one receiving node is transformed to activation by using a transfer function such as the sigmoidal function. Similarly, the transformed signal is transmitted forward in a similar way to a following layer. The process is repeated until outputs are computed at the output side of the network. For one example (data set), the produced outputs are compared to actual (target) outputs and the error at the output side is used to calculate an error function. This function is used along with a learning rule (e.g. modified generalized delta rule) to propagate the error starting from the weights in the last layer and backward to other layers (hence the name backpropagation) in order to modify the weights. The procedure of forward activation of signals and the backpropagation of errors is repeatedly carried out until the error at the output side reduces to prespecified minimum. This process is also performed for all examples (data sets) used to train the network. For more details about the BPNN and other neural networks' algorithms and architectures, the readers are referred to the huge amount of literature on neural computing such as Simpson (1990) and Hassoun (1995).

4.2. MODEL DEVELOPMENT

Neural network development includes training a network on a number of data sets, and testing the accuracy of the developed network on sets never been used during the training process. Testing the network accuracy is performed using two sub-databases : testing database and validation database. The testing database contains all the test sets used to check the prediction capability of the network while the network is being trained on the training data. Alternatively, a validation database is used after selecting the most appropriate network in order to examine the network accuracy in predicting outputs for absolutely unseen cases. This procedure is actually similar to what happens after releasing the network (or any other predicting model) to the customer for use. For the aggregate durability database containing 750 data sets (examples), 548 sets were randomly selected to train the networks, 119 data sets were used to test the networks' generalization during the training process, and the remaining 83 sets were chosen to examine the validity of the developed networks. Although the selection of the sets in each sub-database was random, caution was practiced not to include in the testing or validation sets data sets irrelevant to the training domain. This was performed to prevent the developed networks from extrapolating beyond the domain on which they were trained.

In designing a BPNN, determination of the size of the hidden layer(s) constitutes a crucial step in network development. Unlike the input and output layers, the size of the hidden layer in terms of the number of hidden nodes it contains can not be known *a priori*. The backpropagation algorithm (Basheer and Najjar 1994; Najjar et al. 1996; Najjar and Basheer (1996), Najjar and Basheer 1997 (a,b), and Basheer and Najjar 1996) is encoded in a Fortran program with the ability to perform adaptive learning while building up the network architecture one hidden node at a time. Similarly, the number of epochs (iteration cycles) for one representative architecture (i.e. assuming a certain number of hidden nodes) is also determined during this adaptive learning process. The network adds one hidden node to the hidden layer or terminate iteration within certain architecture when the average prediction error obtained using the testing sets exceeds a prespecified minimum. Hence, in the designed adaptive learning backpropagation model, both the optimal architecture and optimal number of iteration cycles are determined in parallel. Once these are identified, the developed network is further examined for prediction of the validations sets.

In this study, three different types of BPNNs were developed in attempt to obtain the network(s) that generalize better. The three networks were varied in the size and type of their output layer. However, all networks attempted were fixed in the size of their input layer which included 5 input parameters; namely, FT, ABS, GSSD, GDRY, and ACIDR. For network 1, the output layer is designed to include both outputs; viz. DF and EXP. Conversely, networks 2 and 3 were designed to include one single output; namely DF and EXP, respectively.

Two schemes of examining the accuracy of prediction of the networks were adopted. In the first scheme, accuracy based on error incorporated in prediction of validation and testing sets is calculated. In the other scheme, which may be more useful for design purposes, agreement between the predicted output (EXP or DF) and the corresponding experimental values is examined based on whether the pair of data (i.e. predicted and experimental) meet the specifications of whether the aggregate passes or fails to qualify as a durable aggregate. To explain this further, consider the case where the *NN-predicted* DF and the *experimental* DF constitute the pair of data (98, 92). In this arbitrary example, the neural network model states that the aggregate qualifies as good aggregate according to the adopted specifications whereas the experimental results disqualifies this aggregate. Hence, the model is assigned "failure" for accurately predicting this particular case. On the other hand, if a pair of data for DF is represented as (85, 81) then the model is assigned "successful" to predict this case since both prediction and experimental values disqualify this aggregate as durable for construction. Similarly, a pair of data (98, 95) denotes a "successful" model prediction due to the model's capability to qualify the aggregate as good as the experimental investigation does. For further illustration of the accuracy scheme based on classification, Fig. 4.2 shows agreement between prediction (using one DF-NN model) and experimental values of DF. With the DF=95 as the threshold between durable and non-durable concrete, Fig. 4.2 summarizes the various regions with the model capability to perform classification.

It is clear that the first scheme of examining the accuracy of prediction based on the error in the output does not imply any provision for specifications. Hence, it may practically be assumed that the second scheme of testing the accuracy of model prediction can be quite advantageous in the light of specifications regarding the issue of whether to use or not to use a certain aggregate for constructing concrete structural elements. In the following sections, the three BPNNs are presented and comparisons regarding accuracy of prediction are also addressed.

4.3. MODEL ANALYSIS

4.3.1. DF-EXP Neural Network

In this network, both DF and EXP are included in the output layer. The input layer contains the 5 input parameters mentioned earlier. Using the designed adaptive learning BPNN, the performance of the current network was found to be optimum at one hidden node and 400 iteration cycles (epochs) with a momentum coefficient of 0.95 and a learning rate of 0.45. Hence, the neural network is denoted by 5-1-2 to refer to the number of nodes in each layer. The error at the outputs is determined as the Mean of the Absolute value of the Relative Error (MARE) between predicted and actual values for all data sets used in testing the accuracy. Table 4.1

summarizes the errors achieved using the 5-1-2 NN for predicting the data sets in training data, testing data, validation data, and all data combined. Using all data combined, DF was predicted with an average error of 5.78%, while EXP was predicted with a much less accuracy at a MARE of 298%. It is apparent that high values of MARE observed in EXP can be attributed to *Actual* values being close to 0.

Using the second scheme of examining the accuracy of prediction (i.e. in light of specifications), Table 4.2 summarizes the percentage of times the model was capable to accurately predict the DF and EXP. As can be seen from Table 4.2, the DF-EXP model was more accurate in predicting DF at high values and EXP at low values. On the average, the model was able to reflect (classify correctly) the experimental data at a rate=38% for DF and at 74.5% for EXP. Because DF and EXP have to meet specifications in order for a certain aggregate to qualify as durable material for construction, both DF and EXP were simultaneously considered to compute the *overall* accuracy of the DF-EXP neural model. The model was found to be able to accurately classify aggregates in only 24.8% of the instances.

4.3.2. DF Neural Network

In this network, the durability factor, DF, is used as the single output. Similar procedure of developing the DF-EXP-network was adopted to develop this particular model. Upon training on networks with variable architecture, the network with three hidden nodes was found to produce the optimal solution. Hence, this neural network is denoted as 5-3-1. The relative errors computed for the various databases are summarized in Table 4.1. As can be seen from Table 4.1, less errors are observed (compare to DF-EXP-network) when the DF was the single output of the model. This might be due to the potential deviation of the weight vector in the error hyperspace from the point of global minimum when DF is accompanied with another output (i.e. EXP) which might have contained large errors.

Using the other scheme of evaluating the performance of the network, the present network was found to provide two features better than the DF-EXP network. Firstly, the DF network was able to produce a wider resolution for DF at lower values. That is, the DF-EXP-network was only able to map the data in the region between 90 to 96.7 whereas the DF-network produced wider mapping that encloses data ranging from 82 to 100. Secondly, errors associated with qualification or disqualification (classification capability) of the aggregates are reduced using the DF-network as opposed to the errors of the DF-EXP-network. Table 4.2 summarizes the rates of success for predicting DF for different ranges of DF. Using all data combined, the overall success rate of the DF-network model in performing accurate classification of the aggregates is estimated as 63.1% (compare to 38% using the DF-EXP-network). Therefore, the DF-network will be adopted herein as the final network for predicting the DF of aggregates.

4.3.3. EXP Neural Network

This network is designed particularly for prediction of percent expansion, EXP, from the 5 input parameters. Using the adaptive learning backpropagation network, the optimum network was found at 3 hidden nodes. Table 4.1 presents the errors of prediction of the various sub-databases. Using the second scheme of assessing the prediction accuracy, Table 4.2 presents the success rate of prediction of EXP. The *overall* success rate was calculated as 75.8%, slightly better than that of the DF-EXP-network. Therefore, the developed single output DF-network was adopted to predict EXP values.

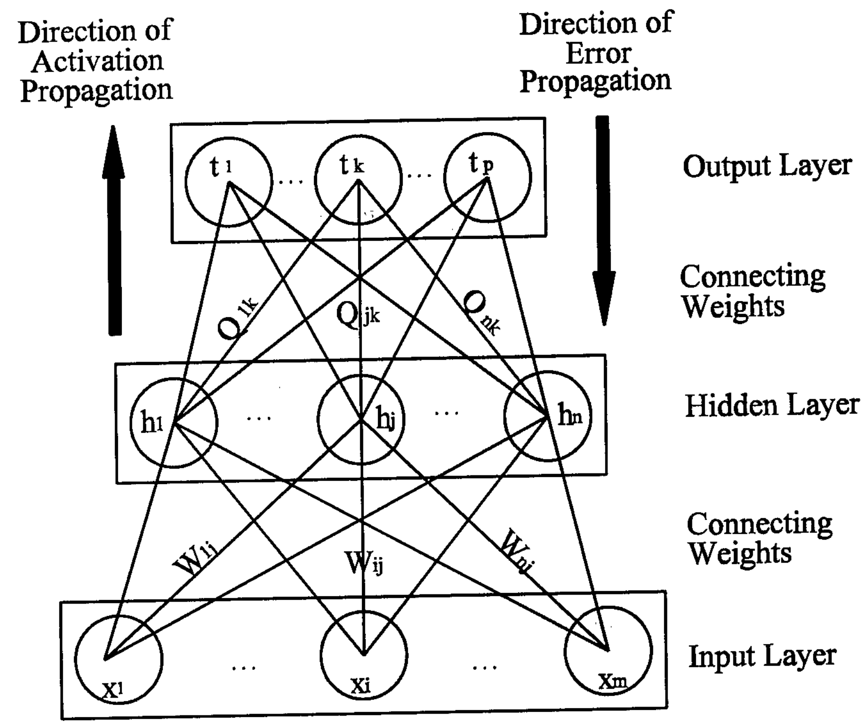


Fig. 4.1 Schematic of three-layers backpropagation neural networks.

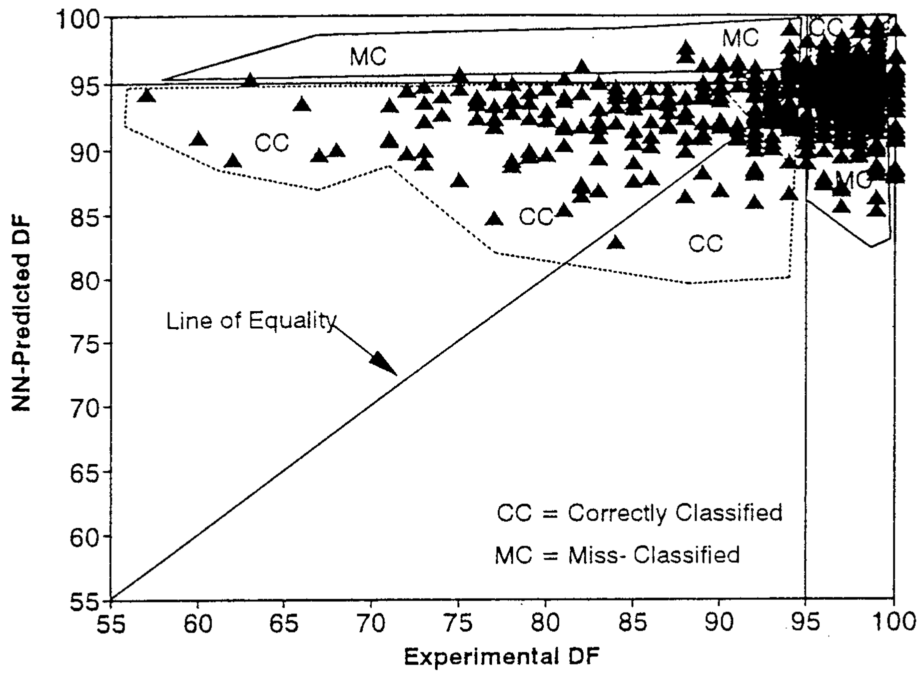


Figure 4.2. Classification accuracy of DF as predicted by the DF-NN model .

Table 4.1 : Errors associated with prediction of DF and EXP using the various developed neural network models.

Network	DATA	No. Sets	MARE(%) (DF)	MARE(%) (EXP)
DF/EXP-Net (5-1-2)	Training	548	5.75	81.60
	Testing	119	5.35	111.10
	Validation	83	6.31	299.00
	All Data	750	5.78	298.00
DF-Net (5-3-1)	Training	548	5.00	
	Testing	119	4.58	
	Validation	83	6.42	
	All Data	750	5.09	
EXP-Net (5-3-1)	Training	548		83.20
	Testing	119		114.10
	Validation	83		34.10
	All Data	750		55.00

MARE(%) : Mean of Absolute Value of Relative Error (%)

Table 4.2: Accuracy of classification of the various developed neural network models.

DF-EXP Network				DF Network		EXP Network	
DF RANGE	*%CC*	*EXP RANGE*	*%CC*	*DF RANGE*	*%CC*	*EXP RANGE*	*%CC*
96-96.7	93	0.006-0.01000	95	98-100	91	0.0055-0.0100	97
95-96	90	0.010-0.01250	96	97-98	92	0.0100-0.0125	100
94-95	12	0.0125-0.0150	93	96-97	87	0.0125-0.0150	95
93-94	23	0.0150-0.0175	93	95-96	86	0.0150-0.0175	92
92-93	39	0.0175-0.0200	84	94-95	66	0.0175-0.0200	87
91-92	41	0.0200-0.0225	65	93-94	44	0.0200-0.0225	72
90-91	48	0.0225-0.0250	69	92-93	44	0.0225-0.0250	75
89-70	60	0.0250-0.0275	46	91-92	43	0.0250-0.0275	46
		0.0275-0.0300	58	90-91	47	0.0275-0.0300	49
		0.0300-0.0325	63	89-90	64	0.0300-0.0325	60
		0.0325-0.0350	56	88-89	57	0.0325-0.0350	72
				87-88	50	0.0350-0.0375	60
				86-87	71	0.0375-0.0400	88
				86-86	50	0.0400-0.0425	75
				82-85	67		

%CC : Percentage of Correct Classification

CHAPTER 5
PREDICTION RELIABILITY

5.1. RELIABILITY BASED ON PHASE 1

Based on the results and analysis of the three networks developed in Chapter 4, the DF-network and EXP-network will be used to predict, respectively, the DF and EXP of concrete specimens in order to assess the durability of a given aggregate based on some known physical properties of the aggregate. The scheme of evaluating the accuracy of prediction based on specification (i.e. accuracy of classification) can be used to associate the computed values of DF and EXP with reliability factors. In other words, this scheme is manipulated to furnish some information regarding the reliability (probability) that the aggregate under consideration will meet the durability specification(s) based on neural network-predicted values of DF and/or EXP.

Table 5.1 presents the reliability associated with stating that the aggregate is durable and recommended for use in construction. For instance, if the predicted value of DF lies within the 95-97 range, then the reliability (probability) of aggregate being durable can be as high as 86%. Additionally, a predicted value of DF in the range 90-95 constitutes only 51% confidence that the aggregate will be durable. Moreover, Table 5.1 shows the reliability factor for all ranges encountered in prediction of EXP. As can be seen from Table 5.1, an aggregate with a predicted EXP value of 0.016 represents a durable aggregate (in terms of EXP) with 94% reliability.

Since both DF and EXP are commonly used as indicators of durable aggregate, reliability of prediction based on these two parameters combined is more reflective than the independent reliability of prediction of DF and EXP. The reliability of prediction via the durability neural model (composed of DF-NN and EXP-NN) was determined by observing the simultaneous accurate classification of both DF and EXP. Hence, reliability is dependent on the quality of prediction of both DF and EXP. A thorough inspection of the predicted data eventually yielded the prediction reliability matrix shown in Table 5.2. To illustrate use of Table 5.2, consider the case where a specific aggregate is estimated using the neural models to yield DF=96.0 and EXP=0.0150. Table 5.2 implies that the given aggregate is believed to be durable (or is recommended for construction) with 87% confidence. It is obvious from Table 5.2 that the reliability (probability) of aggregate being durable decreases with decreasing DF and increasing EXP. The procedure for using the developed ANNs for determining reliability is schematically presented in Fig. 5.1. First, the user calculates DF and EXP separately from DF-NN and EXP-NN, respectively using the basic properties of the aggregate. Then, the calculated values are used to enter the DF/EXP reliability matrix which determines the probability of given aggregate to meet specifications.

5.2. RELIABILITY BASED ON PHASE 2

In this phase, KDOT provided additional experimental data (called herein phase 2 data) for predicting the durability and comparing with corresponding experimental values. Moreover, the data was used to check the accuracy of the reliability matrix obtained in phase 1. The reliability matrix should continuously be updated as new data become available. At a certain level of data availability, the reliability matrix may not require any updating and the matrix is said to be stabilized (i.e. converged).

In phase 2, the new data were obtained from two sources. The first database is called ledge data which contained a total of 120 data sets. Based on this database, the reliability matrix was determined as shown in Table 5.3. Moreover, the second database contained 658 data sets (called production data) showed a reliability matrix as presented in Table 5.4. The entire new data (i.e. 778 data sets) were added and new reliability matrix for this phase was produced. This matrix is displayed in Table 5.5.

The new data was also used to update the reliability matrix obtained in phase 1 of the validation (i.e. the original study). The combined database then included a total of 1528 data sets. The resulting updated matrix from both phases is shown in Table 5.6. Comparison between the updated reliability matrix (i.e. Table 5.6) and the original matrix based solely on phase 1 (i.e. Table 5.2) indicates that only slight differences in the reliability factors in each of DF-EXP cells. The observed stability in reliability factors demonstrates matrix convergence. Therefore, further updating may be unnecessary. The distribution of data (by number of data sets and as percentage from the entire database) within each range of DF and EXP is summarized in Table 5.7.

5.3. SOFTWARE DEVELOPMENT

The neural models developed in this research study were encoded into user-friendly software program. The software asks the user to input the values of the five physical properties of the aggregate. The software then responds by displaying the values of the DF and EXP of the aggregate. Also, the software calculates and displays the reliability of the aggregate to meet the KDOT specifications from the calculated DF and EXP.

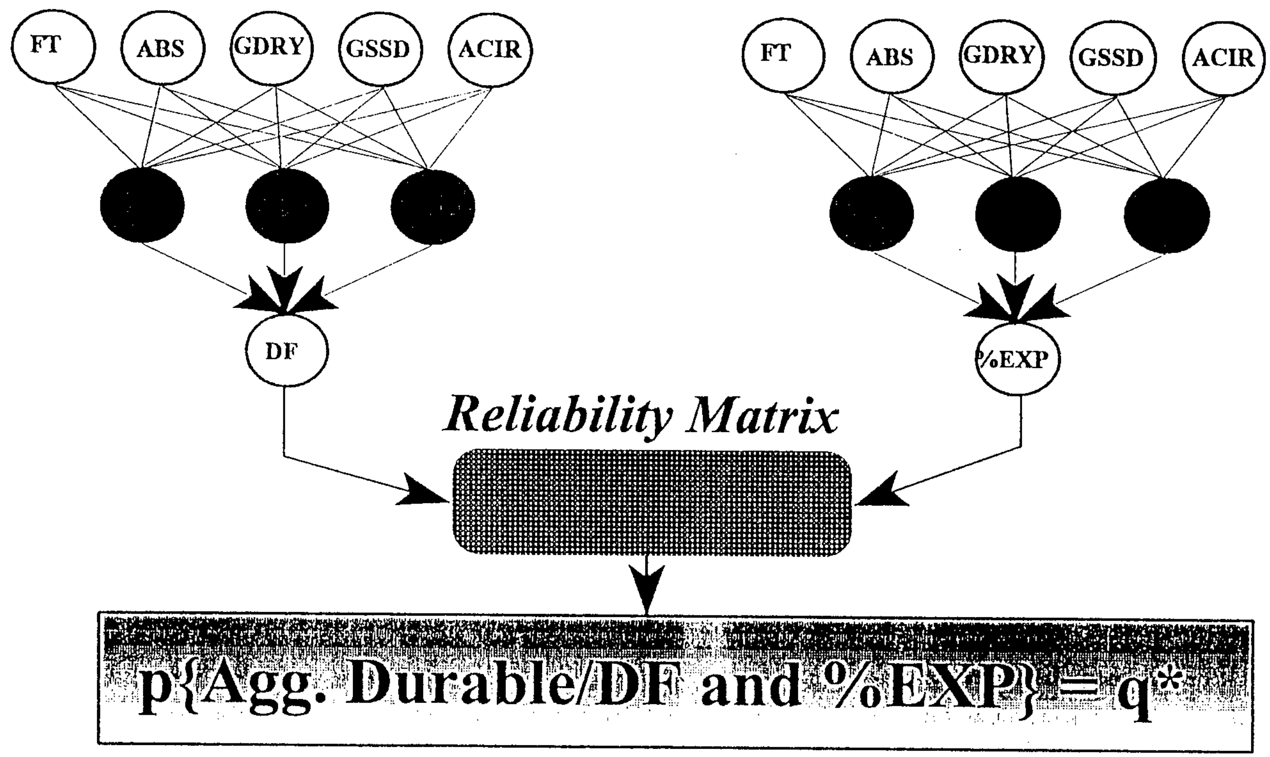


Figure 5.1. Schematic of durability neural network model with reliability prediction

Table 5.1: The reliability of aggregate to meet DF or EXP specifications (using phase 1 data).

(a) If DF is the only criterion

NN-Predicted DF	Reliability (%)
97-100	91
95-97	86
90-95	51
85-90	42
<85	33

(b) If EXP is the only criterion

NN-Predicted EXP	Reliability (%)
<0.0125	94
0.0125-0.0175	87
0.0175-0.0225	64
0.0225-0.0250	60
0.0250-0.0300	52
0.0300-0.0375	36
>0.0375	17

Table 5.2: **The reliability that an aggregate will meet DF and EXP specifications (using phase 1 data).**

RELIABILITY MATRIX

TRAINING (548) + TESTING (119) + VALIDATION SETS (83)
-- (PHASE 1) --
Total Number of Data Sets = 750

Predicted %EXP	**Predicted DF**				
	>= 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
<= 0.013	92 % (13)	90 % (78)	****	****	****
0.013 -- 0.0175	****	87 % (118)	76 % (25)	****	****
0.0175 -- 0.0300	****	66 % (140)	60 % (199)	50 % (78)	****
0.0300 -- 0.0375	****	****	42 % (26)	33 % (60)	****
> 0.0375	****	****	****	12 % (8)	10 % (5)

Number between two parentheses indicates number of data sets.
**** Not enough information to generalize. Experimental testing is recommended.

Table 5.3: **The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data of ledge type).**

RELIABILITY MATRIX

VALIDATION ON LEDGE DATA SETS

-- (PHASE 2-A) --

Total Number of Data Sets = 120

Predicted %EXP	Predicted DF				
	> = 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
< = 0.013	100 % (7)	100 % (16)	****	****	****
0.013 -- 0.0175	****	73 % (11)	40 % (5)	****	****
0.0175 -- 0.0300	****	15 % (13)	29% (34)	7 % (14)	****
0.0300 -- 0.0375	****	****	0 % (2)	0% (17)	****
> 0.0375	****	****	****	****	****

Number between two parentheses indicates number of data sets.

**** Not enough information to generalize. Experimental testing is recommended.

Table 5.4: **The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data of production type).**

RELIABILITY MATRIX

VALIDATION ON PRODUCTION DATA SETS

-- (PHASE 2-B) --

Total Number of Data Sets = 658

Predicted %EXP	**Predicted DF**				
	> = 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
< = 0.013	**92 % (12)**	**95 % (80)**	****	****	****
0.013 -- 0.0175	****	**88 % (120)**	**95 % (20)**	****	****
0.0175 -- 0.0300	****	**73 % (123)**	**76 % (166)**	**73 % (62)**	****
0.0300 -- 0.0375	****	****	**52 % (23)**	**56 % (41)**	****
> 0.0375	****	****	****	**17 % (6)**	**100 % (1)**

Number between two parentheses indicates number of data sets.

**** Not enough information to generalize. Experimental testing is recommended.

Table 5.5: **The reliability that an aggregate will meet DF and EXP specifications (using phase 2 data).**

RELIABILITY MATRIX

VALIDATION ON NEW DATA SETS

-- (PHASE 2) --

Total Number of Data Sets = 778

Predicted %EXP	**Predicted DF**				
	> = 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
< = 0.013	94% (19)	96% (96)	****	****	****
0.013 -- 0.0175	****	87% (131)	84% (25)	****	****
0.0175 -- 0.0300	****	67% (136)	68% (200)	60% (76)	****
0.0300 -- 0.0375	****	****	48% (25)	40% (58)	****
> 0.0375	****	****	****	17% (6)	100% (1)

Number between two parentheses indicates number of data sets.

**** Not enough information to generalize. Experimental testing is recommended.

Table 5.6: **The reliability that an aggregate will meet DF and EXP specifications (using phase 1 and phase 2 data combined).**

RELIABILITY MATRIX

TRAINING (548) + TESTING (119) + VALIDATION SETS (861)

-- Updated from Phase 1 & 2 --

Total Number of Data Sets = 1528

Predicted %EXP	**Predicted DF**				
	> = 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
< = 0.013	92 % (32)	95 % (174)	****	****	****
0.013 -- 0.0175	****	87 % (249)	80 % (50)	****	****
0.0175 -- 0.0300	****	66 % (276)	64 % (399)	55 % (154)	****
0.0300 -- 0.0375	****	****	42 % (51)	33 % (118)	****
> 0.0375	****	****	****	12 % (14)	17 % (6)

Number between two parentheses indicates number of data sets.

**** Not enough information to generalize. Experimental testing is recommended.

Table 5.7: **The distribution of number of data sets (using phase 1 and phase 2 data) in reliability matrix.**

DATA DISTRIBUTION MATRIX

TRAINING (548) + TESTING (119) + VALIDATION SETS (861)

-- Updated from Phase 1 & 2 --

Total Number of Data Sets = 1528

Predicted %EXP	**Predicted DF**				
	> = 98.0	*94.5 -- 98.0*	*92.0 -- 94.5*	*86.0 -- 92.0*	*< 86.0*
< = 0.013	2.1 % (32)	11.4 % (174)	****	****	****
0.013 -- 0.0175	****	16.3 % (249)	3.3 % (50)	****	****
0.0175 -- 0.0300	****	18.1 % (276)	26.1 % (399)	10.1 % (154)	****
0.0300 -- 0.0375	****	****	3.3 % (51)	7.7 % (118)	****
> 0.0375	****	****	****	0.9 % (14)	0.4 % (6)

**** **Less than 5 data sets were observed.**

Number between two parentheses indicates number of data sets.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATION

In this report, indicators of aggregate durability and resistance to freezing and thawing is modelled based on data pertaining to limited number of physical properties of the aggregate. These indicators are the durability factor, DF and the percent expansion of the concrete beam, EXP (ASTM C-666 Method B). The aggregate physical properties are the modified freeze-thaw (soundness), absorption, specific gravity (saturated surface-dry and dry), and the total acid insoluble residue. Backpropagation neural networks were developed which enable prediction of the durability parameters, DF and EXP. The networks were designed to provide prediction of these parameters in the light of their agreement with the available specifications for designating aggregates as durable (i.e. DF not less than 95 and EXP not greater than 0.025%). Two networks, one for each indicator, were found to be able to predict DF and EXP with a relatively good accuracy. The DF-network were able to classify the data with an overall accuracy of 63%, with a much higher accuracy being observed at high values of DF. It was observed that DF predictions in excess of 95 (i.e. durable aggregate) range in reliability between 86% to 91%. Similarly, the developed EXP-network predicted the data with an overall accuracy of 76%. The two networks, when combined, can be used to compute the reliability of a given aggregate as a durable aggregate.

Since both models (i.e. DF and EXP-NNs) were developed from an experimentally obtained database, it is obvious that any data beyond the region of applicability can impart a significant error in model prediction. The models developed are applicable to aggregates with properties falling within the following ranges: FT (0.80-1.0), ABS (0.0-12.0), GDRY (1.50-3.00), GSSD (1.50-3.00), and ACIDR (0.0-40.0). These ranges, however, cover a wide spectrum of aggregates commonly obtained from quarries.

CHAPTER 7

BIBLIOGRAPHY

ASTM:C666 (1992), "Standard Test Method for Resistance of Concrete to Rapid Freezing and Thawing," American Society of Testing and Materials, Philadelphia, PA.

Basheer, Imad A. and Najjar, Yacoub M. (1994)," Designing and Analyzing Fixed-Bed Adsorption Systems with Artificial Neural Networks," J. Env. Sys., Vol. 23, No. 3, pp. 291-312.

Basheer, Imad A. and Najjar, Yacoub M. (1996)," Predicting Dynamics Response of Adsorption Columns with Neural Nets," J. Comp. Civ. Engrg., Vol. 10, No. 1, pp. 31-39.

Hassoun, M. (1995), Fundamentals of Artificial Neural Networks, MIT Press, Cambridge, MA.

Huang, Y.H. (1993), Pavement Analysis and Design, Perntice Hall, Englewood Cliffs, NJ.

Janssen, D.J. and Snyder, M.B. (1994), Resistance of Concrete to Freezing and Thawing, Strategic Highway Research Program, National Research Council, SHRP-C-391, Washington, DC.

Najjar, Yacoub M., Basheer, Imad A., and Naouss, Wissam A. (1996)," On the Identification of Compaction characteristics by Neuronets," Computer and Geotechnics, Vol. 18, No. 3, pp. 167-187.

Najjar, Yacoub M. and Basheer, Imad A. (1996),"Utilizing Computational Neural Networks for Evaluating the Permeability of Compacted Clay Liners," J. of Geotechnical and Geological Engrg., Vol. 14, No. 3, pp. 193-212.

Najjar, Yacoub M., Basheer, Imad A., and McRynolds, Richard L. (1996), "Neural Modeling of Kansas Soil Swelling," *Trans. Res. Rec.,* No. 1526, pp. 14-19.

Najjar, Yacoub M., Basheer, Imad A., and McReynolds, Richard L. (1997)," A Neuronet-Based Approach to Modeling Durability of Aggregate in Concrete Pavement Construction," *Trans. Res. Rec., TRB,* In Press.

Simpson, P. K. (1990), Artificial Neural Systems: Foundations, Paradigm, Applications, and Implementations, Pergamon Press, New York.

To obtain a copy of the aggregate

durability neural netwok-based software

CONTACT

Bureau of Materials and Research

Kansas Department of Transportation

Topeka, Kansas 66611

Phone (913) 296-7410

Fax (913) 296-2526

U.S. DEPARTMENT OF COMMERCE
Technology Administration
National Technical Information Service
Springfield, VA 22161 (703) 487-4650