# Long Term Monitoring of Moisture under Pavements

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16. Abstract

Monitoring of the environmental instrumentation installed under select pavement sections constructed by the Ohio Department of Transportation (ODOT) in 1995 on US 23 in Delaware County, Ohio was continued. The measurements made consisted of soil moisture, temperature and frost depth profiles.

OSU constructed and installed tensiometers to directly measure the porewater pressures in the subsurface soils at seven locations at the DEL23 SHRP test road (four during original road construction and three more in 2002). Tensiometers were also installed and monitored at seven additional locations within the state. Those devices were monitored throughout the duration of the current project.

A laboratory testing program was conducted to identify relationships between static soil properties and the design resilient modulus for compacted cohesive subgrade soils. Resilient modulus as well as classification and strength tests were performed on cohesive soil samples. The program to establish the relationships between dynamic soil behavior and static properties is described and a predictive tool developed through the use of artificial neural networks is presented.

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# Long Term Monitoring of Moisture under Pavements

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# 1. INTRODUCTION

The research program discussed in this report consisted of three parallel activities. The first activity was a continuation of the monitoring of environmental instrumentation under select pavement sections originally constructed by the Ohio Department of Transportation (ODOT) in 1995 on US 23 in Delaware County, Ohio. The measurements made by the OSU team at that site consisted of soil moisture, temperature and frost depth profiles. The installation procedures along with the data collected over an eight year period were described in two previous reports ("Seasonal Instrumentation of SHRP Pavements – The Ohio State University State Job No. 14586(0); Contract No. 8011," dated September, 1998, and "Seasonal Instrumentation Of SHRP Pavements, Final Report – The Ohio State University State Job No. 14586(0); Contract No. 8011," dated June 2004). In the second activity, OSU constructed and installed tensiometers to directly measure the pore water pressures in the subsurface soils at seven locations at the DEL23 SHRP test road (four during original road construction and three more in 2002). Those devices were monitored throughout the duration of the current project.

As part of the existing research program, tensiometers were installed between 2003 and 2005 at four locations identified by ODOT engineers. The data from tensiometers installed at three additional sites in 2006-07, while not part of the actual scope work of the project, are included in this report to increase the range of conditions under which pore pressure readings have been recorded. The data from all the readings are presented and discussed in subsequent sections.

In the third activity, begun during the previous contract, a testing program was conducted to identify relationships between static soil properties that can be routinely measured in the laboratory, and the design resilient modulus for compacted cohesive subgrade soils. Approximately 800 laboratory resilient modulus tests were performed on cohesive soil samples collected by OSU and ODOT personnel. The laboratory program to establish the relationships between dynamic soil behavior and static properties was described in detail in the 2004 report, as was the regression model developed from the experimental data to predict the resilient modulus. In this report the laboratory testing performed on the additional soil samples is presented and the predictive tool is substantially modified and improved through the use of artificial neural networks.

## 2. RESEARCH OBJECTIVES

The present program is a continuation of the field study begun with the 1995-1997 long term pavement performance program and the laboratory investigation of subgrade performance that started in 2000. This additional laboratory effort was included because the numerical models being used in the design of pavements are becoming increasingly more capable of incorporating direct measurements of the response of subsurface materials to changing states of stresses into the description of the behavior of subgrade materials. Therefore, it should be possible for engineers/researchers, when evaluating long term pavement performance at the DEL23 pavement sections, to relate the observed and/or measured performance to subsurface soil conditions.

In modern pavement system designs, an essential input is the dynamic elastic stiffness of the supporting soil layers. In this project, we developed a rational method to predict the elastic response of the supporting soil using data readily obtained in ODOT laboratories.

The regression model developed as part of the previous project (The Ohio State University State Job No. 14586(0); Contract No. 8011) and described in our 2004 report requires inputting nine different soil parameters ($q_u$, $w$, $P_{\#200}$, PI, LL, $\gamma_{opt}$, $w_{opt}$, $w_c$, and $S_r$), and two boundary conditions ($\sigma_c$ and $\sigma_d$). However, in the early (planning) stages of a project, not all these parameters may be known, and yet accurate estimates of soil properties are needed to develop reasonable preliminary designs of pavement system cross-sections. In addition, even when laboratory data are available, past testing programs may not have included all the laboratory testing required to thoroughly characterize the soil layers.

One of the more powerful applications of the neural networks employed in the current resilient modulus study is the use of the algorithms to generate estimates of missing input data points. In fact, the artificial neural networks developed were used as data mining tools to extract implicit information from existing data pools.

The final version of the program delivered to ODOT upon completion of the research program has the ability to estimate missing input values as described in the following section.

# 3. DESCRIPTION OF THE RESEARCH

## 3.1  Literature Review

A review of the literature on the behavior of the saturated and unsaturated soil was presented in the 1998 and 2004 reports of the pavement monitoring projects. While a discussion of earlier research is summarized in this document, the reader is referred to our previous reports for more complete reviews of resilient modulus testing and modeling efforts as well as discussions on the uses of tensiometers in estimating the in-situ stresses and water content.

Because the mathematical model we developed is based on an application of artificial neural networks (ANNs), a topic that has not been covered in our earlier reports, we include a discussion of this methodology in this report. It is not a comprehensive review however, and the reader is directed to any of the several thorough presentations of ANNs available from both print and electronic sources (e.g. Schmidt, [1996], Haykin [1994]).

### 3.1.1 Resilient Modulus

Seed, et al. (1962) suggested that the most important subsurface response parameter in the characterization of pavement system response is the ratio of applied cyclic stress ($\sigma_d$) to the resulting elastic strain ($\varepsilon_r$). The Resilient Modulus ($M_R$), which Seed proposed as the measure of the dynamic stiffness, is obtained in the controlled environment of a laboratory cyclic triaxial test at loads typical of those found when pavement subgrades are loaded. In methods developed since Seed's proposal, $M_R$ has been used either directly to design flexible pavements, or converted to a modulus of subgrade reaction (k-value) typically used in the design of rigid (concrete) pavements.

Although simple in concept, a direct measure of the resilient modulus requires a time consuming testing program, specialized equipment and specifically trained personnel.  Even with these three components in place, current standards for resilient modulus testing don't always produce consistent and/or reproducible results, probably due to differences in test equipment, instrumentation, sample preparation, or sample end conditions. To minimize the effects of these difficulties with the resilient modulus test procedure, researchers have invested considerable effort in the development of methods to estimate appropriate design values for the resilient moduli using basic, usually static, engineering properties.

#### 3.1.1.1 Factors Affecting Resilient Modulus

A review of the literature and our own earlier test results have shown that the measured resilient modulus is affected by a number of factors, including: stress state

(deviator and confining stress), moisture content, soil type and density. Decreases in $M_R$ with increasing deviator stress have been observed (Seed, et al. (1962), Fredlund, et al. (1977), Drumm, et al. (1990), Li and Selig (1994), Pezo and Hudson (1994), Lee et al. (1995), Mohammad, et al. (1999), and Kim (1999), Lee (2002). $M_R$ was shown to increase with increasing confining stress (Kim (1999), Li and Qubain (2003)). Subgrade resilient modulus has been shown to be highly dependent on the soil water content, with smaal increases in water content resulting in large decreases in $M_R$ ((Seed, et al. (1962), Fredlund, et al. (1977), Li and Selig (1994), Pezo and Hudson (1994), Burczyk et al (1994) Lee, et al. (1995), Drumm, et al. (1997), Kim (1999), Masada and Sargand (2002), Lee (2002), Butalia, et al. (2003), and Li and Qubain (2003)).

### 3.1.1.2 Prediction of $M_R$ - Current Popular Models

As mentioned above, the cost, time, difficulty, and lack of repeatability of results in resilient modulus tests have forced a search for alternative methods for predicting the resilient modulus. Several different models have been developed using simple laboratory tests and correlation equations. The existing models can be divided into two broad categories: 1) linear models, such as the United States Department of Agriculture (USDA) Model, Texas Department of Transportation (TxDOT) model and the Ohio Department of Transportation (ODOT) model, and 2) non linear models which include the Hyperbolic Model, Georgia Department of Transportation (GDOT) model and the OSU Model.

A description of the models commonly used by federal and state highway agencies was presented in our earlier (2006) report. Table 3.1, which presents the most important aspects of several common models in use, is an update of the table presented in our 2006 report.

| Existing Model | Author(s) | Input Parameters | Advantages | Limitations |
|---|---|---|---|---|
| **LINEAR MODELS** | | | | |
| USDA Model | Carmichael and Stuart, 1986 | USCS soil type, PI, $w$, %- No. 200 sieve, $\sigma_3$, $\sigma_d$ | Includes effect of: $w$, $\sigma_3$, PI | Soil type |
| TxDOT Model | Pezo & Hudson, 1994 | $w$, $\gamma_d$, $\gamma_{d,max}$, PI, Sample age, $\sigma_3$, $\sigma_d$ | Includes effect of: $w$, - $\sigma_3$ - PI, Sample age | Narrow range for input parameters |
| ODOT Model | ODOT, 1999 | GI (LL, PI, % -No. 200 sieve), CBR | Simplicity of model | $\sigma_3$ and $\sigma_d$ not considered |
| **NON LINEAR MODELS** | | | | |
| Hyperbolic Model | Drumm, et al., 1990 | $q_u$, % *clay*, PI, $\gamma$, S, % -200 sieve, $a$, LL, $\sigma_d$ | Includes effect of PI, $q_u$, S | $\sigma_3$ not considered |
| GDOT Model | Santha, 1994 | $w$, $w_{opt}$, $\gamma_d$, $\sigma_d$, $P_a$ $\gamma_{d,max}$, %silt, %clay, % swell, LL, PI % -No. 40 sieve, S, % shrinkage, | Includes effect of - $w$ and $w_{opt}$ S, LL and PI $P_a$ | $\sigma_3$ not considered Complex model, many tests required |
| OSU Model | Kim, 2004 | $w$, $w_{opt}$, $\gamma_d$, % passing No. 200 sieve, S, LL, PI, $\sigma_d$, $\sigma_3$ | Includes effect of $w$ and $w_{opt}$ S, LL and PI $\sigma_d$ and $\sigma_3$ | Difficult to incorporate new data |

Table 3.1 Current Popular Models (After Table 3.2 in 2004 Final Report to ODOT)

### 3.1.1.3 Data from Published Reports

Published resilient modulus test results from four recent studies were collected and analyzed (Table 3.2). The results of the studies conducted at Purdue University and the University of Mississippi were added to the experimental data generated at OSU and are included in our analyses. These two studies were selected to help validate the present $M_R$ model because they included sufficient soil property information, plus directly measured resilient modulus laboratory test results allowing predicted and measured moduli to be properly compared.

| Title | Conducted by | Year |
|---|---|---|
| Subgrade Resilient Modulus for Pavement Design and Evaluation | Purdue University, Indiana DOT (IDOT) and FHWA | 1993 |
| Resilient Modulus for New Hampshire Subgrade Soils for use in Mechanistic AASHTO Design | U.S Army Cold Region Research and Engineering Laboratory (CRREL) | 1999 |
| Prediction of Resilient Modulus from Soil Index Properties | University of Mississippi for Mississippi DOT and FHWA | 2004 |
| Laboratory Characterization of Cohesive Subgrade Materials | University of Akron | 2005 |

Table 3.2 Examples of Published Reports Reviewed

### 3.1.1.3.1 Purdue University Study

Resilient modulus tests were performed on five cohesive soils and one granular soil in accordance with the AASHTO specification current at the time (AASHTO T 274-82). Both laboratory and field compacted samples were tested. The effects of freeze-thaw cycles were studied as well. Resilient response was correlated with the fabric parameters, clay content, and pore water content.

Resilient modulus test results from laboratory compacted soil samples from two sites were included into the database used in the present study (Tables 3.3, Information on Sampling Sites, and 3.4, Engineering Properties).

| Site | I.D | Location | Station | Soil Classification | Date Compacted | Date Sampled |
|---|---|---|---|---|---|---|
| South Bend | SB | US20 Bypass | 140 - 141 | A-4 / A-6 (CL) | Aug 89 | Jan; May; July 90 |
| Washington | WA | US50 Bypass | 290 | A-6/ A-4 (CL) | June 89 | Jan 91 |

Table 3.3 Information on Sampling Sites for Indiana Soils

| Site | $g_{max}$ (pcf) | $w_{OMC}$ (%) | GS | LL | LP | PI |
|---|---|---|---|---|---|---|
| South Bend | 129.5 | 9.4 | 2.76 | 21 | 14 | 7 |
| Washington | 114 | 14.9 | 2.74 | 30 | 21 | 9 |

Table 3.4 Engineering Properties of Indiana Soils

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3.1.1.3.2 University of Mississippi Study

Samples of soils from subgrade sections representing different districts in Mississippi were tested to determine the physical properties of the selected soils. Laboratory tests to measure $M_R$ were performed according to the TP46 Protocol (AASHTO T294-94).  The study concluded that the most important index properties influencing $M_R$ were moisture content, degree of saturation, percentage of material passing No. 200 sieve, plasticity index and density. Input data are presented in Tables 3.5 and 3.6.

Resilient modulus laboratory results, as well as static soil properties from the Mississippi tests were used in the present OSU study to assess the performance of the neural network approach in general and in the proposed model in particular for predicting $M_R$ for soils originating outside Ohio.

| County/ Road Designation | Unified Soil Classification | AASTHO Classification |
|---|---|---|
| Montgomery/US 82 W | CL | A-4 |
| Hinds / Norrel W | CL | A-6 |

Table 3.5 Information on Sampling Sites for Mississippi Soils

| County/ Road | $g_{max}$ (pcf) | $w_{OMC}$ (%) | $G_S$ | LL | LP | PI | UCS (psi) |
|---|---|---|---|---|---|---|---|
| Montgomery/US 82 W | 115.20 | 13.80 | 2.72 (assumed) | 22 | 16.20 | 6.10 | 15.4 |
| Hinds / Norrel W | 105.60 | 17.80 | 2.67 (assumed) | 37.20 | 24.10 | 13.10 | 26.9 |

Table 3.6 Engineering Properties of Mississippi Soils

3.1.2 Neural Network Algorithms to Predict Resilient Modulus

Artificial Neural Networks are designed to mimic the response of the human nervous system. McCulloch and Pitts (1943) published an algorithm to imitate neurobiological activity and Rosenblatt (1962) developed a simple neural network. Werbos (1974) introduced the back propagating algorithm for neural network systems. The back-propagation algorithm has since become the most popular learning algorithm.

In pavement design and in the geotechnical field, neural network algorithms have been used to solve a variety of design problems. Meier & Rix (1994, 1995) and Brendenhann and van de Ven (2004) used back-propagation neural networks to estimate stiffness of a flexible pavement layer. Bayrak et al. (2005) used ANNs to evaluate the resilient moduli of flexible pavement materials. Hashash et al. (2006) developed an ANN to predict soil stress-strain behavior.

### 3.1.2.1 Background

The biological nervous system that an artificial neural network is designed to simulate is composed of a large number of simple elements operating in parallel. The four key elements in every biological neuron; the cell bodies, dendrites, axons and synapses, are illustrated in Figure 3.1. In the figure, axons and dendrites are the cell filaments extending from the cell bodies. The synapse is the gap between an axon of one neuron and the dendrite of another. Information contained in a cell body is sent through the system in the form of an electric impulse (signal). When a dendrite detects a signal, it forwards it to the cell body to which it is connected. The cell body sums up the signals received from its dendrites until the sum of incoming signals exceeds a specified limit. When this limit is exceeded, the cell body then transmits a signal to its axon. As the dendrites of other nearby neurons detect the incoming signals, the signal is processed through the system. Learning is the process by which the effectiveness of the signals sent from axons through the synapses is adjusted so that the influence of one neuron on another changes to achieve the conditions where predicted responses match (within acceptable limits) the observed outcomes. However, unlike their natural counterparts, artificial neural networks have a specified number of neurons and the firing rules are clear and fixed. The standard structure of an ANN consists of input receptors, at least one output layer and a number of hidden layers (Figure 3.2). Each ANN layer contains a number of artificial neurons, called nodes. Nodes are connected to adjacent nodes by networking lines to represent dendrites, axons, and synapses.
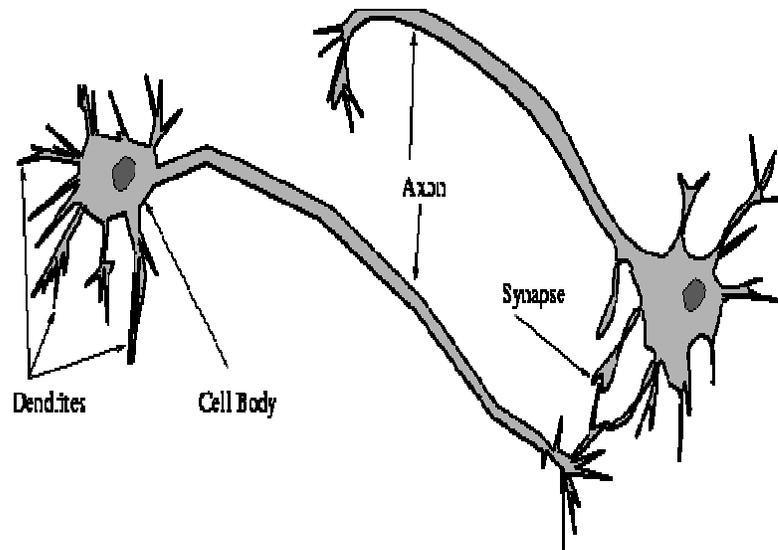
Figure 3.1  A simplified biological neuron network system

      (source from: http://www.teco.edu/~albrecht/neuro/html/node7.html by
         Schmidt, 1996)

      A weighting function, representing the information used by the net to solve the problem, is assigned to each link. This weight is used to modify the transmitted signals. The net uses the input data and a combination of weights to predict the corresponding outputs or targets. Inside the network, the net randomly assigns a weight to each link, this weight is updated in an iterative manner until the predicted output data are as close as possible to the actual data corresponding to the input data. A node connected to a second node by a line with a large weight has a great potential to impact output of the second node.  Each node also inherits a transfer or activation function which is the firing/inhibitory rule. The strength of the output signal from each node depends on its input value, its activation function, and the specified weighting function.  The engineering structure of each node is as characterized in Figure 3.3.

**Output**
**Layer**

**Inputs**

**Single layer neural networks**

**Output**
**Layer**

**Hidden**
**Layer**

**Inputs**

**Multi-layer neural networks**
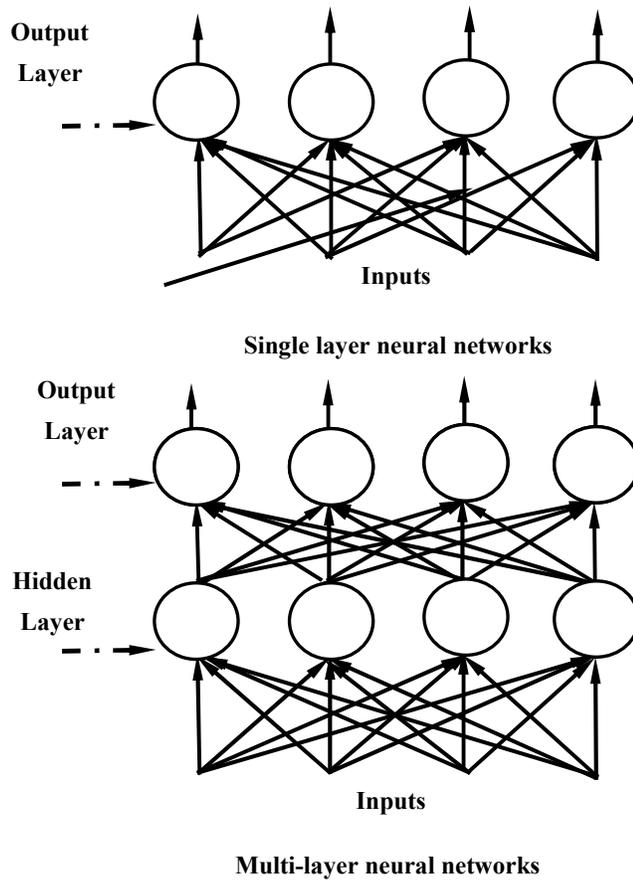
Figure 3.2  A simplified engineering structure of feed forward and back-propagation neural networks

During a training session, the weight associated with each line is adjusted to improve the final output.  A learning rate, which is simply a control parameter to determine the step size for any weight adjustments, is also assigned to each node. The learning rate can be a fixed value or a function designed to vary during the training session.  Each artificial node is connected to, and integrated into a networking structure. Data are submitted to each node, manipulated then sent to the next node in a different layer. Data can be transported back and forth to many nodes through different layers according to an established set of rules.

x(1)

w(1)

x(2)    w(2)

w(i)

Node i with n inputs
x(3)    w(3)    and an activation
function

Output(i)

w(n)

x(n)
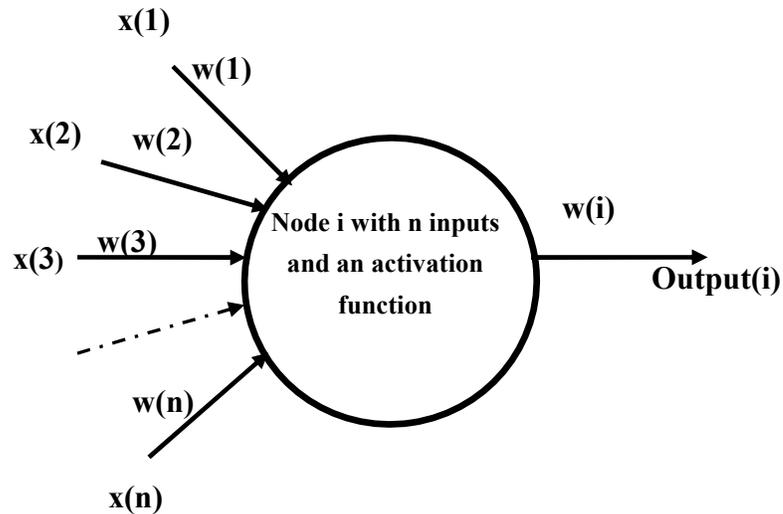
Figure 3.3  A simplified engineering neuron (node)

An input data set contains a recorded value for each defined input parameter. When the data set is input into the neural networks, information is gathered from each recorded data set.  The final output signal for each node in the output layer is the response to all input data provided.  The sum of the responses from all output-layer nodes is the system solution for each input data set. As with the biological nervous system, complex problems require a number of nodes and a complex neural structure to process realistic outputs.  However, unlike their biological counterparts, two neural layers generally suffice to solve a typical non-linear problem.

There are a number of types of ANNs that have been introduced to solve specific problems. Supervised learning mechanisms behave similarly to a teacher with knowledge and ability to provide correct responses.  Differences between an ANN's predicted response and the measured response can be detected and adjustments made iteratively so that the calculated response mimics the targeted response. ANNs with unsupervised learning algorithms do not have a teaching mechanism to oversee the learning process and there is no targeted response to compare to.  Each node competes with the others to be active and influential.  Responses are gradually improved as the networks organize themselves.

3.1.2.2 Back-Propagation Modeling Algorithms

The network structure of back-propagation is laid out in layers as shown in
Figure 3.2. There may be several hidden layers but only one output layer. There is no
direct connection between the nodes in the same layer, but each node is connected to all
the nodes in any adjacent layer. As shown in Figures 3.4 and 3.5, back-propagation can
be separated into feed-forward propagation and backward propagation phases depending
on the direction of the flow of information through the neural network layers.
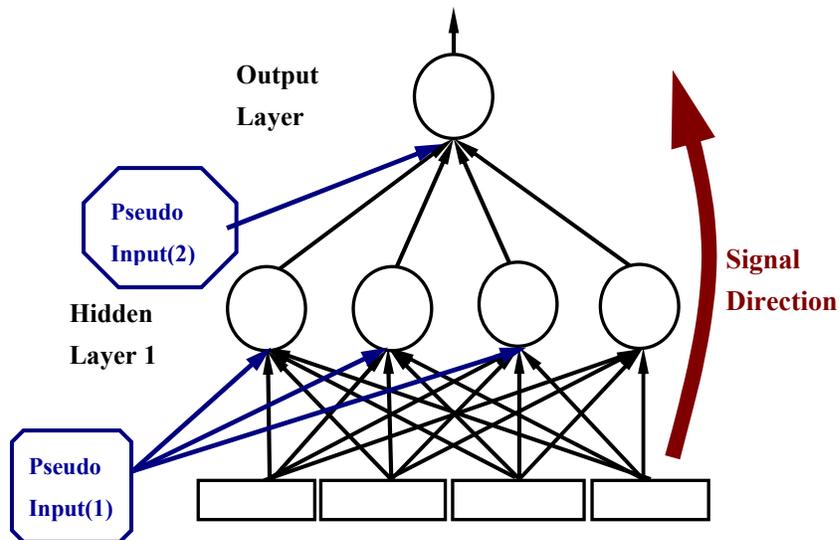


Figure 3.4  Flow forward procedures in a two layer back-
propagation neural network (after Hanittinan)
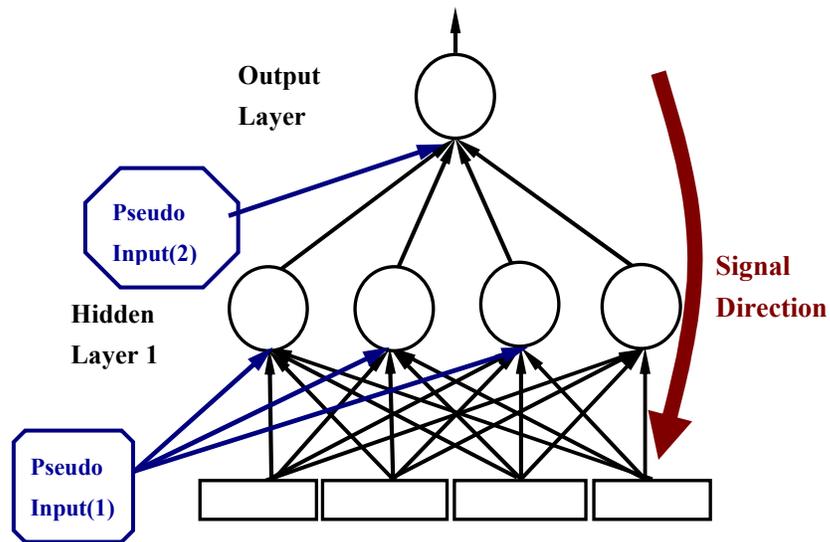
Figure 3.5  Flow backward procedures in a two layer back-
propagation neural network (after Hannitinan)

In the feed forward phase, the information flow starts at the inputs to each node in the first hidden layer and from there to the nodes in the output layers (Figure 3.4).  An incoming signal to each node can be calculated by summing the product of an input value and a corresponding weight transmitted along each directly connected line (Eq. 3.1 or Eq. 3.2).

$$Input(i) = x(1) \times w(1) + x(2) \times w(2) + x(3) \times w(3) + .......... + x(n) \times w(n) \qquad \text{Eq.3. 1}$$

$$Input(i) = \sum_{j=i}^{n} \left[ x(j) \times w(j) \right] \qquad \text{Eq.3. 2}$$

| | | |
|---|---|---|
| w (1), w(2), w(3),…, w(n) | = | weights assigned to lines 1,2,3 connected to node i, |
| x (1), x(2), x(3),…, x(n) | = | signal transmitted along lines 1, 2, 3 …to node i, |
| n | = | the total number of incoming signals to node i |
| Input (i) | = | sum of incoming signals or inputs to node i, |
| Output(i) | = | the output signal or response for node i, |
| | = | x(1), x(2), x(3), …for node in the next layer |
| w(i) | = | a weight assigned to the line i between two nodes |

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Commonly, the initial weights are picked randomly within specified ranges. During training sessions the weights may change as the network is adjusted. The output of one node becomes an incoming signal for a node in the next connected layer and this process continues through to the nodes in the output layer. The signals of the output layer nodes are the predicted responses for that training round. At that point, the first forward propagation cycle is completed. An error at each output layer node is determined by comparing calculated with measured responses. A backward flow is called for when the difference between the design responses and the calculated responses exceeds prescribed allowable error levels. In such an occurrence, the output layer responses are modified by iterating and adjusting all the weights in the neural network. In order to calculate the adjustment needed for each weight, a local gradient at each node needs to be defined. For any node in the output layer, the local gradient can be estimated as:

$$\text{Delta(i)} = \text{Output(i)} \times \left[1 - \text{Output(i)}\right] \times \left[\text{Target(i)} - \text{Output(i)}\right] \qquad \text{Eq. 3.3}$$

Delta(i)   = a local gradient for node i, the node of interest
Target(i)  = the targeted response for node i, in the output layer

A local gradient for any node in a hidden layer can be determined, once the local gradient of its immediately connected node in the next layer closer to the output layer is defined.

$$\text{Delta(i)} = \text{Output(i)} \times \left[1 - \text{Output(i)}\right] \times \text{Weight(i+1)} \times \text{Delta(i+1)} \qquad \text{Eq.3.4}$$

Delta(i+1)    = a local gradient for a node in the layer closest to the output layer
                 immediately connected to node i
Weight(i+1)   = a weight for the line from a node in the layer closest to the output layer
                 immediately connected to node i

Adjusted weights for each line connected to the node of interest are each the product of the old weight and the amount of change needed. The adjusted weight can be expressed as:

$$\text{Weight(i}_{new}) = \text{Weight(i}_{old}) + \Delta\text{Weight(i)} \qquad \text{Eq. 3.5}$$

$$\Delta\text{Weight(i)} = \text{Learningrate} \times \text{Delta(i)} \times \text{Input(i)} \qquad \text{Eq.3.6}$$

Learning rate  = rate assigned during each iteration (taken to be constant in this study)
Weight(i$_{new}$)  = new weight for the line from the layer away from the output layer
                 immediately connected to node i

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Weight($i_{old}$)   = old weight for the line from the layer away from the output layer
          immediately connected to node i

$\Delta$ Weight(i)   = adjusted amount given to a weight for the line from the layer away from
          the output layer immediately connected to node i

Figure 3.6 illustrates a simple neural network and its processing procedures. A full forward and backward propagation is counted as one iteration. Once the desired response is obtained, all weights are fixed. During a runtime session, the estimated response obtained in the output layers is the ANN prediction.
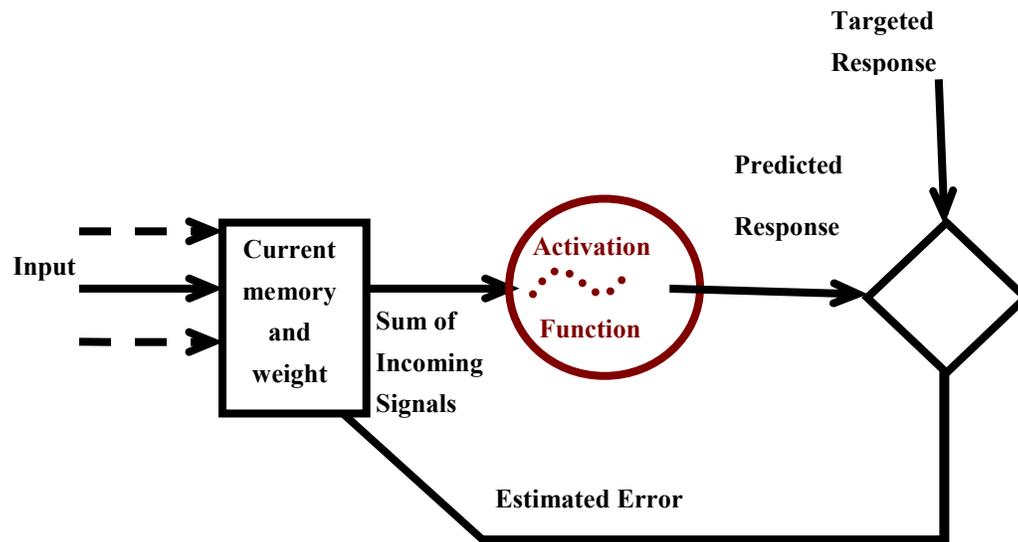
Figure 3.6  A simplified engineering diagram of a neural network

### 3.1.2.3 Application to the Resilient Modulus Study

In the developed network, one hidden layer and the output layer were set to handle the modulus estimation. Data were divided into three main groups based upon soil types (A-4, A-6, and A-7-6) with one neural network established for each soil type.  The number of nodes in the first hidden layer was set to be the same as the number of input parameters.  Only one node in the output layer, corresponding to the single valued estimate of modulus, was specified.

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An appropriate number of nodes in the hidden layer is typically determined by trial and error. For the current study a ratio 1.5 hidden nodes to one input yielded the most reasonable results.

An ANN with a small learning rate learns slowly because only a small adjustment can be made to each weighting function during an iteration. However, too large a learning rate may cause weights to fluctuate and outputs to become unstable. Therefore a small learning rate was specified for the resilient modulus study.

### 3.1.2.4 Experimental data usage in model development

Recorded data for each soil type group were randomly divided into three categories for training, validating and testing purposes. The training data sets contained about 60% of the recorded data, with the remaining 40% being divided equally between model validation and testing.

### 3.1.2.5 Estimating Resilient Modulus from Incomplete Data Sets

The Neural Networks developed were designed to and can be used to estimate missing data in input data sets. The following sections briefly explain the required input parameters for the neural networks developed in this study including the ANNs created from the existing data sets to estimate unconfined compressive strength ($q_u$).

Eight $q_u$ prediction neural networks were proposed for the three soil types studied. Six $q_u$ prediction neural networks, $ANN_{a/A-4}$; $ANN_{a/A-6}$; $ANN_{a/A-7-6}$; $ANN_{b/A-4}$; $ANN_{b/A-6}$; $ANN_{b/A-7-6}$, were identified for each soil type and specific input parameter combinations. Separate training sessions were conducted for each of the three soil types. A combined characterization of the unconfined compressive strength ($ANN_{a/All}$ and $ANNb_{/All}$.) was also made for all fine grained soil data. These neural networks are described in Table 3.7 which provides the input combinations that were used to develop the $q_u$ prediction neural networks.

Although potentially less precise than the model that uses all the recommended inputs, it is useful to provide algorithms to derive $M_R$ when only limited information is available. The neural networks: $ANN_{1/A-4}$; $ANN_{1/A-6}$; $ANN_{1/A-7-6}$; $ANN_{2/A-4}$; $ANN_{2/A-6}$; $ANN_{2/A-7-6}$; $ANN_{3/A-4}$; $ANN_{3/A-6}$; and $ANN_{3/A-7-6}$, were developed for different combinations of known parameters for each specific soil type. In addition, three ANNs ($ANN_{1/All}$; $ANN_{2/All}$; and $ANN_{3/All}$) were constructed to determine $M_R$ using as the database all the fine grained material data collected in this study without segregating the test results into categories based on the AASHTO classification. The input combinations for these $M_R$ prediction ANNs are shown in Table 3.8.

### 3.1.2.5.1 $q_u$ prediction ANNs

As shown in the Row a of Table 3.7, the ANNs: $ANN_{a/A-4}$; $ANN_{a/A-6}$; $ANN_{a/A-7-6}$; and $ANN_{a/All}$, require as input parameters $P_{\#200}$, PI, and LL, $w_{opt}$, $w_c$, and $S_r$ in the estimation of $q_u$. Instead of $P_{\#200}$, PI, and LL input parameters (Row b, Table 3.7), soil type is used as the critical input parameter in $q_u$ estimation for $ANN_{b/A-4}$; $ANN_{b/A-6}$; and $ANN_{b/A-7-6}$.

### 3.1.2.5.2 $M_R$ prediction ANNs

The key input parameters typically used to estimate CBR are $P_{\#200}$, PI, and LL. The CBR value is, in turn, commonly used to estimate $M_R$. The neural networks developed in this activity were designed to require only $P_{\#200}$, PI, and LL as input parameters for an $M_R$ prediction (Row 1, Table 3.8). If desired, these ANNs: ($ANN_{1/A-4}$; $ANN_{1/A-6}$; $ANN_{1/A-7-6}$; and $ANN_{1/All}$) can be used to compare the $M_R$ results predicted directly from CBR values. However, if the model is used this way, a broad range in predicted values of $M_R$ should be expected, since many soils may share similar $P_{\#200}$, PI, and LL combinations.

The neural networks $ANN_{2/A-4}$; $ANN_{2/A-6}$; $ANN_{2/A-7-6}$; and $ANN_{2/All}$ required all numerical input parameters to calculate $M_R$. These required input parameters are $P_{\#200}$, PI, and LL, $w_{opt}$, $w_c$, $S_r$, $q_u$, $\sigma_3$, and $\sigma_d$ (Row 2, Table 3.8). Because all relevant numerical inputs are used in developing ANNs, these ANNs are able to respond with a precise estimate of $M_R$ to a wide range of input data.

When a soil type can be assumed but its measured $P_{\#200}$, PI, and LL data are not available, it is convenient to use the soil type as the representative input parameters in $M_R$ prediction. $ANN_{3/A-4}$; $ANN_{3/A-6}$; $ANN_{3/A-7-6}$, and $ANN_{3/All}$ accept soil type, $w_{opt}$, $w_c$, $S_r$, $q_u$, $\sigma_3$, and $\sigma_d$ as inputs and generate an estimate of $M_R$ as the response (Row 3, Table 3.8)

| ANN | $P_{\#200}$ | LL | PI | Soil Type | $w_{opt}$ | $w_c$ | $S_r$ |
|-----|------|------|------|-----------|-------|-------|-------|
| A | Yes | Yes | Yes | N/A | Yes | Yes | Yes |
| b | N/A | N/A | N/A | Yes | Yes | Yes | Yes |

Table 3.7  Options for estimating $q_u$ using ANN simulations (3 soil types for each option)

| ANN | $P_{\#200}$ | LL | PI | Soil Type | $w_{opt}$ | $w_c$ | $S_r$ | $q_u$ | $\sigma_3$ | $\sigma_d$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Yes | Yes | Yes | N/A | N/A | N/A | N/A | N/A | N/A | N/A |
| 2 | Yes | Yes | Yes | N/A | Yes | Yes | Yes | Yes | Yes | Yes |
| 3 | N/A | N/A | N/A | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Table 3.8 Available options for $M_R$ ANN simulations (3 soil types for each option)

Note: N/A = not applicable

## 3.2 Summary

The artificial neural network is trained (the learning process) with the objective of recognizing interactions between inputs and the resulting response patterns. The ANN learns by example, it will associate a set of input values with the corresponding set of output values, and will remember the associated patterns for future comparisons. A network can be trained using the process of back propagation, in which the difference between the predicted and target $M_R$ values are minimized and the error is redistributed to all neurons in the previous layer. A feed forward, back propagation network was used in the present study to estimate $M_R$. This type of network is the most common of ANN used to solve problems where the exact mathematical functions are unknown. The network needs to be trained all available information, but once trained, it can be used to make projections given new input data.

Training and validating activities have been competed for the large data set (>800 resilient modulus tests) introduced in our earlier (2004) report and supplemented with the data presented in Section 6 of this final report. The numerical program provided includes artificial neural networks suitable for $M_R$ evaluation on a personal computer operating in the Windows environment (XP or higher). The program selects which of the ANNs is appropriate to the task of determining a design $M_R$ based on the information provided on the input screen. All the ANNs have been trained and verified using the data generated in the experimental program conducted in the soil mechanics laboratory at OSU.

## 4. FIELD INSTRUMENTATION SITE DETAILS

Monitoring the subsurface conditions at the SPS experimental sites of US23 in Delaware, Ohio continued throughout the duration of the project. In addition to the DEL23 locations, tensiometers were installed at seven more sites with a variety of subgrade conditions. The locations of all the instrumented and monitored sites are shown on Figure 4.1.  A typical tensiometer installation consisted of three measurement points separated vertically by 12 inches so that the shallow pore pressure could be recorded. Each is discussed in the following.

### 4.1 DEL 23

Monitoring the responses of the instrumentation embedded in the test sections assigned to OSU at the DEL 23 SHRP test road continued throughout the project duration. Actual locations of the original test sections as well as the added tensiometer locations have been described in the earlier referenced reports. For reference, the schematic locating the test sections which was given in those reports is presented here as Figure 4.2. Instruments at stations 390109, 390263, and 390212 were damaged or destroyed at different times during the project.
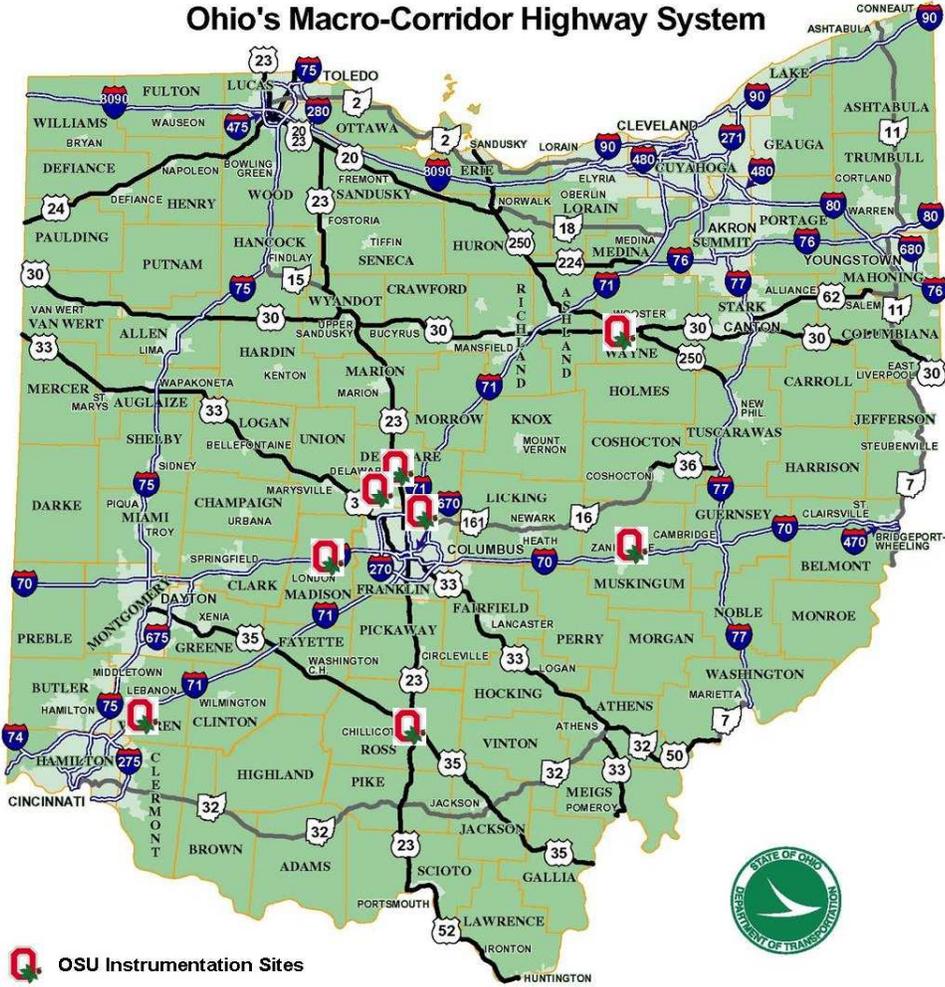
Figure 4.1 Locations of OSU Instrumentation Sites
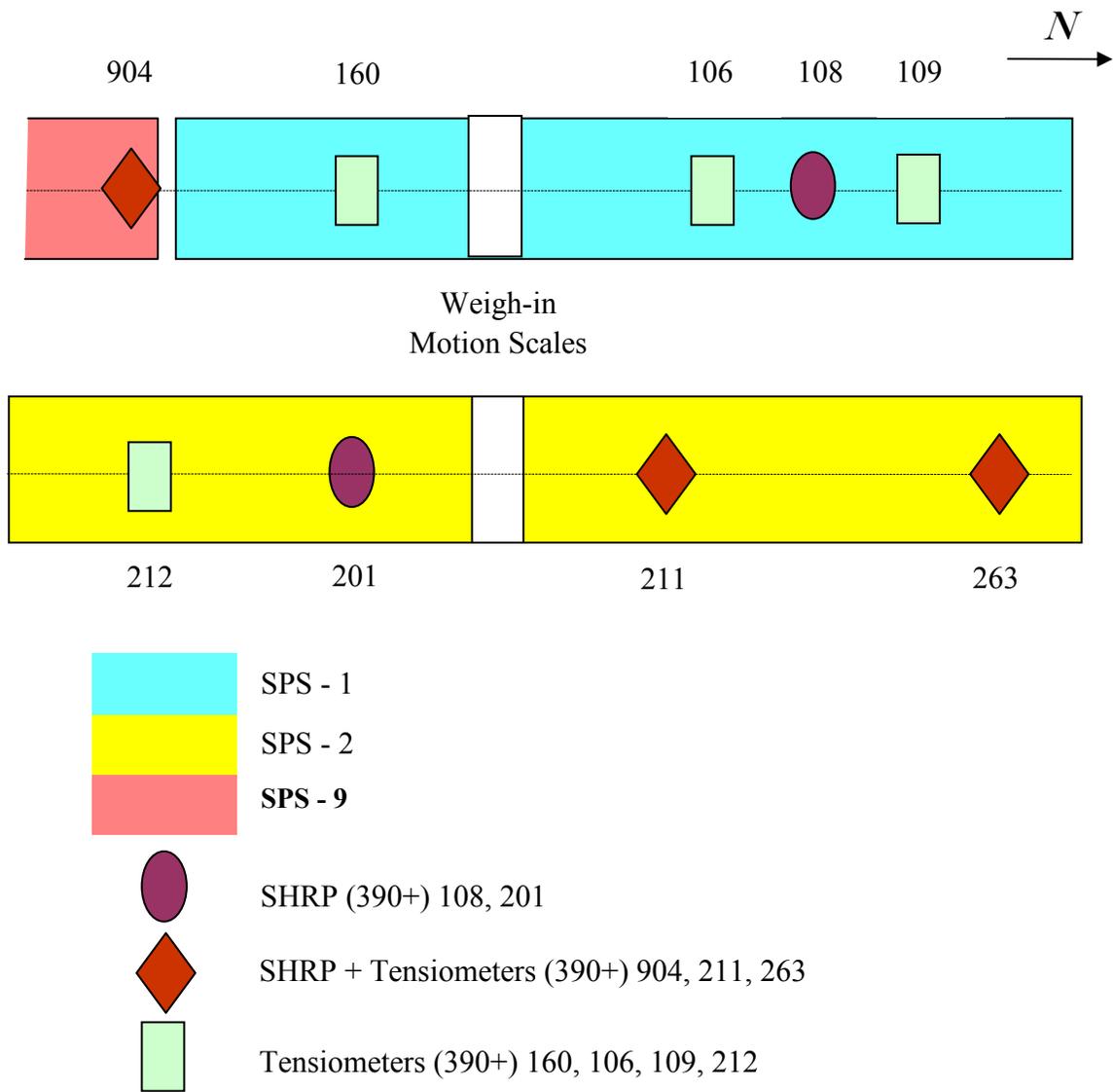
Figure 4.2 Locations of OSU Field Instrumentation at DEL23

## 4.2 WAY 30

The WAY 30 test pavement is a four-lane highway relocation of US 30 in Wayne County, Ohio. The test pavement begins just east of the city of Wooster, OH at an interchange with State Route 83 and extends east to Kansas Rd. near State Route 57. A perpetual asphalt pavement and a long lasting Portland cement pavement were designed and constructed. Pavement instrumentation was installed during construction to monitor the load and environmental conditions. Tensiometers were installed by OSU to monitor the pore water pressure profile in the subgrade at four stations (Figure 4.3). At station three, the sensors were damaged when the concrete pull box was moved by the contractor after installation (Figure 4.4).
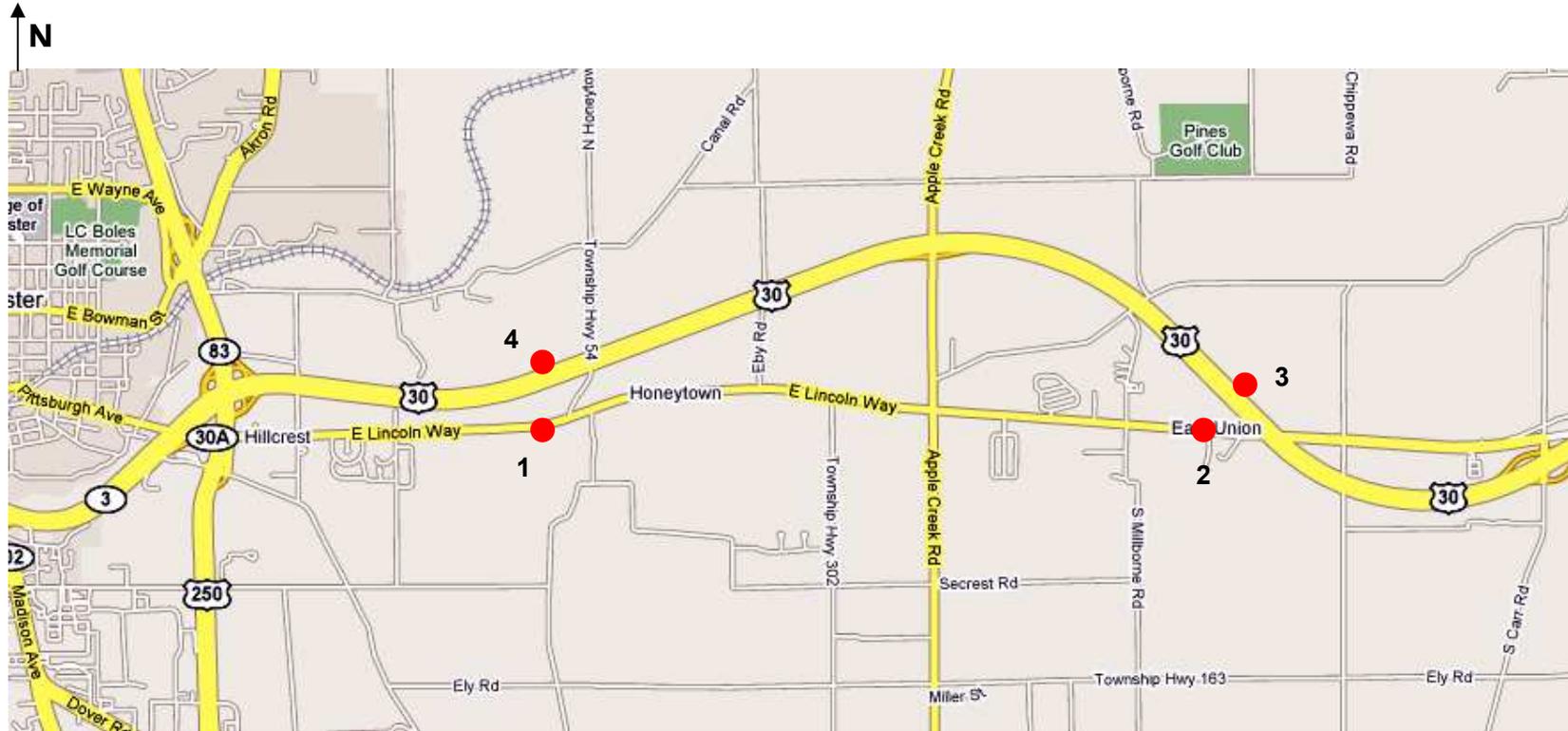
Figure 4.3 OSU WAY 30 Site Station Layout

PULL BOX, 18"

EDGE OF SHOULDER

4'

**Cracks**

14"

???

???

3'

TOP SENSOR      SUBGRADE

**Pull box moved by contractor**

12"

**Cracks**

MIDDLE SENSOR

24"

BOTTOM SENSOR

NOT TO SCALE
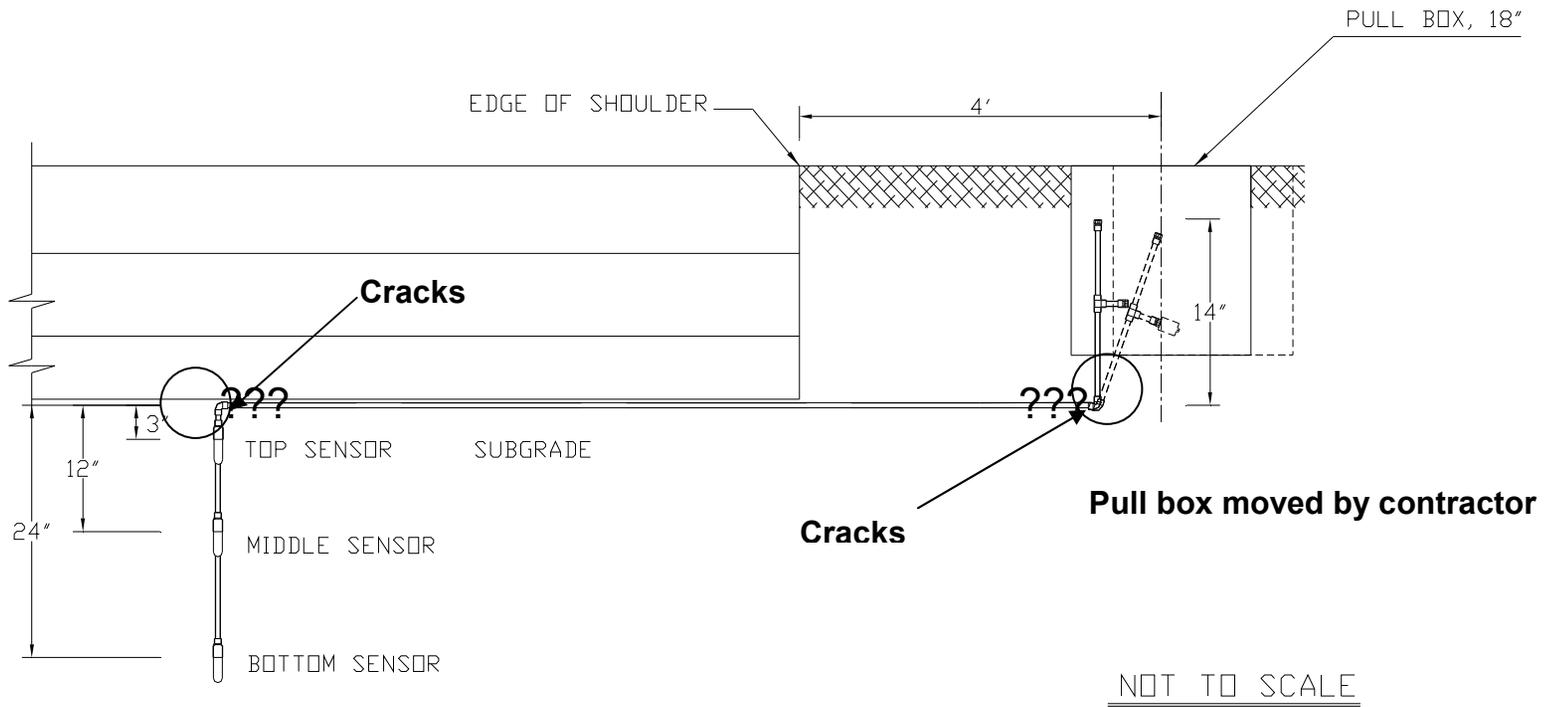
Figure 4.4 Damaged Sensors at WAY 30 Station Three

4.3 MAD 70

The MAD 70 site is located on the Madison/Clark County I-70 reconstruction project. The overall project was 14 miles long, extending from US 42 in Madison County to State Route 54 in Clark County. It involved resurfacing or full-depth reconstruction of the existing lanes and the addition of a third lane in each direction, deck repair, repair or repaving nine ramps and replacement or widening of 13 bridges. One tensiometer station was initially installed in September 2005 in the eastbound lanes of I-70 near the intersection of US 42. However, the sensors were damaged by construction crews shortly after the installation (Figure 4.5). Two replacement stations were installed under the MAD 70 westbound lanes in 2006 west of the US 42 overpass (Figure 4.6).



Figure 4.5 Instrumentation Damaged at MAD 70 Eastbound after Installation

Figure 4.6  OSU MAD 70  Site Location Layout
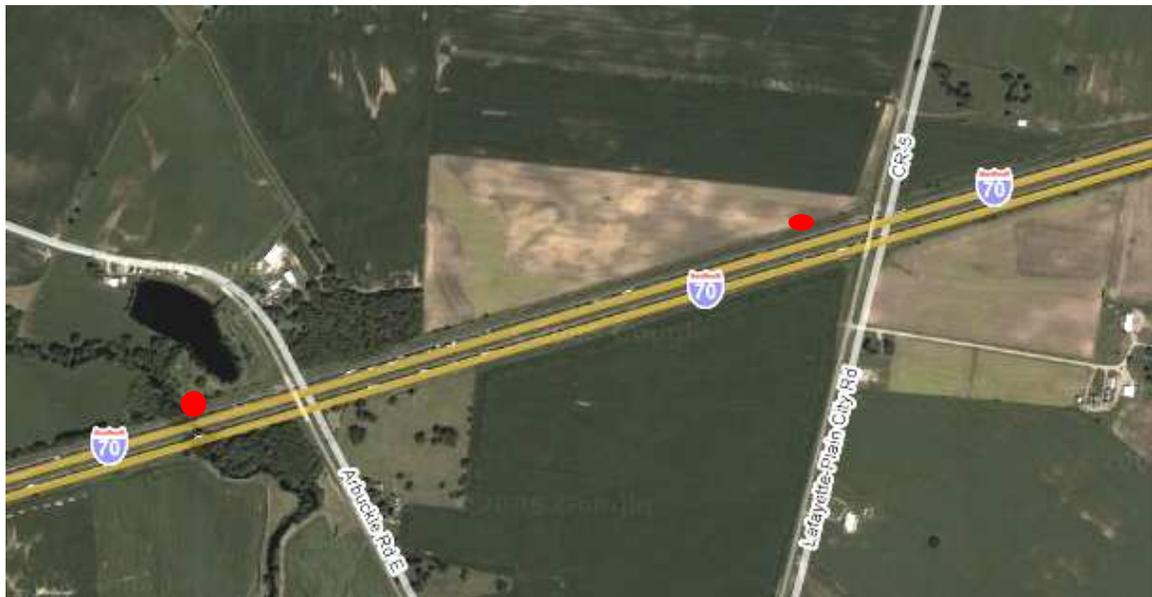


Figure 4.7 OSU MAD 70 Site Station Layout – Aerial View

4.4 ROS 207

The ROS 207 connector project involved the construction of a 2.67-mile, two-lane highway from State Route 104 at the Ross County Fairgrounds to U.S. Route 23 near Delano Road (Figure 4.8). The site for the tensiometer instrumentation was selected to be the culvert on the northeast bound lane of the connector near the intersection of State Route 104. The subgrade consisted of sandy soils from a nearby borrow pit.



Figure 4.8 OSU ROS 207 Site Station Layout

Figure 4.9 ROS 207 Site Instrumentation Location

4.5 I -71/I -270 Interchange

Three tensiometers were installed on ramp M at the interchange of I -270 and I- 71 in northern Franklin County (Figure 4.10).  Following convention established in our earlier tensiometer installations, three sensors were arranged vertically with the uppermost sensor at the top of the subbase, with the second and third tensiometers 12 and 24 inches beneath the top sensor. However, heavy equipment damaged the topmost tensiometer during roadway construction shortly after installation.
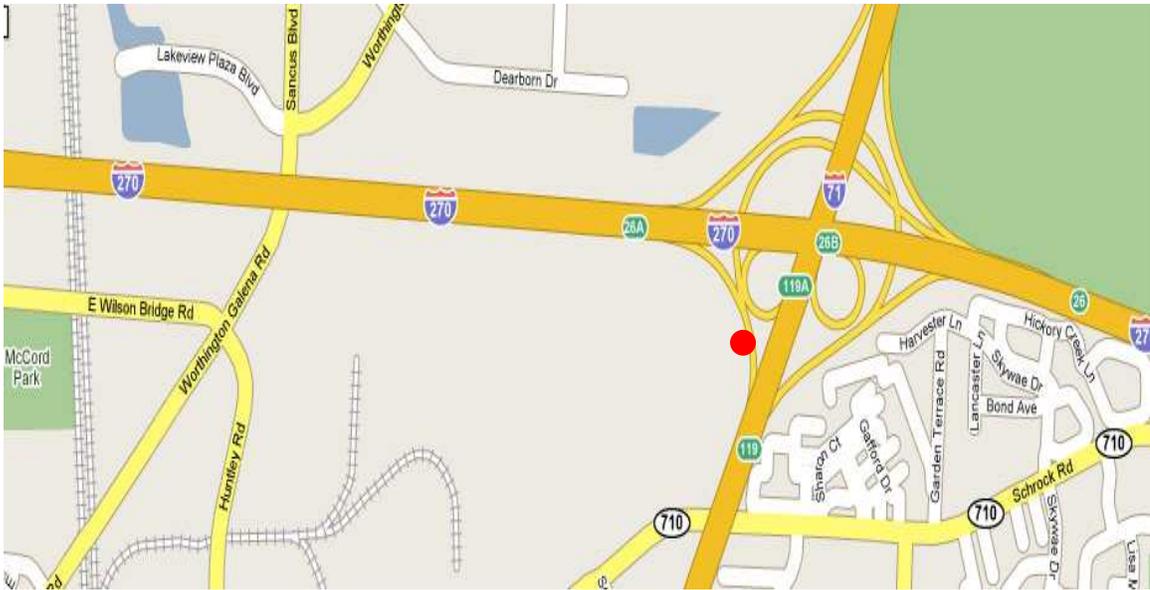
Figure 4.10 OSU I-71/I-270 Site Station Layout



Figure 4.11 OSU I-71/I-270 Site Station Layout – Aerial View

## 4.6 OSU FDR Sites

Tensiometers were also installed at the OSU Full Depth Reclamation (FDR) test pavement sites in Delaware, Warren and Muskingum counties. In this on-going study, three severely deteriorated Ohio county roads were rehabilitated using the FDR technology with different stabilizing agents including fly ash, lime-kiln dust, cement, and bituminous emulsions. The construction of the first two sites (in Delaware and Warren Counties), was completed in September 2006. During construction, tensiometers were installed along with load response (pressure cells, LVDTs, and strain gauges) and environmental sensors (lysimeters) to monitor pavement response and subsurface water quality. Standard FWD tests and pavement response data were collected and monitored regularly after the completion of construction.  Figure 4.12 shows the plan view of the FDR test pavement sections in Delaware County.  Tensiometers were also installed at the third FDR site located in Zanesville, Ohio in August 2007.
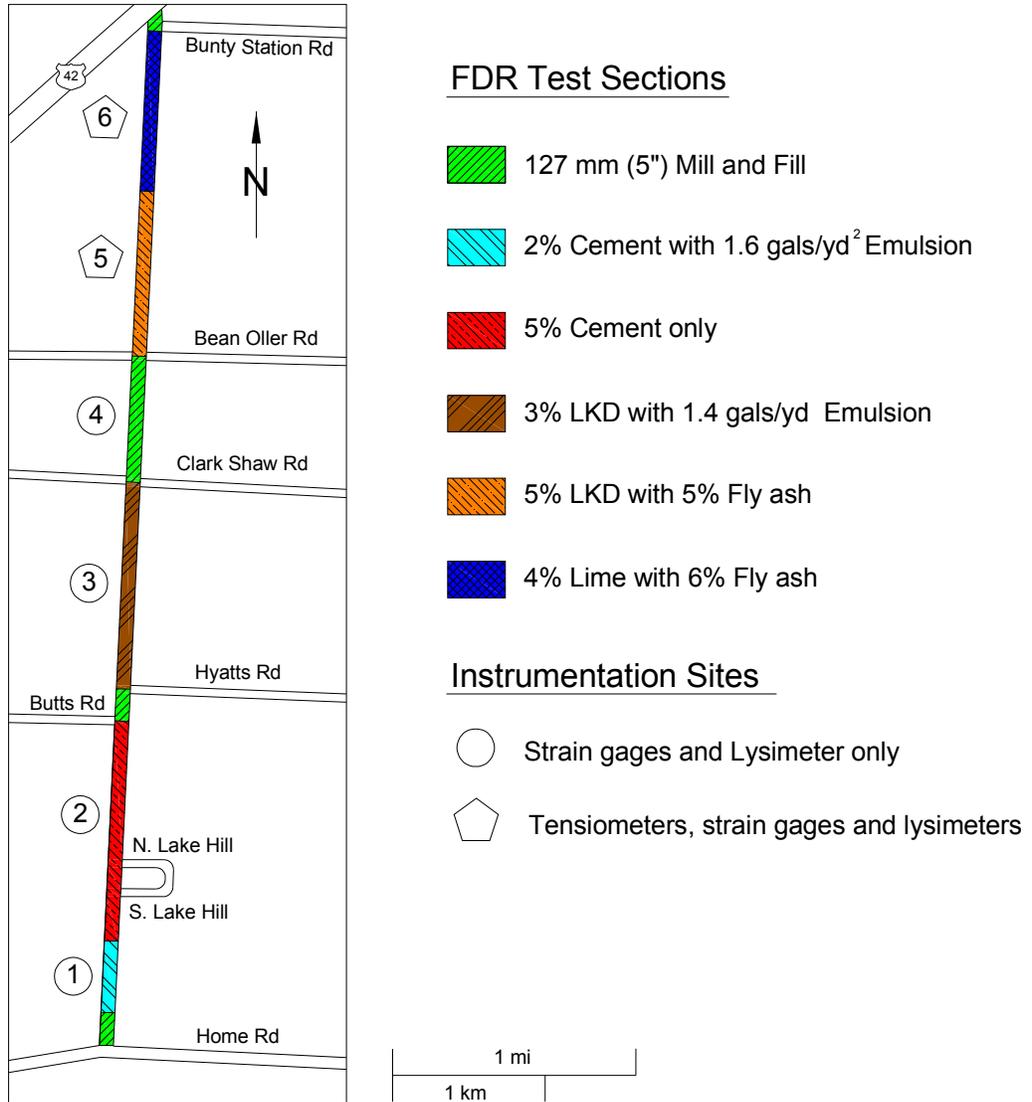
Figure 4.12 Plan View of OSU FDR Pavement Site at Delaware County, Ohio

Figure 4.13 OSU S. Section Line Rd. Site Station Layout
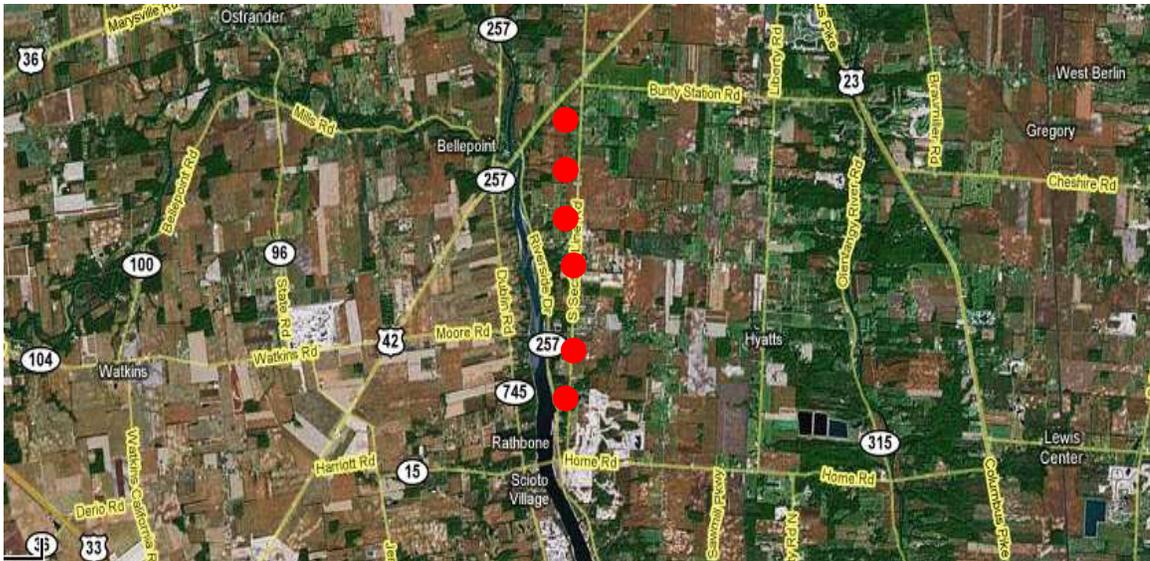


Figure 4.14 OSU S. Section Line Rd. Site Station Layout – Aerial View

Figure 4.15 OSU Warren County Site Station Layout



Figure 4.16 OSU Warren County Site Station Layout – Aerial View

Figure 4.17 OSU Muskingum County Site Station Layout
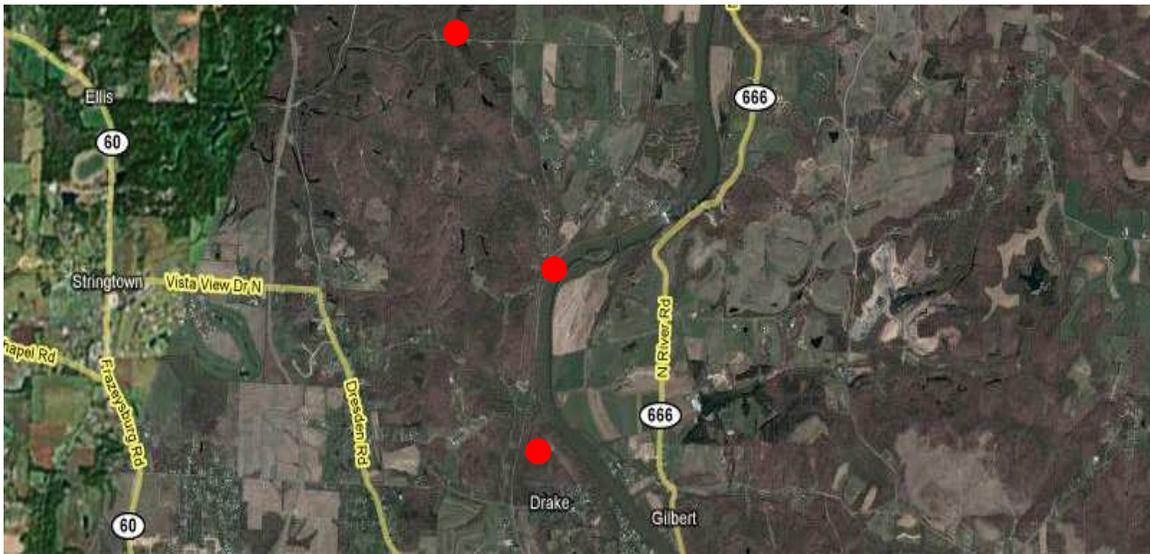


Figure 4.18 OSU Muskingum County Site Station Layout – Aerial View

## 4.7 Summary

Several sites were selected to represent a variety of subsurface conditions. These sites were monitored for periods of up to ten years. At the DEL23 site, LTPP instrumentation continued to be monitored for the life of the instruments. Many of those instruments reached the end of their useful lives during this phase of the project. Tensiometers capable of measuring either positive or negative pore water pressures and thereby giving a record of water effects on the soils supporting the overlying pavement systems, were installed at all the sites studied. The tensiometers require some care in manufacture, during and shortly after installation as evidenced by the number of instruments damaged or destroyed by highway construction crews within days of installation. However, once installed, the tensiometers have been shown to be rugged devices with a very high survival rate even after extended test periods. The data collected from all the installed instrumentation are presented in the following section.

## 5. FIELD MEASUREMENTS

At the DEL23 site, SHRP prescribed instrumentation was installed at the locations as shown in Figure 4.2. The several instruments were monitored during the initial construction period. Installation procedures and post-construction values were presented in our reports dated September 1998 and June 2004. Instrumentation hardware, recording procedures, as well as problems with reliability and longevity were discussed in detail in those two reports. Data collected, including tensiometer data, up to the date of the respective reports was also presented.  Presented in this section is a summary of the data collected during the period 2004 to 2007.

### 5.1 DEL 23

#### 5.1.1  SHRP Instrumentation

Table 5.1 lists the design parameters for each section at the DEL 23 site sampled by the OSU team, including the sections added after the original construction period. Figure 5.1 presents an example of a typical SHRP configuration of the installed instrumentation (here represented by test section 390263).  Our previous reports have provided descriptions of the data collected and methods for reporting and storing responses. Since the methods of data collection and storage and preservation were unchanged, the reader is referred to those two reports for details.

##### 5.1.1.1  Moisture Content

Using Section 390904 as an illustration of the data collected, moisture content (from TDRs) data can be plotted as shown in Figure 5.2 for the year 2007. The data are presented as seasonal averages (SU = Summer, AU = Autumn, WI = Winter, SP = Spring). They clearly show seasonal fluctuations in the moisture with the highest moisture contents occurring in the summer. Figures 5.3 through 5.6 show the same variations during the preceding years. The moisture content data over the full duration of the project (three reports) as a function of instrument location in the subsurface profile (Figures 5.7 through 5.10) highlight the seasonal variations in subgrade moisture content. It is apparent that, in the last four years of data collection, the average annual moisture content in the subgrade has remained at approximately 25%. Our earlier reports observed continuing increases in moisture content for several years after construction. However, our later data show that once full saturation was reached, increases in water content appear to have been limited to seasonal fluctuations. This observation is supported by the tensiometer data presented in Section 5.1.2 where predominantly positive pore pressures have been measured for several years.

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Moisture content data are presented for section 390263 for comparison purposes. The same seasonal variations are observed at all depths, but despite considerable data scatter, it is apparent that the annual mean moisture content has remained approximately constant since 2003-04 (Figures 5.11 through 5.14).

### 5.1.1.2   Soil Temperature

The sections for which temperature data were collected during the period 2004 through 2007 are given in Table 5.1. Temperatures recorded for most of the thermistors indicated faults in either the sensor or the data logger during much of the study period. Temperature readings collected were uploaded to the project data base but were insufficient to show trends so were not included herein.

### 5.1.1.3   Resistivity

The soil resistivity profiles collected were of questionable quality for much of the project study period due either to electrical problems with the collection system or sensor failure. The stations at which resistivity gages were installed are given in Table 5.1.

### 5.1.2   Tensiometers

Tensiometers were installed under seven pavement sections plus the weather station. The locations are shown in Figure 4.2. The tensiometers at sections 390211, 390263 and 390904 and the weather station were all installed in 1996 when the original SHRP instrumentation was placed. The tensiometers at sections 390160, 390106, 390121 and 390109 were installed in 2002 and 2003. With the exception of the weather station location which had only two tensiometers installed, pore pressures were recorded at three depths at each location, typically at the interface between the base and subgrade and at depths of 12 and 24 inches (30, and 60 cm) below the base into the subgrade.

The time history of the water pressures for the DEL 23 sections are presented in Figures 5.15 through 5.19. By the spring of 2004, the tensiometers recorded positive pore water pressures (except at the weather station) and although there were seasonal fluctuations in the value of the water pressure at each location, the data were typically positive, meaning the static water table had risen to and stayed between the surface of the roadway and the sensor. At the time of installation, the pore pressure values recorded by the tensiometers installed in 2002 and 2003 were all negative (less than atmospheric pressure) at the interface with the base, but at 12 and 24 inches into the subgrade, positive pore pressures existed by the time the first readings were taken. In general, the pore pressures continued to increase through the following months. At the end of the recording period, the pore water pressures recorded were typically positive at all three elevations. It is interesting to note that the observation made in our earlier reports concerning the pore pressure measurements at the weather station were observed during this final phase of the project as well. The pore pressure measurements taken at the weather station

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fluctuated more widely at the 12 inch depth than at any location under any pavement section. The effect of sealing the surface and thereby eliminating surface infiltration and evapo-transporation as moisture regulating mechanisms was to reduce the seasonal variability in ground water levels while increasing the mean groundwater elevation as well as the average water content. A review of the pore pressures recorded at the weather station from the time the tensiometers were installed is presented in Figure 5.20.
As stated in our 2004 report, these tensiometer data strongly suggest that water is being drawn up into the profile from depth. The continued high water levels over the most recent four year period support the observation made in 2004 that the base and subbase should not be considered as free draining.

### 5.2 WAY 30

As discussed in Section 4.2, the tensiometers installed under the WAY30 test pavements at locations 2 and 3 were field modified. Further, the tensiometers placed at location 3were damaged beyond repair when the pull box was displaced by the contractor shortly after installation was completed. The change in pore pressure over an eight month period beginning in the spring after installation the previous summer is shown for location 1 in Figure 5.21. The pore pressures remained consistently negative, meaning the water table was below the sensor level, throughout this period. However, during a load test in the spring following installation, dynamic pore pressure response was recorded under the test pavements. As can be seen in Figures 5.22, 5.23, and 5.24, the effect on the pore water of the loaded trucks passing over the sensor was clearly recorded as a rapid increase in the static pore pressure indicating saturated conditions at all sensor locations at all three stations. The dynamic pore pressures were recorded in October when a truck passed over the tensiometers at Station 1 during a scheduled monthly reading. Figure 5.25 presents the results of those dynamic pore water pressure readings. As was the case the previous spring, the passing of the loaded truck was recorded as an instantaneous increase on pore water pressure. Although the pore water pressure returned to the preload conditions immediately after the truck passed the sensors, the fact that the sensors recorded the passing truck in real time means that the subsurface is saturated.

### 5.3 MAD 70

Tensiometers were installed in the westbound lanes of Interstate 70 west of the US 42 overpass in summer 2006. The pore pressure history over a 15 month period is shown for Station 1 in Figure 5.26 and for location 2 in Figure 5.27. Although pore pressures were negative shortly after installation, positive pore pressures were the norm in less than one year, indicating a high water table strongly indicating saturated conditions existed in the supporting soil beneath the pavement.

5.4 ROS 207

Pore pressure distribution recorded at the Ross County site is shown in Figure 5.28 for a 16 month period. It is interesting to note that at this location pore water pressure in the spring following the tensiometer installation was positive at the two lower sensors. At all other times and for the topmost tensiometer, the pressures were negative indicating a shallow but seasonally fluctuating groundwater table.

5.5 I-71/I-270 Interchange

The tensiometers installed in the ramp from I-270 to I-71 were damaged during installation. No reliable readings were retrieved at this location.

5.6 OSU FDR Sites

An example of the data collected at the instrumented full depth pavement reclamation sites discussed in Section 4 is presented in Figure 5.29. Pore water pressure response was recorded as heavy trucks passed over the Station 6 instrumentation. As has been seen at other instrumented locations, the pore water response was coincident with the applied load indicating the likelihood that saturated conditions prevailed under the reclaimed pavement sections.

5.7 Summary

By the end of the project, the temperature and resistivity gauges installed at the five locations at the DEL23 test pavement assigned to the OSU researchers had failed. Almost all the moisture content sensors (TDRs) were still functioning satisfactorily and data were collected up to the conclusion of the current work effort. The tensiometers installed as an extra source of data on the condition of the subsurface soils are still monitoring pore pressures. What has been determined from the TDRs is the moisture content under the paved sections varied seasonally but the mean value continued to rise for several years. In the latter years of the investigation the mean water content was essentially constant. The tensiometers that were installed to record the pore pressures also measured a response that varied seasonally but trended to higher and higher pore pressures with time. At most of the sites studied, the pore pressures became positive within one or at most two years after installation and remained positive for most of the year. This information combined with the TDR data strongly indicates that saturated soils were encountered at all sites studied and similar conditions should be expected to exist under other Ohio highways.
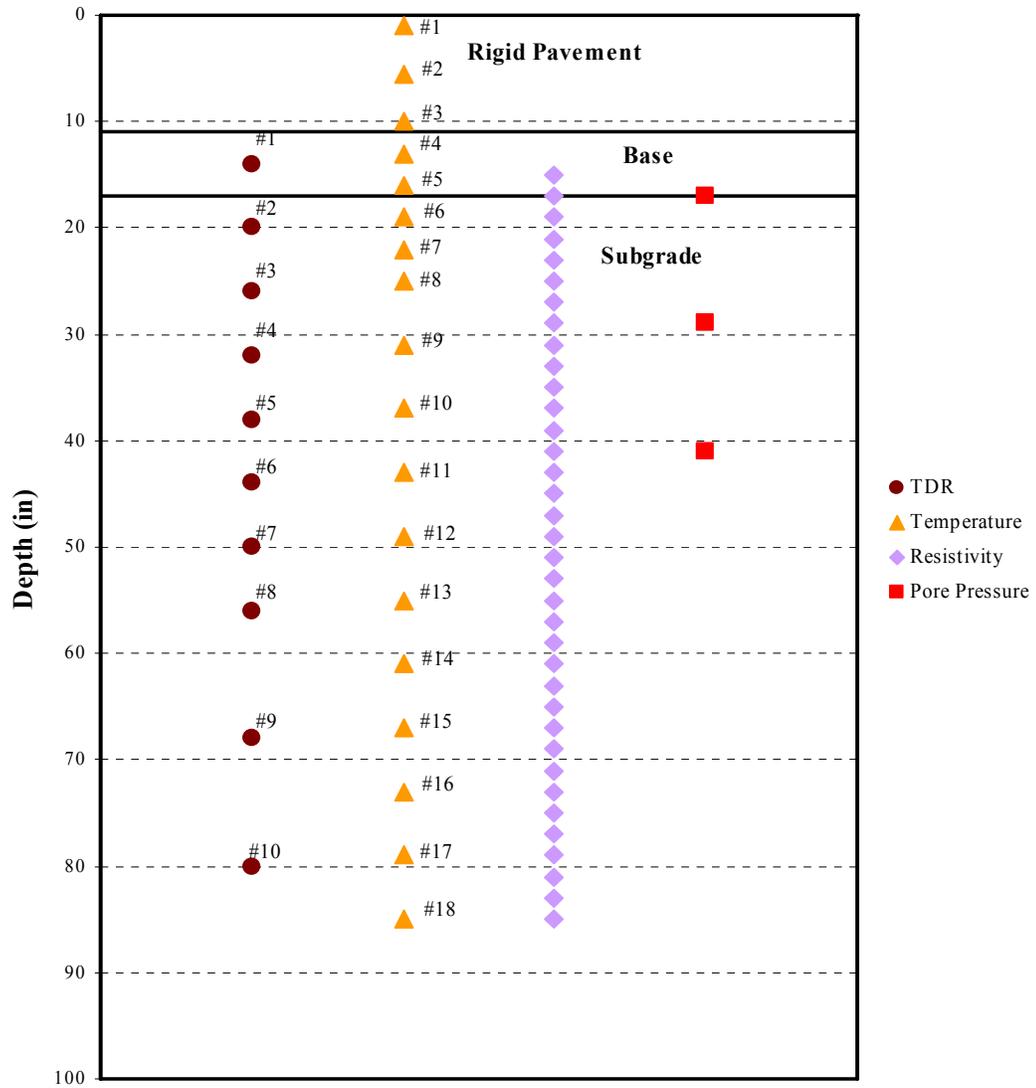
**390263**



Figure 5.1 Instrumentation Configurations (390263 from 2004 report)

| ID | Section | Designation | Thickness (in) | | | Base | Drain | Environment Instrument |
|---|---|---|---|---|---|---|---|---|
| | | | AC | PC | Base | Type | | |
| 390108 | J8 | SPS-1 | 7 | | 12 | 4" PATB/ 8" DGAB | Yes | Temperature Moisture Frost Depth |
| 390160 | S7 | SPS-1 | 4 | | 15 | 11" ATB/ 4" DGAB | Yes | Soil Suction |
| 390106 | J6 | SPS-1 | 7 | | 12 | 8" ATB/ 4" DGAB | No | Soil Suction |
| 390904 | SHRP | Experimental SHRP Mix SPS-9 | 4 | | 22 | 12" ATB/ 4" PATB/ 6" DGAB | Yes | Temperature Moisture Frost Depth Soil Suction |
| 390201 | J1 | SPS-2 | | 8 | 6 | DGAB | No | Temperature Moisture Frost Depth |
| 390211 | J11 | SPS-2 | | 11 | 8 | 4" PATB/ 4" DGAB | Yes | Temperature Moisture Frost Depth Soil Suction |
| 390212 | J12 | SPS-2 | | 11 | 8 | 4" PATB/ 4" DGAB | Yes | Soil Suction |
| 390263 | S4 | SPS-2 | | 11 | 6 | DGAB | Yes | Temperature Moisture Frost Depth Soil Suction |

SPS-1:  Strategic study of structural factors for flexible pavement        AC: Asphalt Concrete

SPS-2:  Strategic study of structural factors for rigid pavement        PCC: Portland Cement Concrete

SPS-9:  Asphalt program field verification studies.

DGAB: Dense Graded Aggregate Base        ATB: Asphalt Treated Base        PATB: Permeable Asphalt Treated Base

Table 5.1 Ohio State University DEL 23 Test Sections
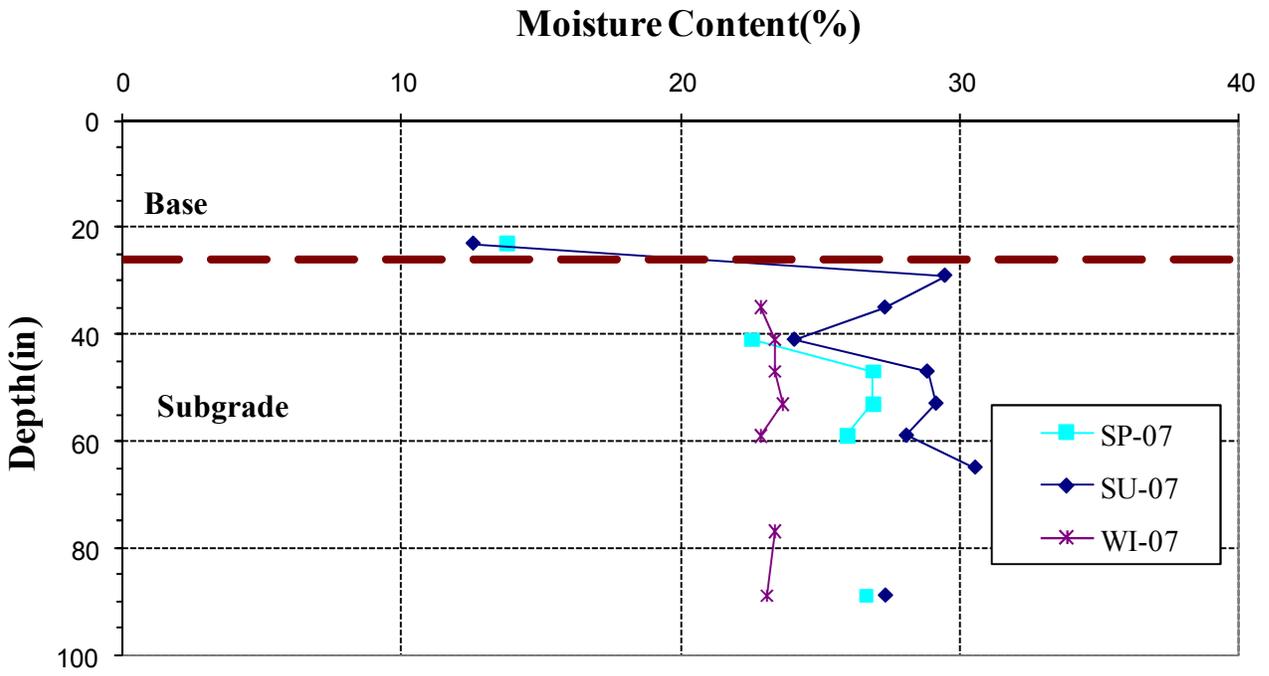
Figure 5.2 Seasonal Moisture Content for 2007 (390904)
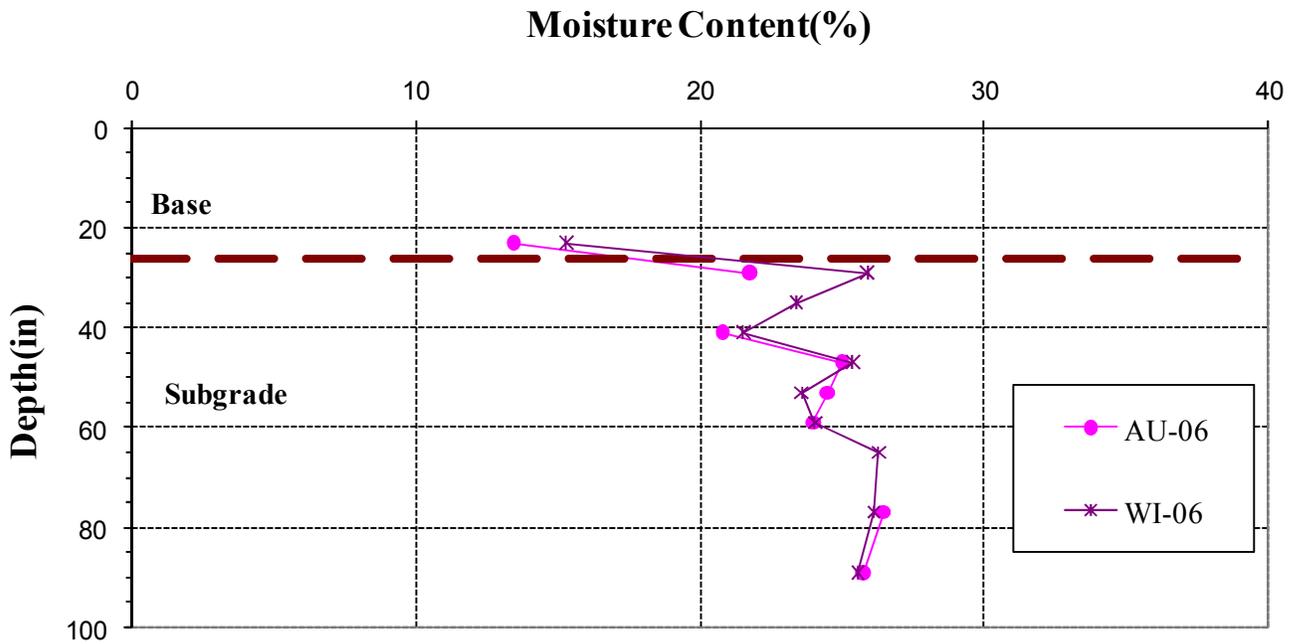


Figure 5.3 Seasonal Moisture Content for 2006 (390904)
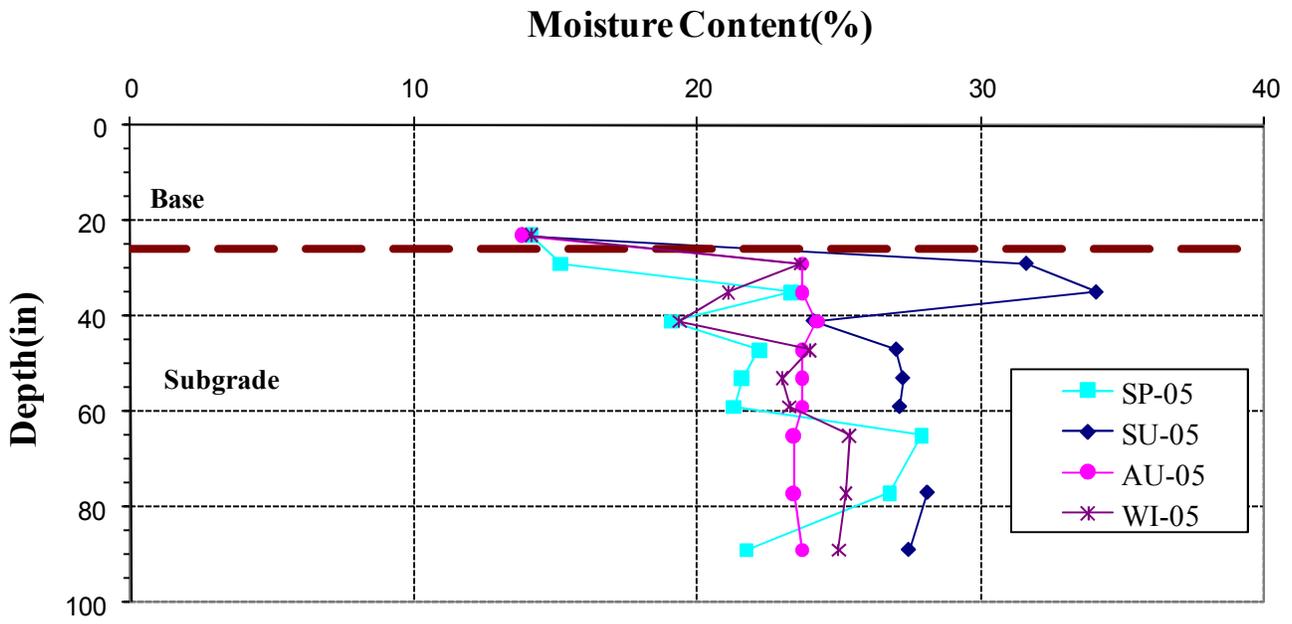
Figure 5.4 Seasonal Moisture Content for 2005 (390904)
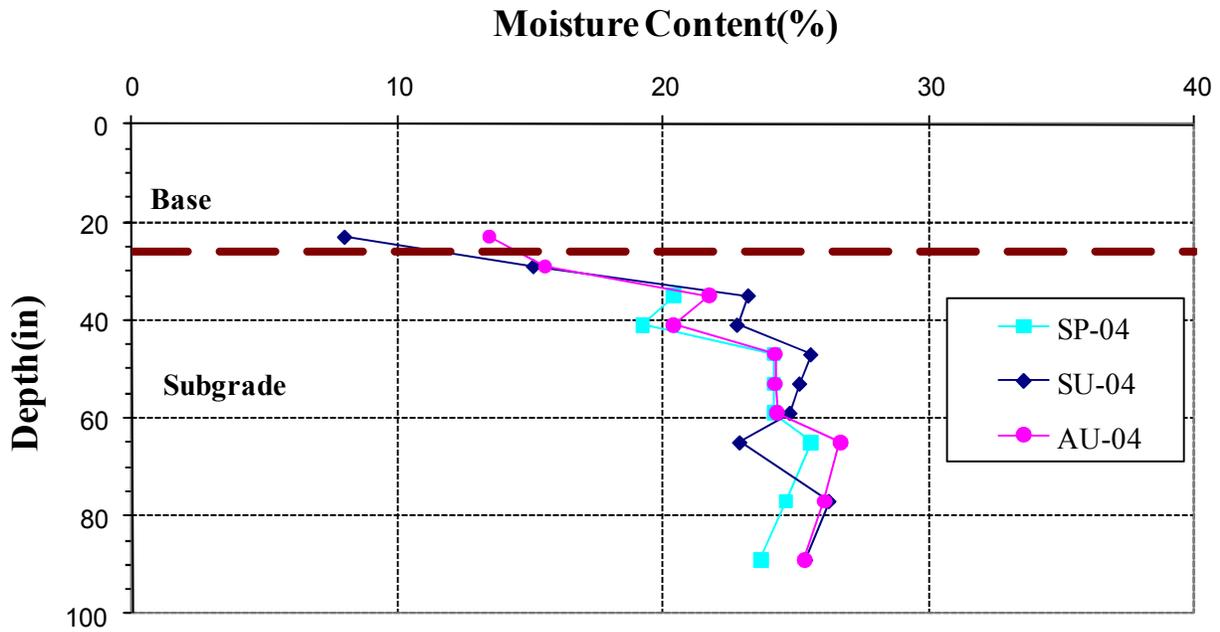


Figure 5.5 Seasonal Moisture Content for 2004 (390904)
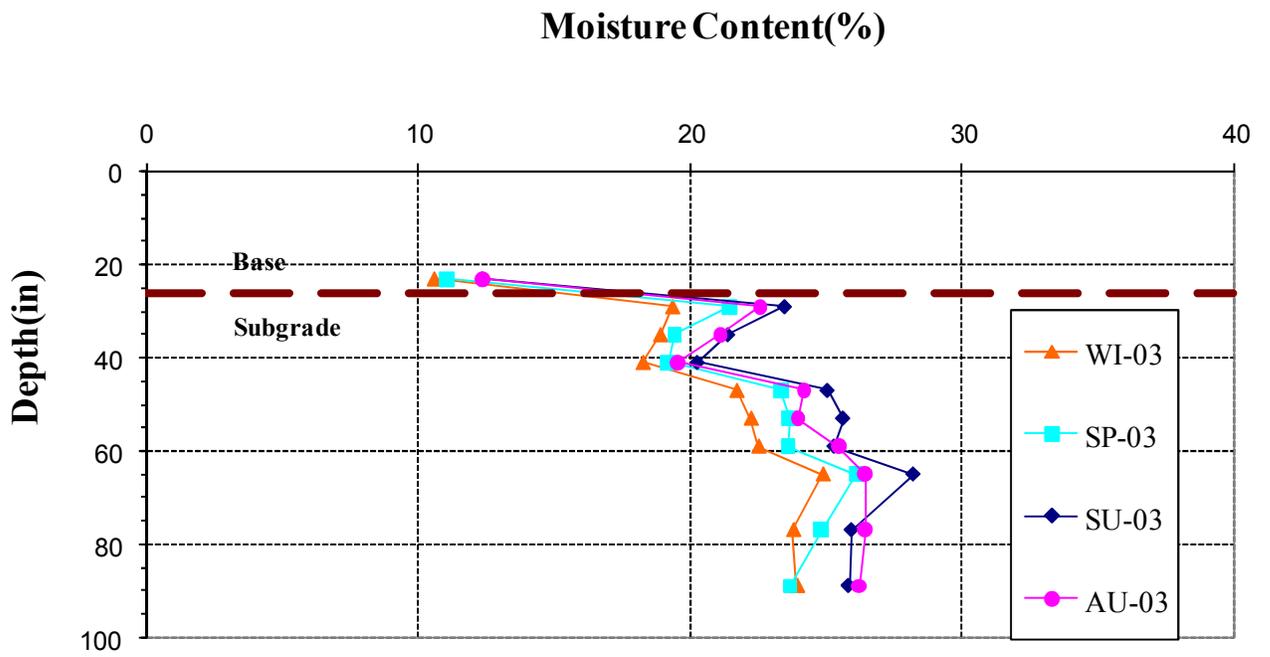
Figure 5.6 Seasonal Moisture Content for 2003 (390904)
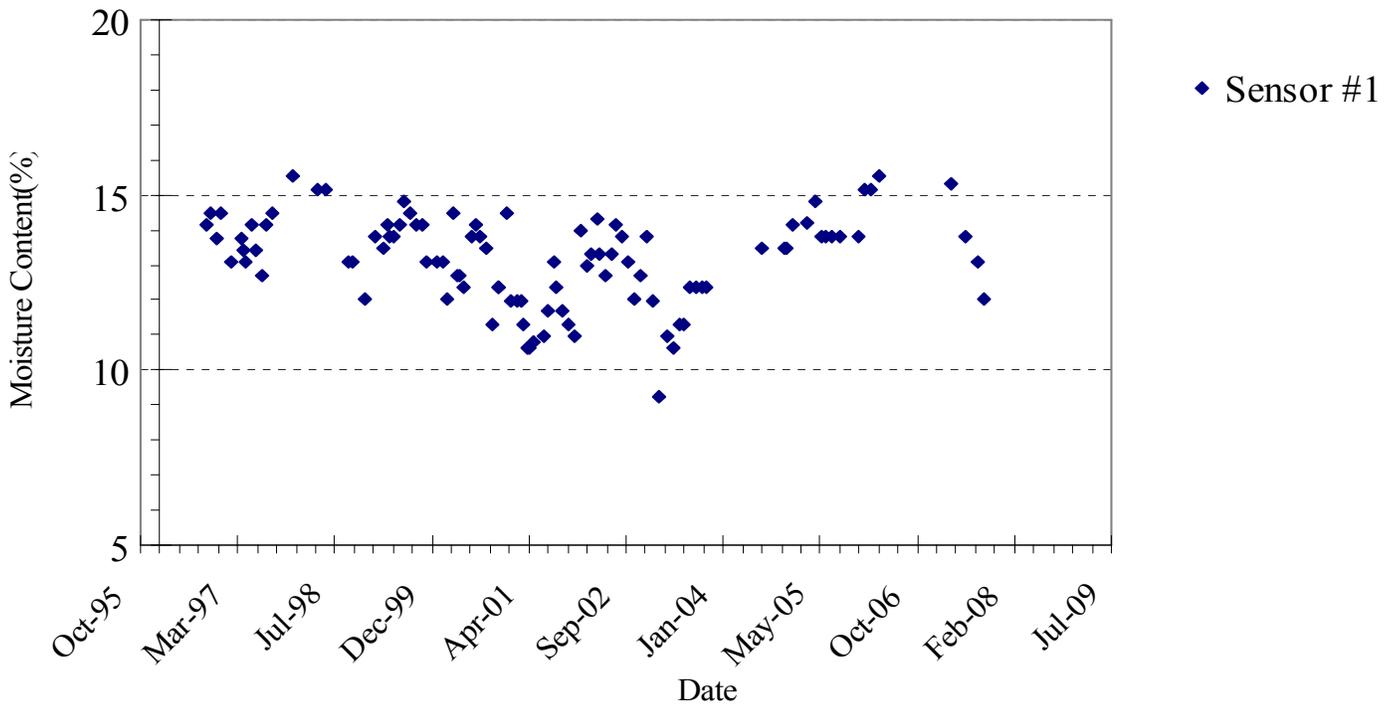
Figure 5.7 Moisture Content (390904) Topmost TDR 1996-2007
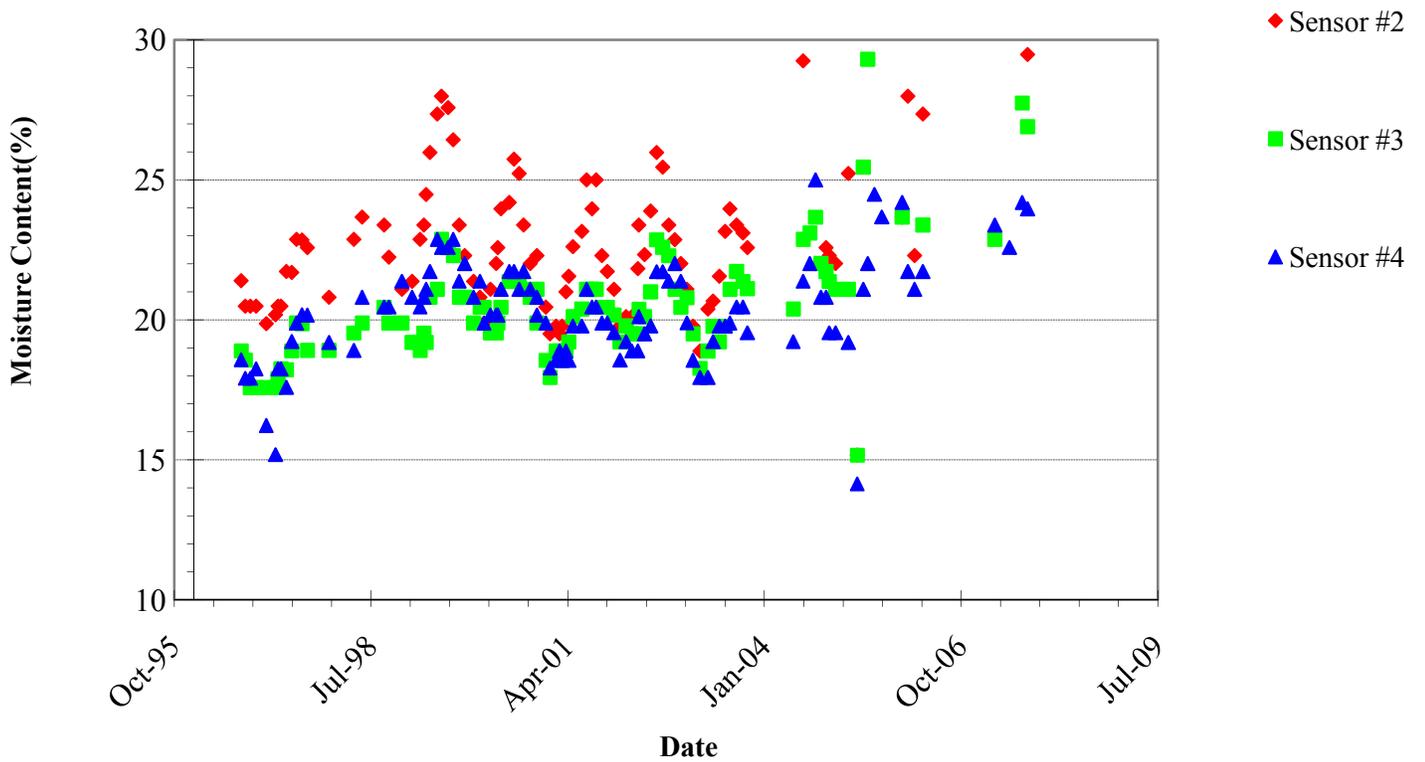


Figure 5.8 Moisture Content (390904) Top of Subgrade 1996-2007
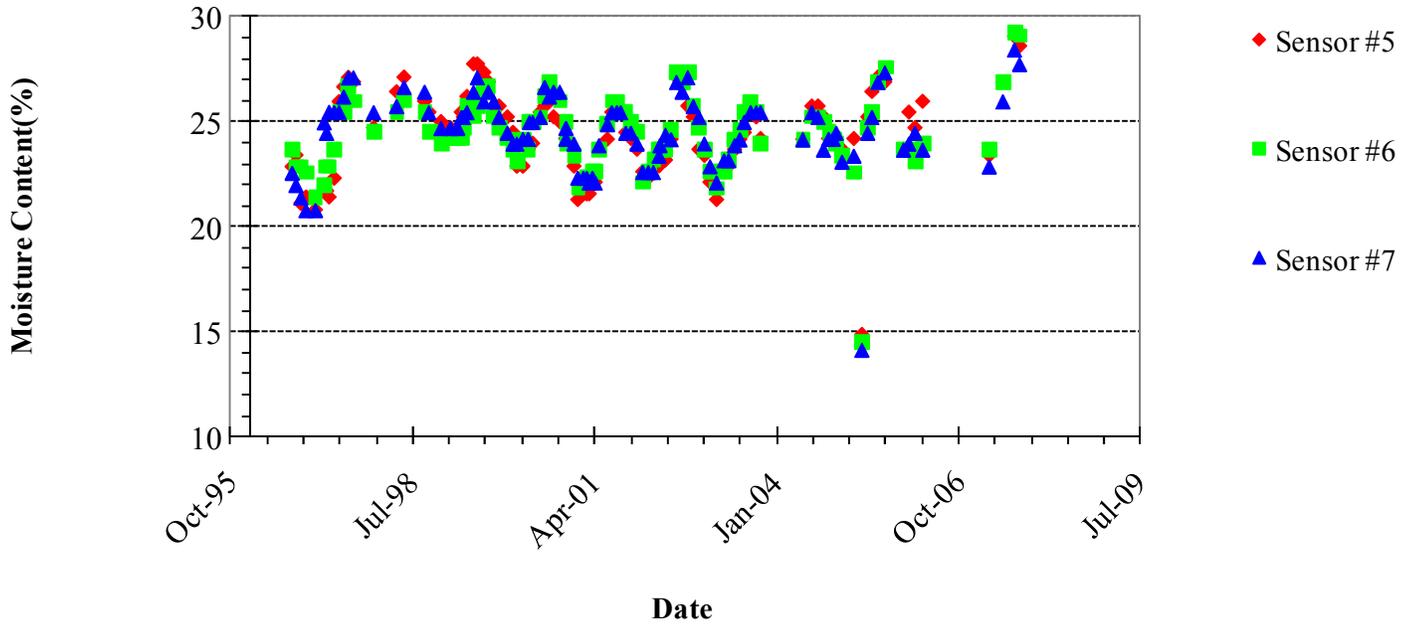
Figure 5.9 Moisture Content Middle of Subgrade 1996-2007 (390904)
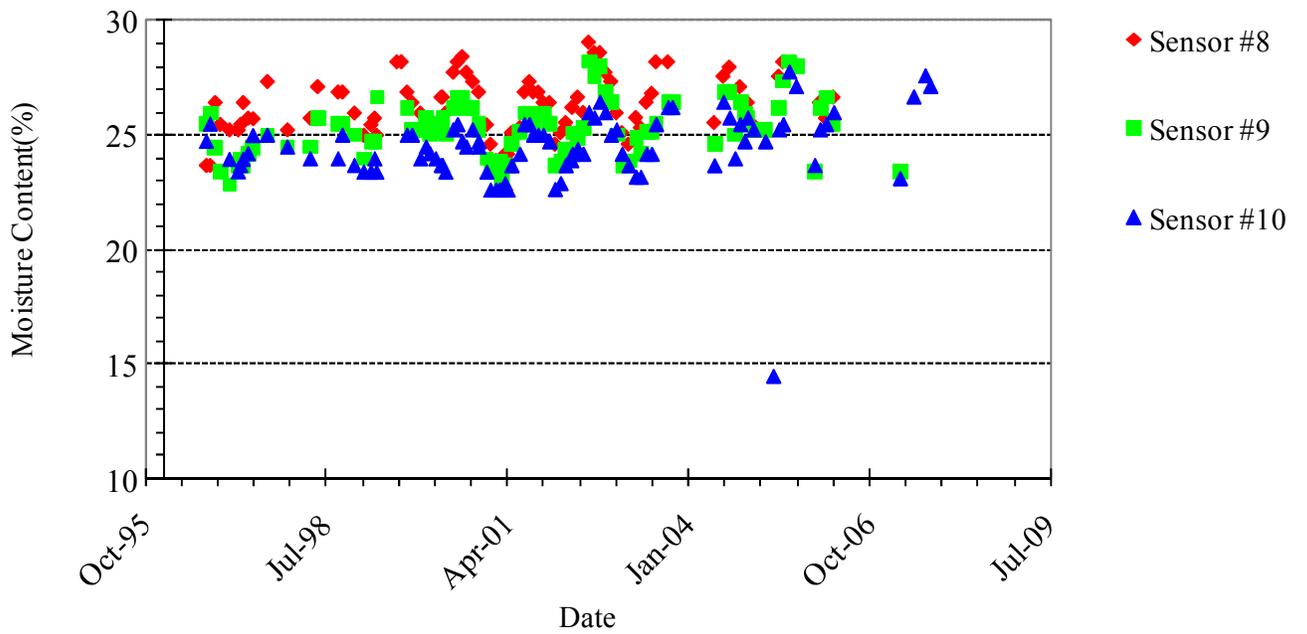
Figure 5.10 Moisture Content Bottom of Subgrade 1996-2007 (390904)
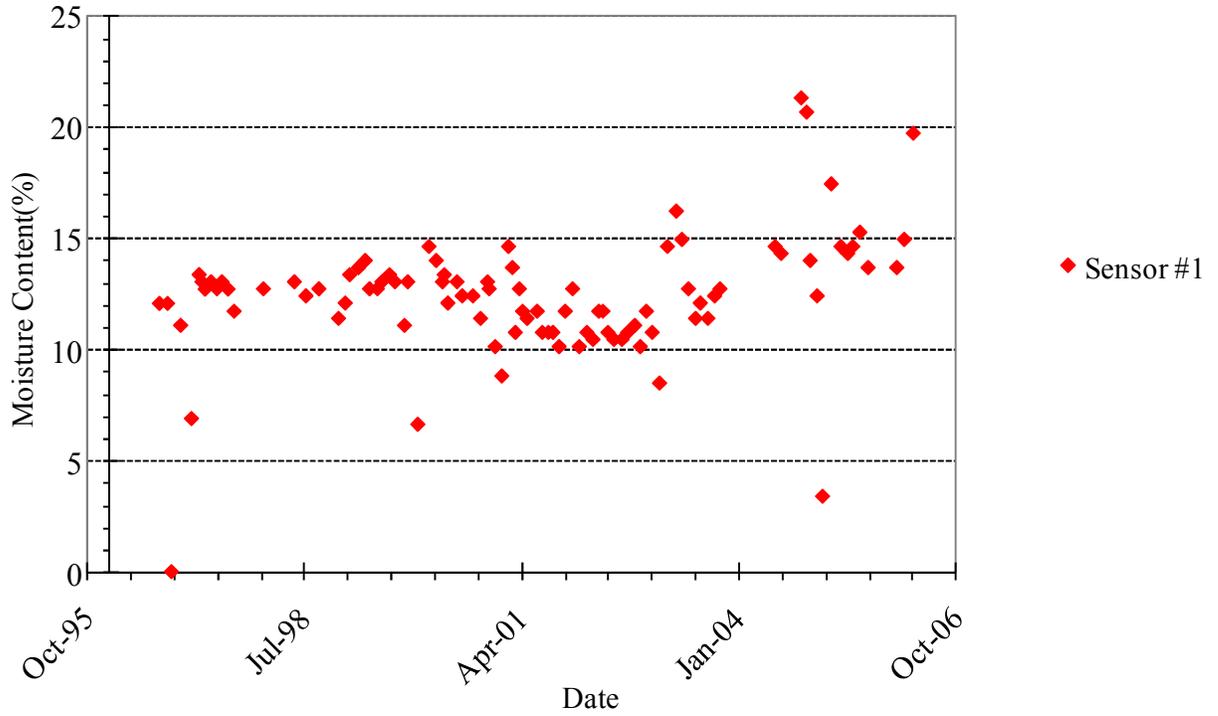


Figure 5.11 Moisture Content at TDR in Base 1996-2006 (390263)
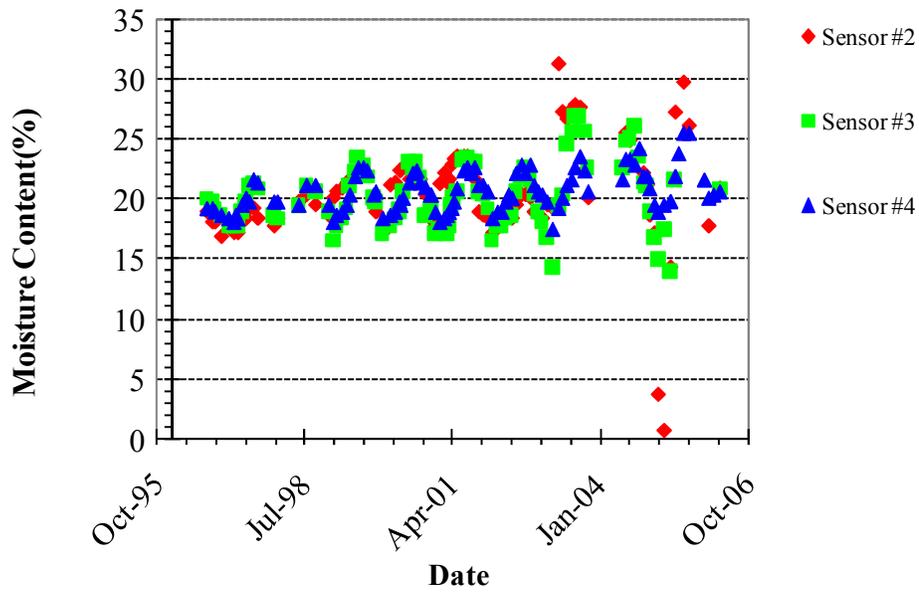
Figure 5.12 Moisture Content at Top of Subgrade 1996-2006 (390263)
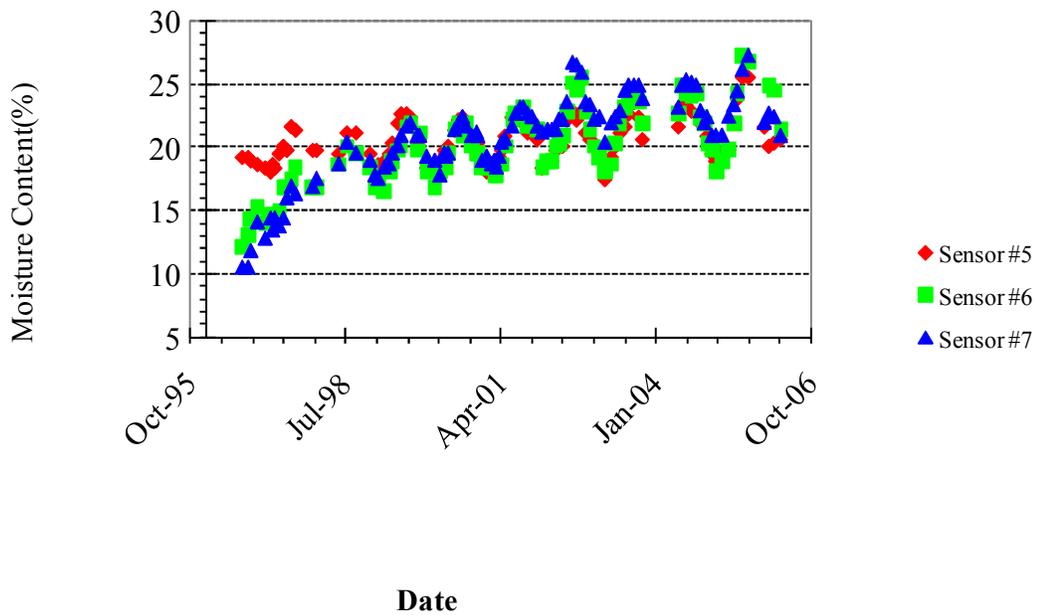


Figure 5.13 Moisture Content Middle of Subgrade 1996-2006 (390263)
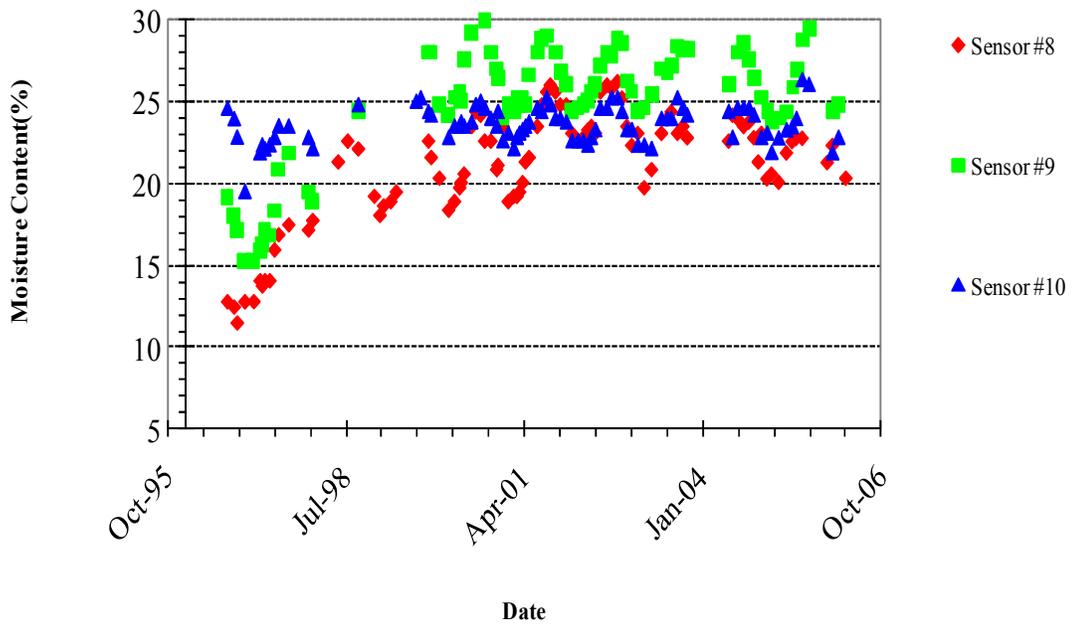
Figure 5.14 Moisture Content Bottom of Subgrade 1996-2006 (390263)
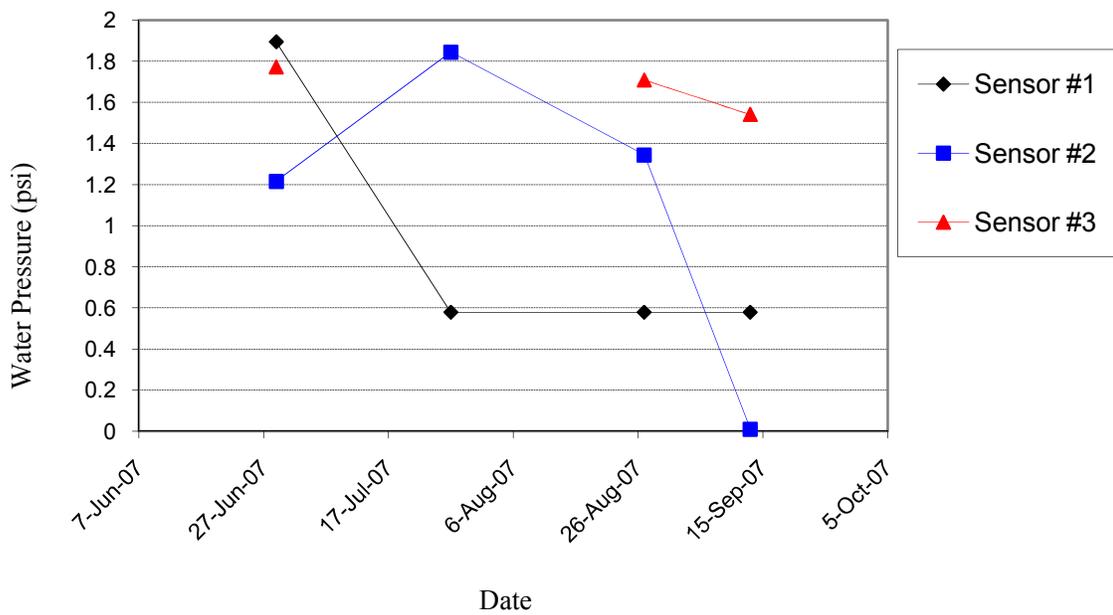


Figure 5.15 Pore Water Pressure at Section 390904
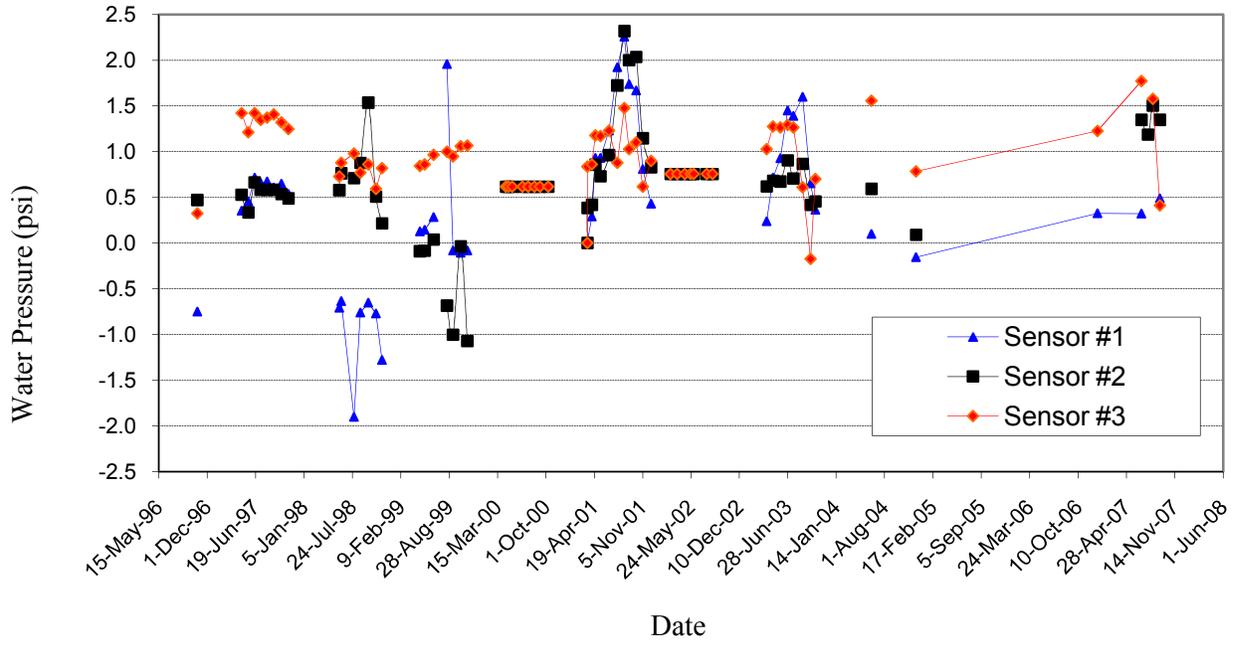
Figure 5.16 Pore Water Pressure at Section 390211
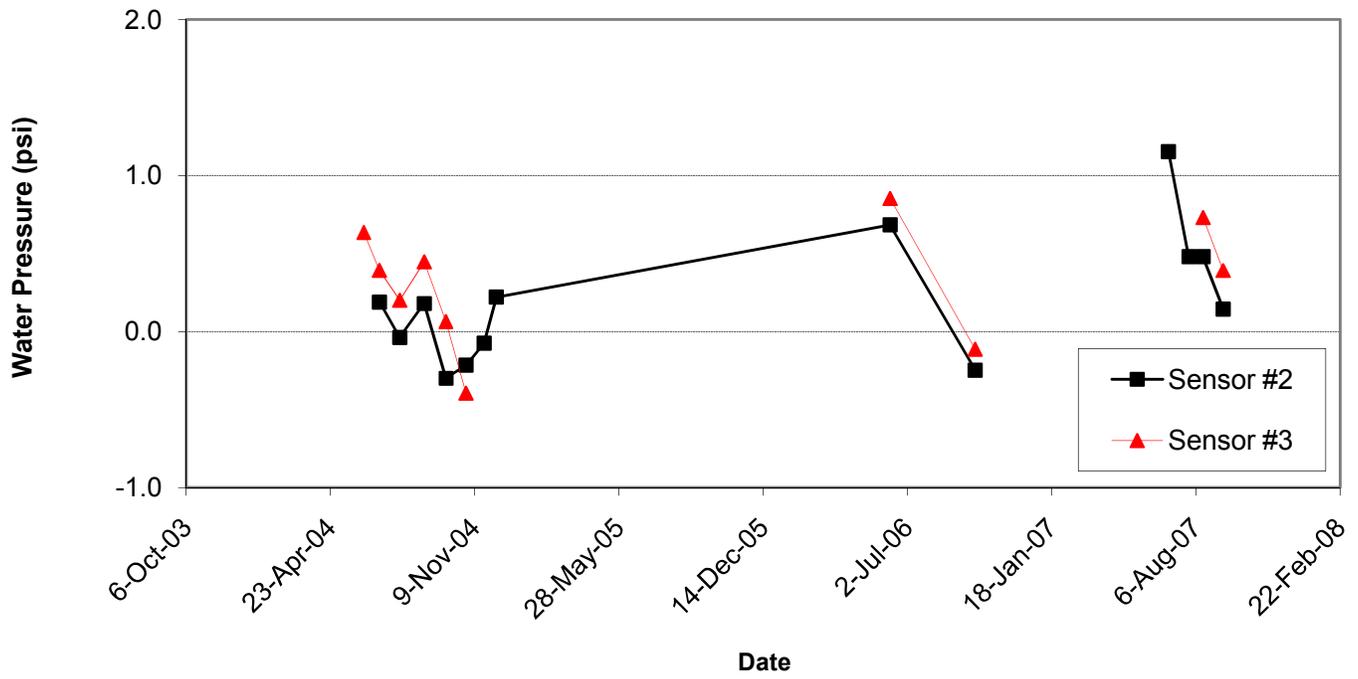
Figure 5.17 Pore Water Pressure at Section 390160
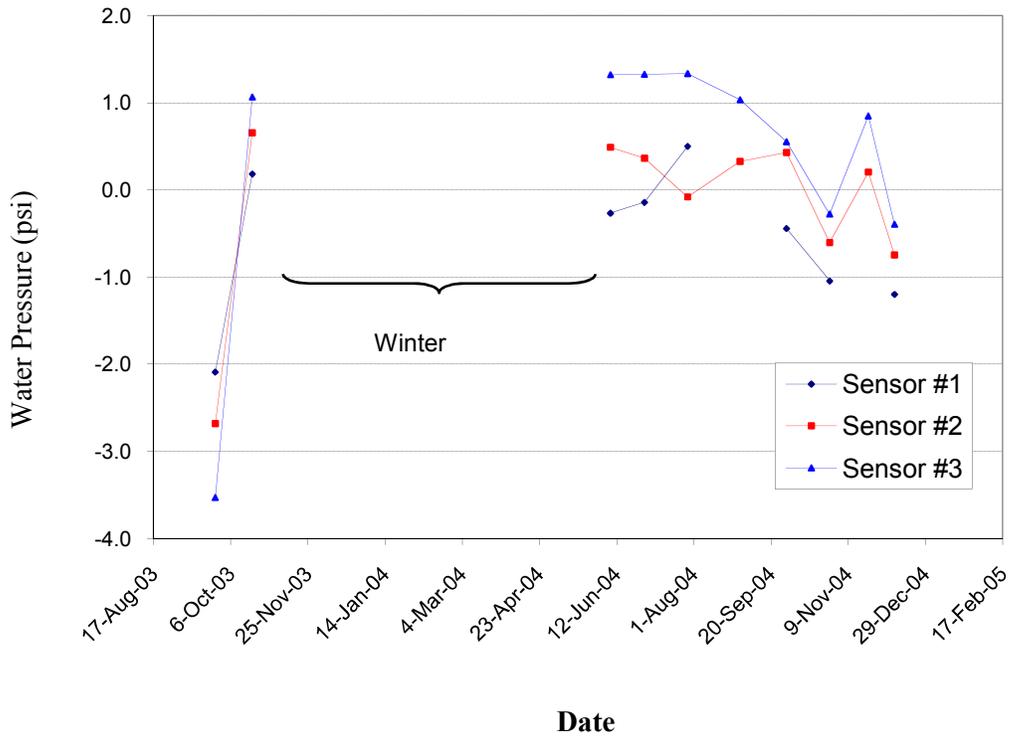


Figure 5.18 Pore Water Pressure at Section 390901

51
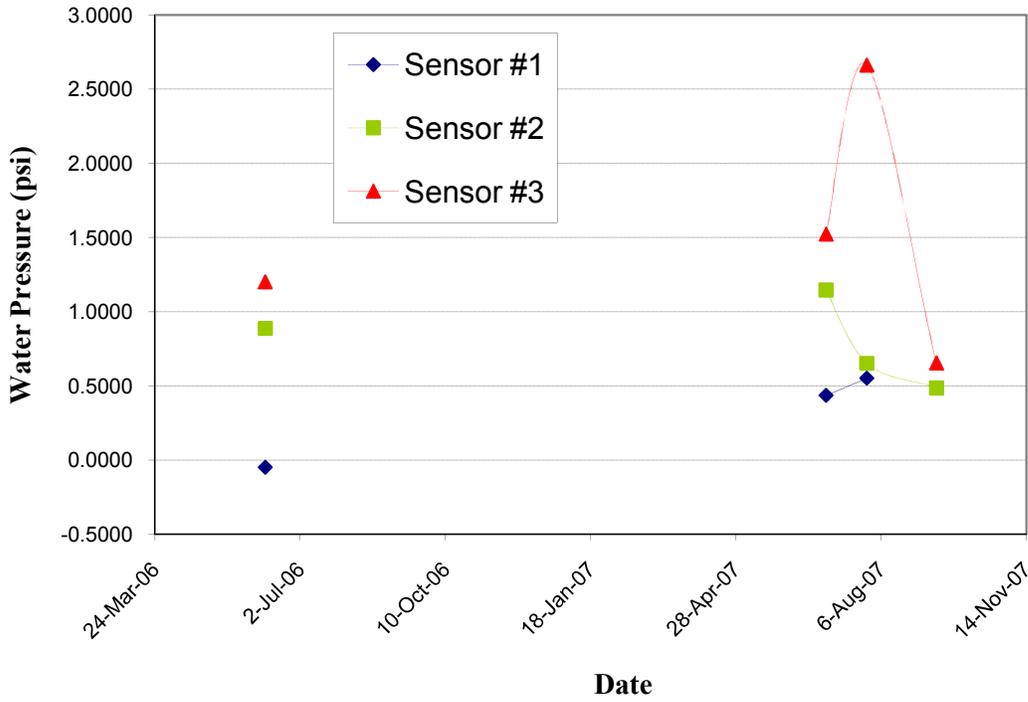
Figure 5.19 Pore Water Pressure at Section 390106
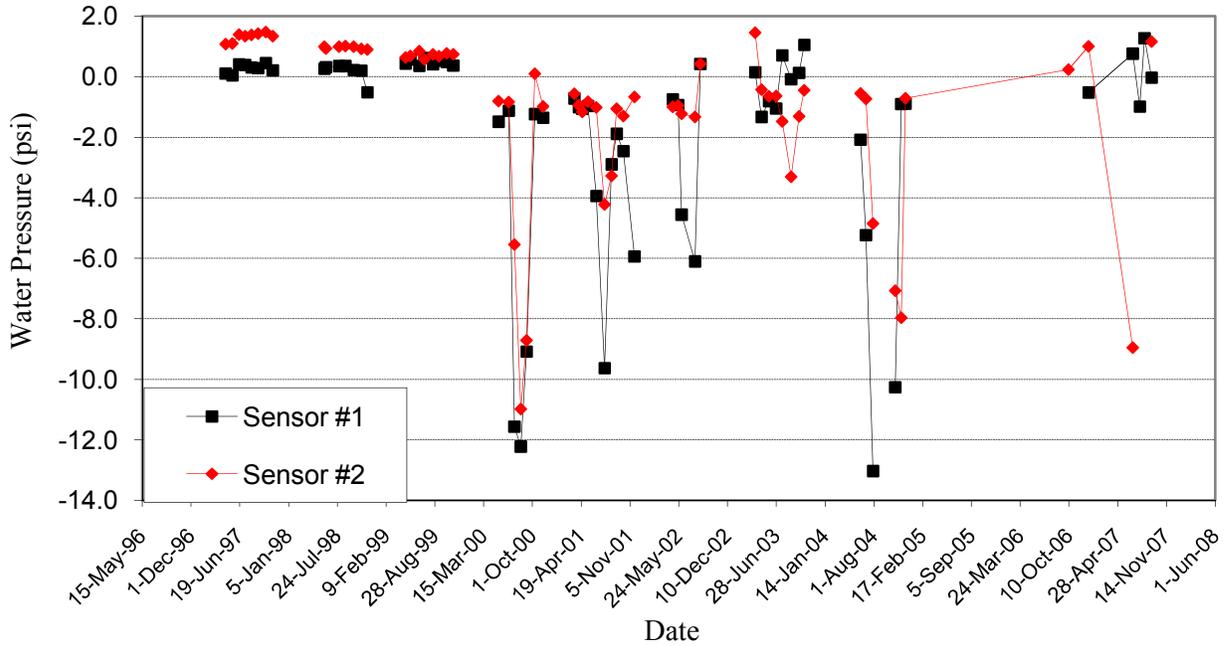


Figure 5.20 Pore Water Pressure at Instrumented Weather Station
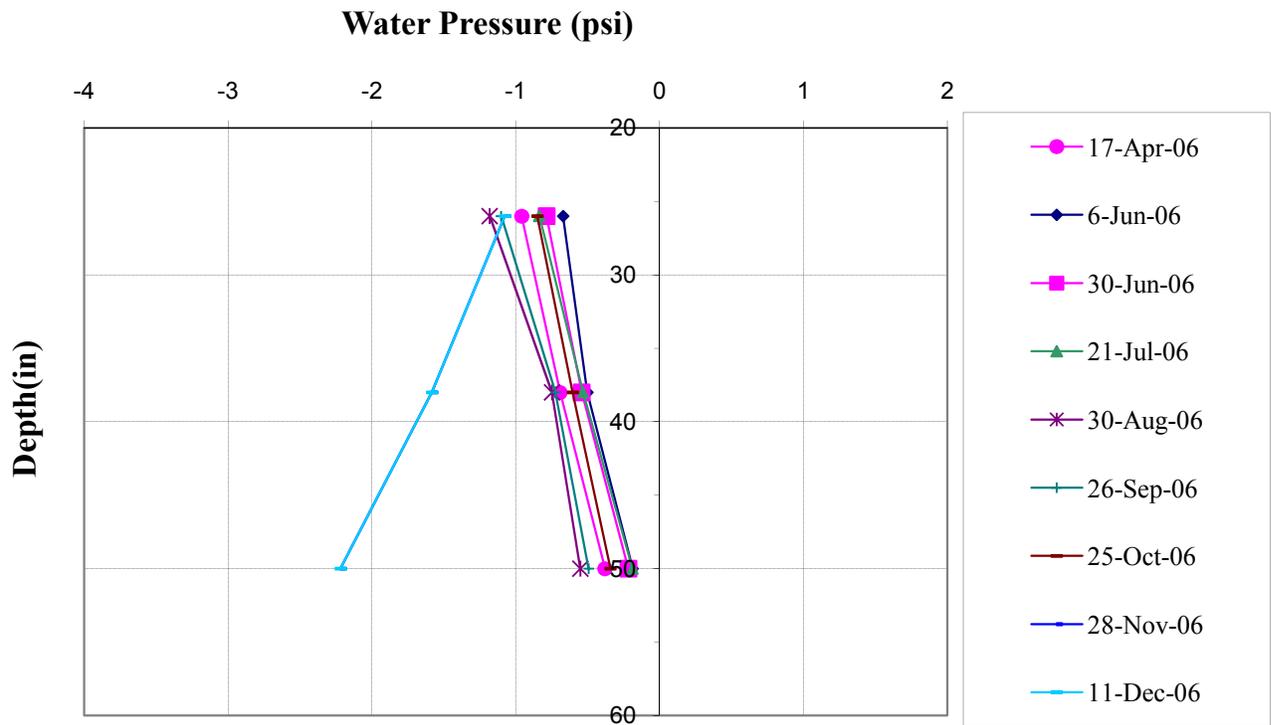
Figure 5.21 Pore Water Pressure at WAY 30 Station 1
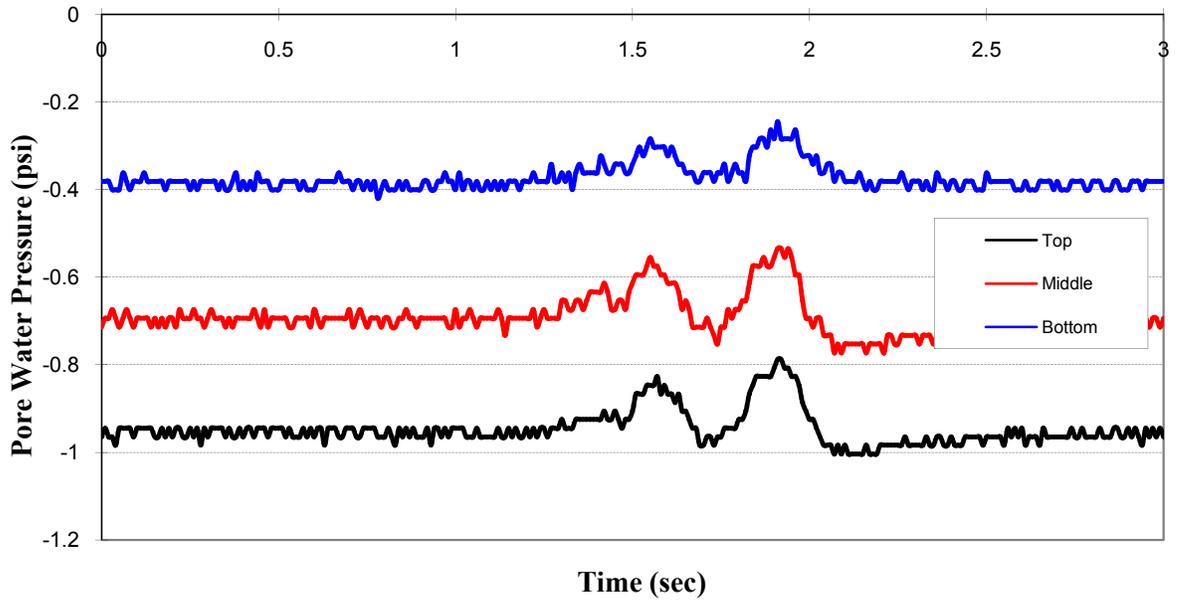


Figure 5.22 Dynamic Pore Pressure Response at WAY 30 Station 1 (April 06)
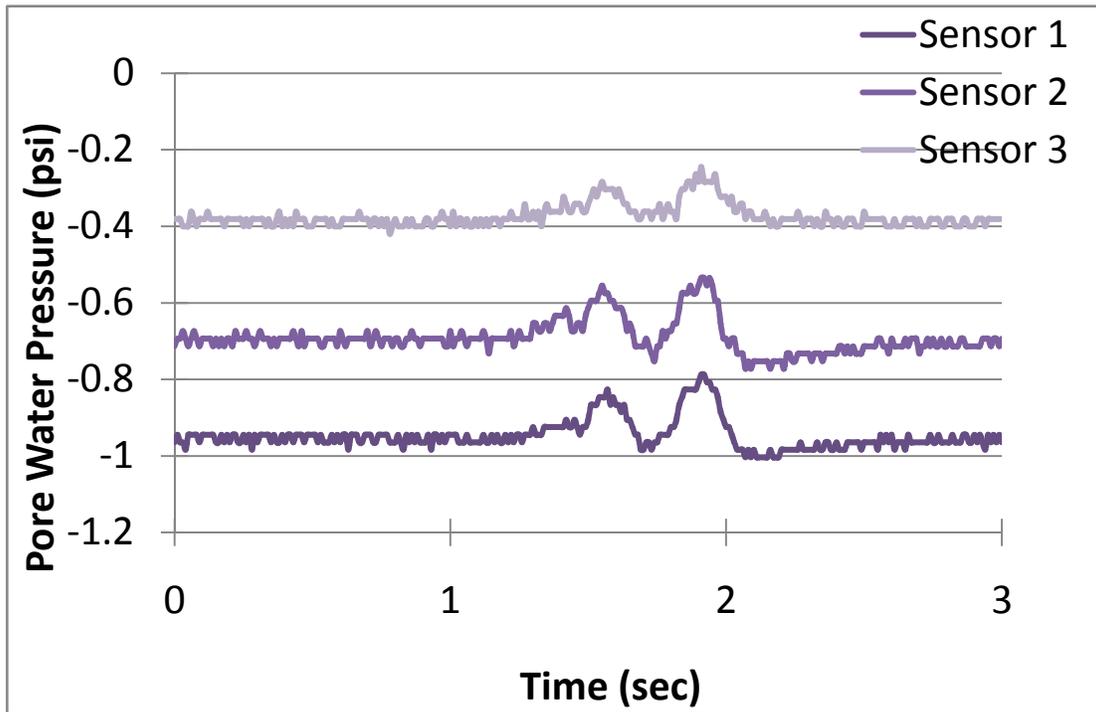
Figure 5.23 Dynamic Pore Pressure Response at WAY 30 Station 2 (April 06)
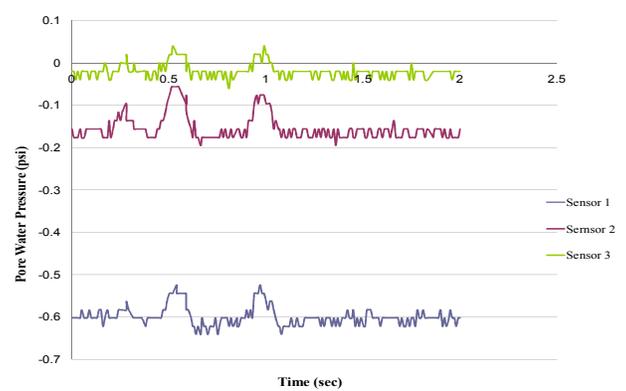


Figure 5.24 Dynamic Pore Pressure Response at WAY 30 Station 4 (April 06)
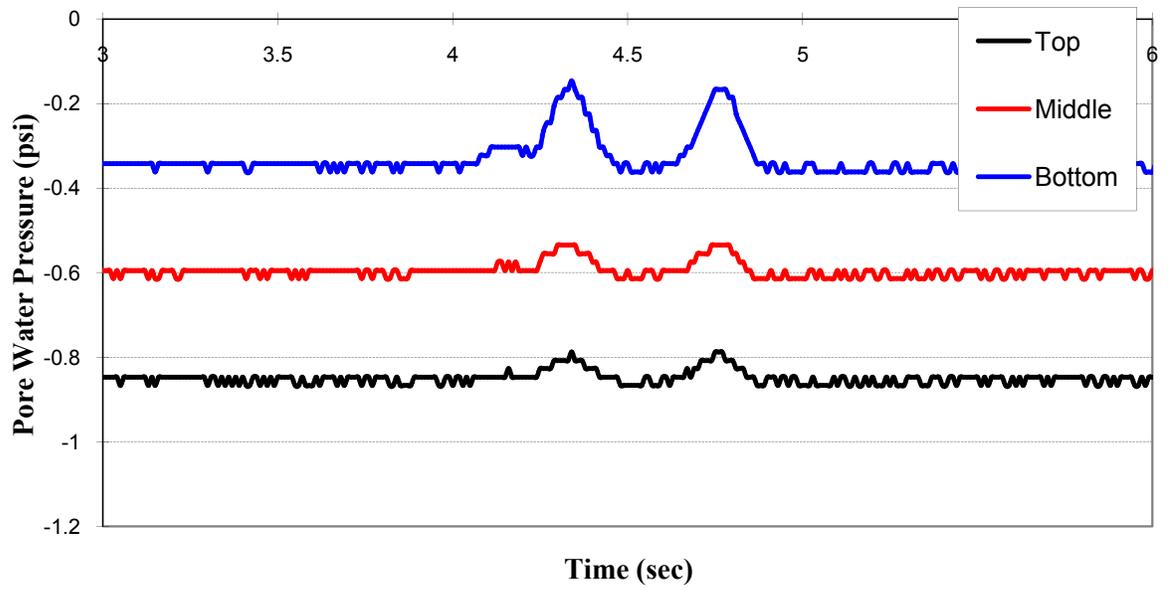
Figure 5.25 Dynamic Pore Pressure Response at WAY 30 Station 1 (October 06)
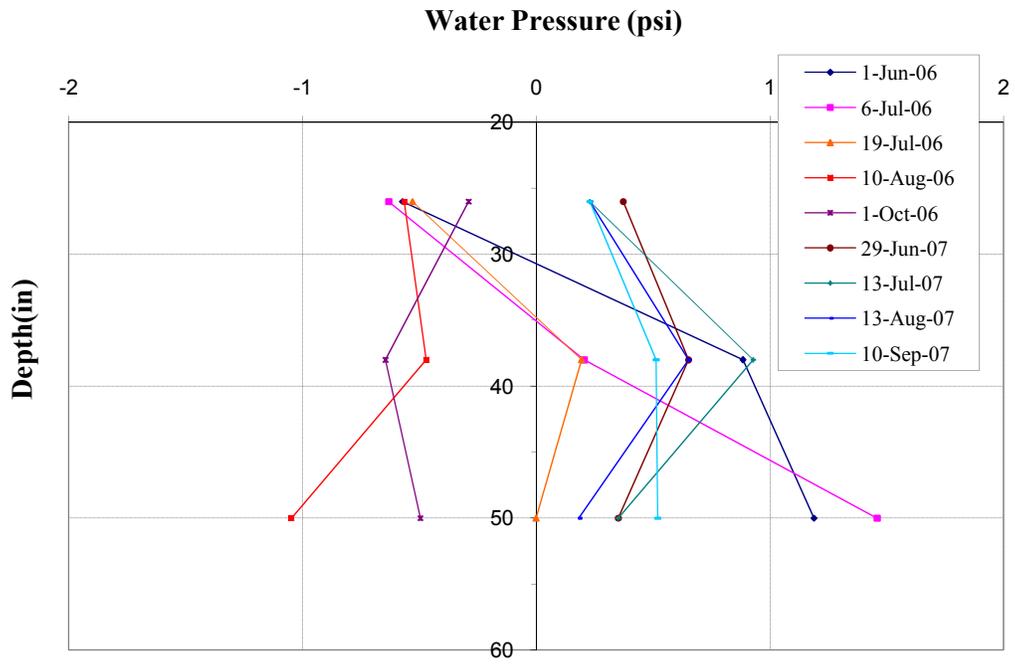
Figure 5.26 Pore Water Pressure at MAD 70 Station 1
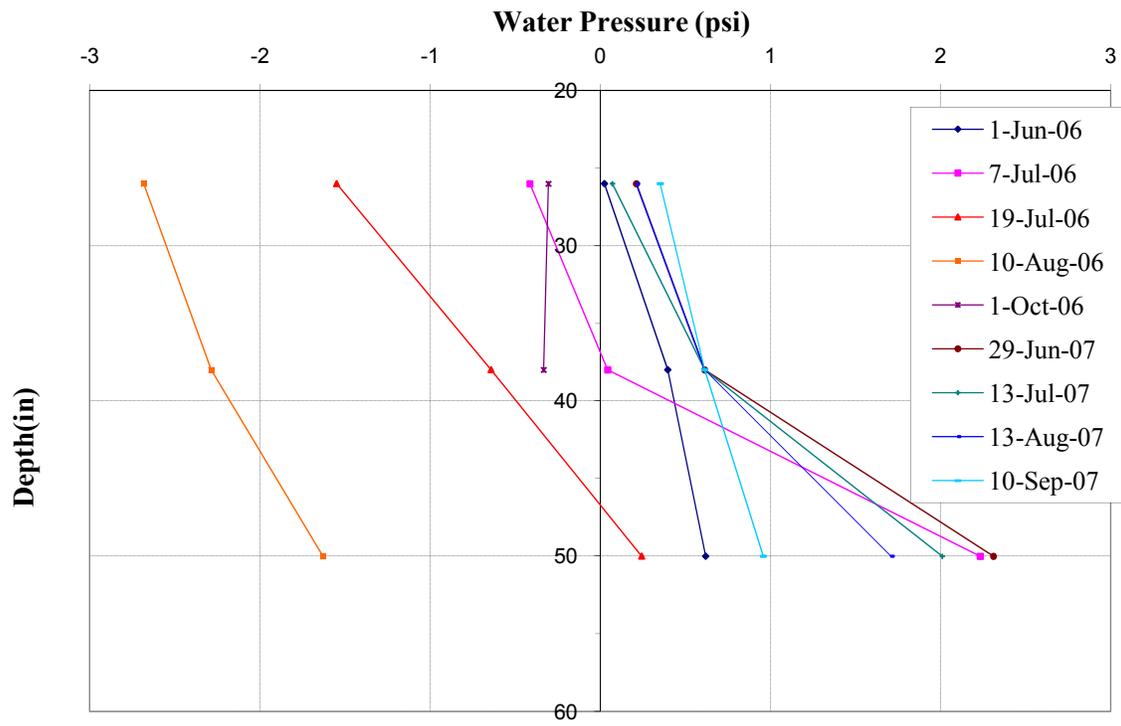
Figure 5.27 Pore Water Pressure at MAD 70 Station 2
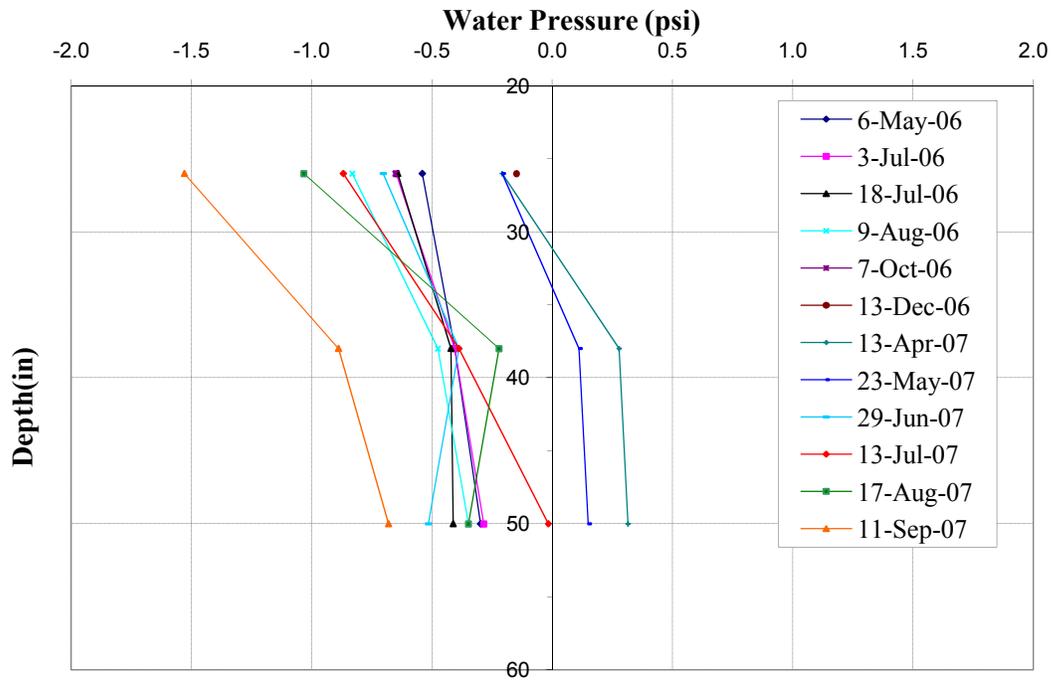
Figure 5.28 Pore Water Pressure at ROS 207
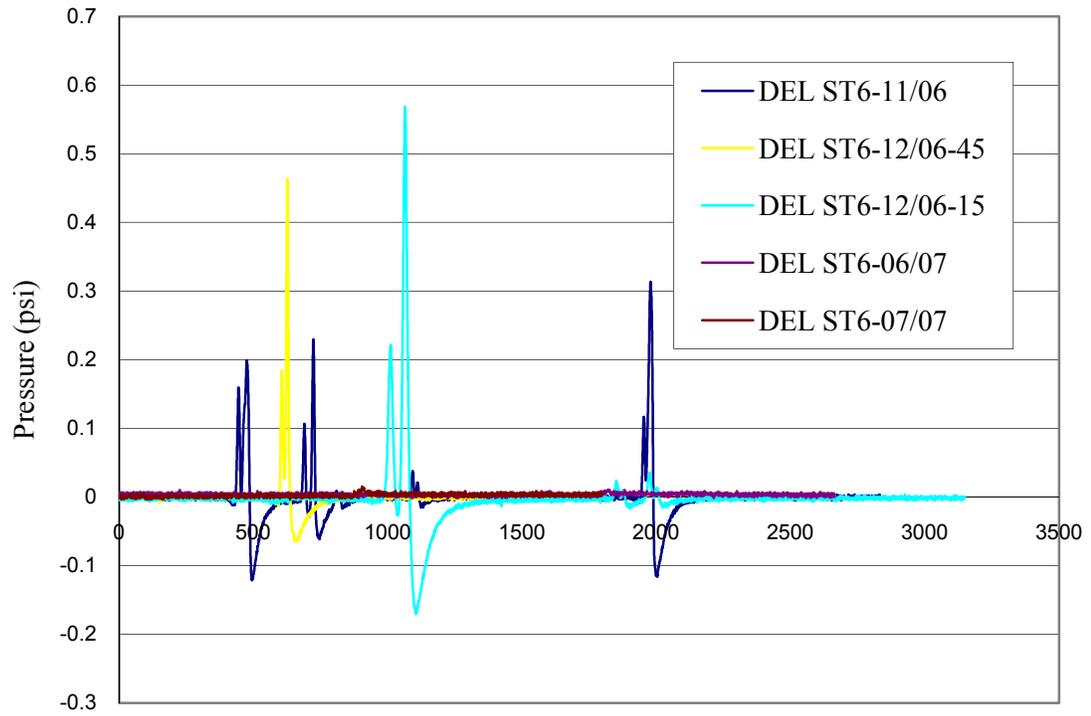
Figure 5.29 Dynamic Pore Water Pressure at Section Line Rd Station 6.

# 6 ADDITIONAL LABORATORY RESILIENT MODULUS TESTING

Laboratory tests were conducted on samples of the soils collected from the tensiometer installation locations at the WAY30, and MAD70 sites described in Section 4. As was typical of previous laboratory resilient modulus testing programs, Standard Proctor compaction, particle size analysis, Atterberg Limits, unconfined compressive strength and specific gravity tests were performed. Table 6.1 lists when and where the samples were collected and their respective soil types.

| Soil Type | Location | Sample Name | Date Collected |
|---|---|---|---|
| A-4 | WAY 30 Station 1 | W30ST1 | SUMMER 05 |
| A-4 | MAD 70 | MAD | SUMMER 05 |
| A-4 | WAY 30 Station 2 | W30ST2 | SPRING 06 |

Table 6.1 Sample Description and Location

Using the characterization protocol of earlier laboratory programs, all the samples were identified by location, moisture condition (dry, optimum or wet of optimum) and Sample #. For example: W30ST1WETS1, identified a sample from WAY 30 Station 1, compacted wet of optimum, sample #1.

6.1 Classification Tests

All tests were performed in accordance with the appropriate industry standards.

| Soil Type | | Sample Name | Liquid Limit | Plastic Limit | Plasticity Index | % Passing #200 | % of sand | % of silt | % of clay | $G_S$ |
|---|---|---|---|---|---|---|---|---|---|---|
| AASHTO | USCS | | | | | | | | | |
| A-4 | ML | W30ST1 | 25 | 23 | 2 | 61 | 20 | 54 | 7 | 2.75 |
| | CL | MAD | 26 | 17 | 9 | 62 | 29 | 48 | 15 | 2.76 |
| | CL-ML | W30ST2 | 26 | 20 | 6 | 59 | 24 | 51 | 8 | 2.74 |

Table 6.2 Classification and Engineering Properties

Table 6.3 presents the values for optimum moisture content and maximum dry density for each of the three soils.

| Soil Type | Sample Name | Optimum Moisture Content (%) | Maximum Dry Density (kg/m$^3$) |
|---|---|---|---|
| A-4 | W30ST1 | 14 | 1929 |
| | MAD | 13 | 1941 |
| | W30ST2 | 14.5 | 1918 |

Table 6.3 Optimum Moisture Content and Maximum Dry Density

6.2 Unconfined Compression Tests

Specimens were tested 24 hours after compaction to allow for uniform moisture content throughout the specimen. The UCS tests were performed on each soil sample at three different moisture contents: 2% dry of optimum (DRY), at optimum (OMC) and 2% wet of optimum (WET) (Table 6.4).

| Soil Type | Sample Location | OMC (%) | Max. Dry Density (g/cm$^3$) | Sample Number | Sample Moisture Content (%) | Sample Dry Density (g/cm$^3$) | $q_u$ (psi) | $q_u$ (kPa) |
|---|---|---|---|---|---|---|---|---|
| A-4 | WAY 30 Station 1 | 14 | 1.928 | DRY S3 | 11.27 | 1.91 | 103.8 | 715.74 |
| | | | | OMCS1 | 13.7 | 1.9 | 72.6 | 500.56 |
| | | | | WET S3 | 15.88 | 1.86 | 73.7 | 508.14 |
| A-4 | MAD70 | 13 | 1.941 | DRY S3 | 10.42 | 1.88 | 90 | 620.52 |
| | | | | OMCS2 | 12.29 | 1.94 | 77.64 | 535.30 |
| | | | | WET S6 | 15.37 | 1.88 | 27.15 | 187.19 |
| A-4 | WAY30 Station 2 | 14.5 | 1.918 | DRY S3 | 12.46 | 1.92 | 62.29 | 429.47 |
| | | | | OMCS1 | 14.35 | 1.89 | 43.9 | 302.68 |
| | | | | WET S2 | 16.29 | 1.81 | 27.23 | 187.74 |

Table 6.4 Unconfined Compressive Strength Test Results

## 6.3 Resilient Modulus Tests

The resilient modulus was determined in accordance with AASHTO T294-94 (Resilient Modulus of Unbound Granular Materials and Subgrade Soils- SHRP Protocol P46) testing procedure. At the beginning of the test, the sample was subjected to a preconditioning stage (1000 load cycles) followed by five steps (100 cycles each) with a confining pressure of 41, 21 and 0 kPa (6, 3 and 0 psi) for a total of 2500 cycles. As specified in the standard, the response to each load cycle was recorded. A plot of $M_R$ vs. deviator stress for each confining pressure was generated for each test. As illustration of the data, test results for WAY 30 Station 1 OMC S2 are presented in figure 6.4. Figures 6.5 through 6.13 show typical $M_R$ test results for WAY30 Station 1, MAD70 and WAY30 Station 2.
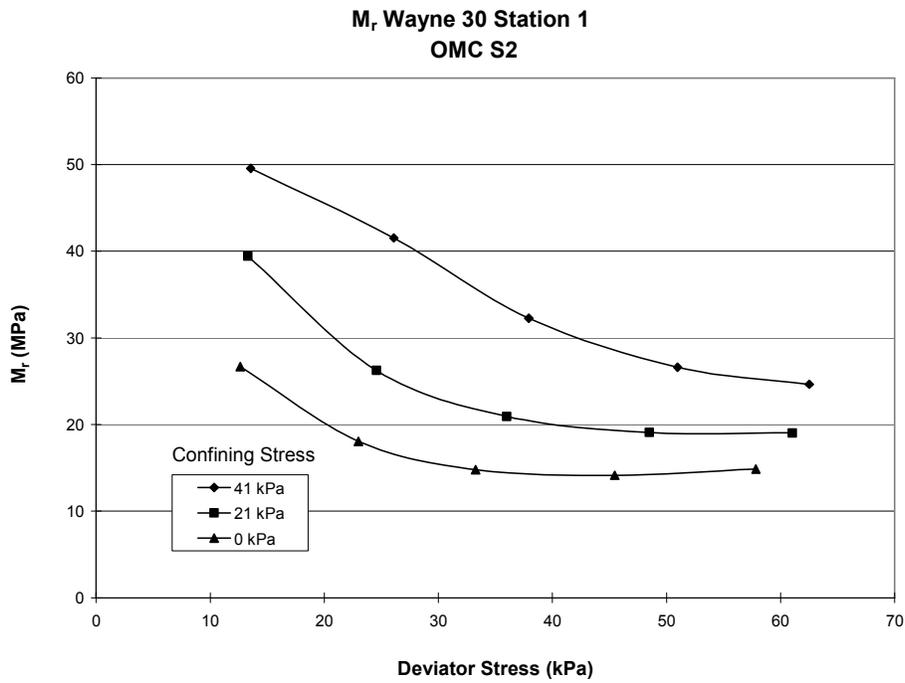


Figure 6.4 $M_R$ test results for W30ST1OMCS2

**M<sub>r</sub> Wayne 30 Station 1 at 41 kPa Confining Stress**
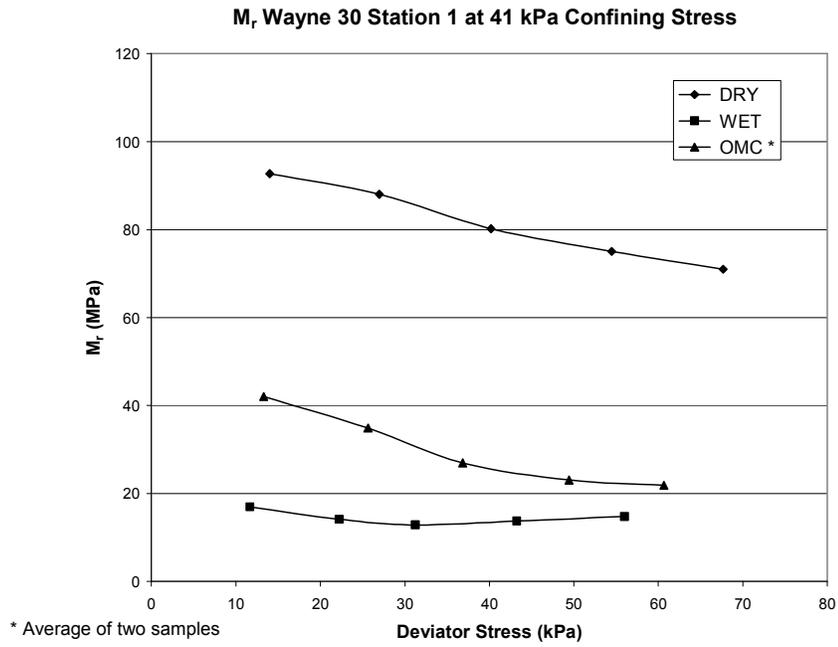


Figure 6.5 $M_R$ test results for WAY 30 Station 1 at 41 kPa Confining Stress

**M<sub>r</sub> Wayne 30 Station 1 at 21 kPa Confining Stress**
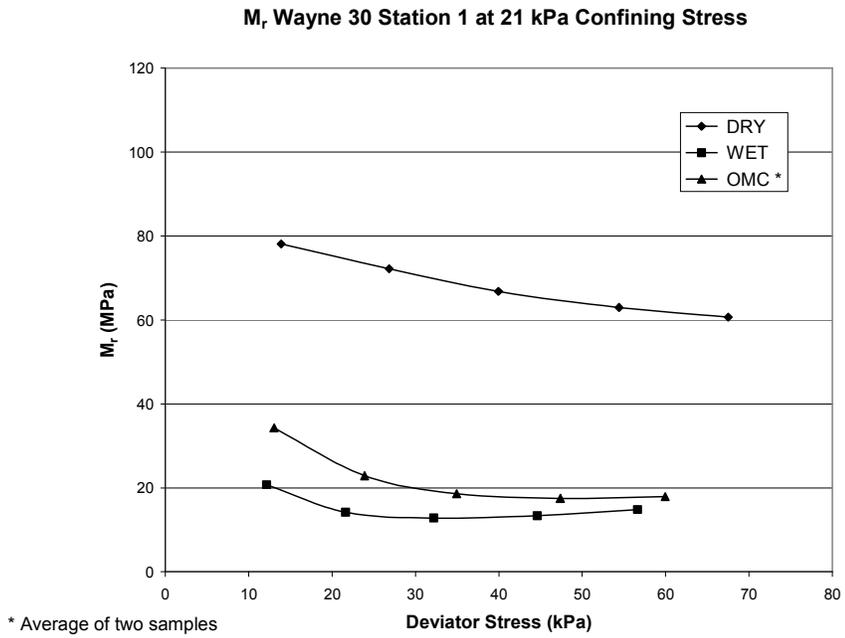


Figure 6.6 $M_R$ test results for WAY 30 Station 1 at 21 kPa Confining Stress

**M$_r$ Wayne 30 Station 1 at 0 kPa Confining Stress**



* Average of two samples
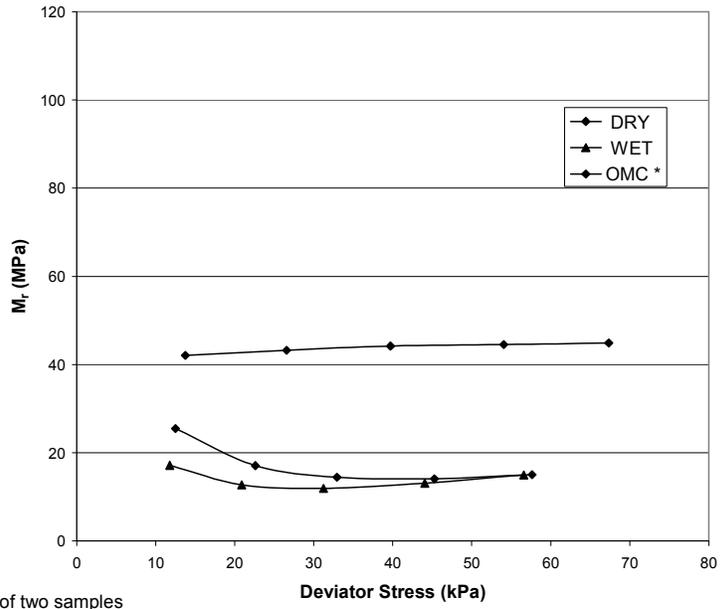
Figure 6.7 M$_R$ test results for WAY 30 Station 1 at 0 kPa Confining Stress

**M$_r$ Madison County at 21 Confining Stress**
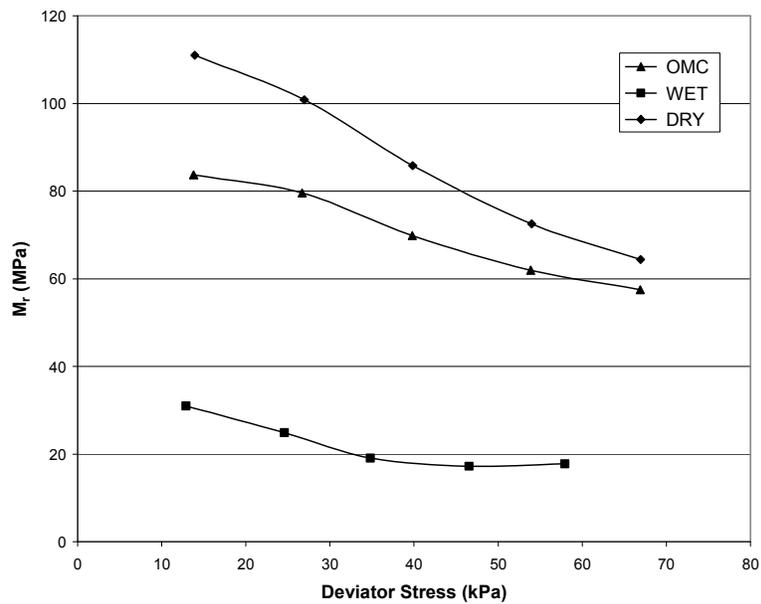


Figure 6.8 M$_R$ test results for MAD 70 at 41 kPa Confining Stress

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**M$_r$ Madison County at 21 kPa Confining Stress**
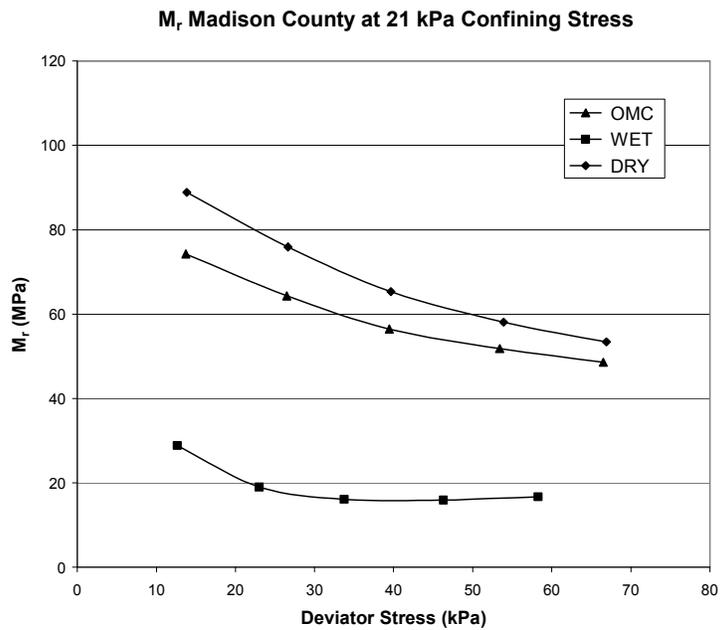


Figure 6.9 M$_R$ test results for MAD 70 at 21 kPa Confining Stress

**M$_r$ Madison County at 0 kPa Confining Stress**
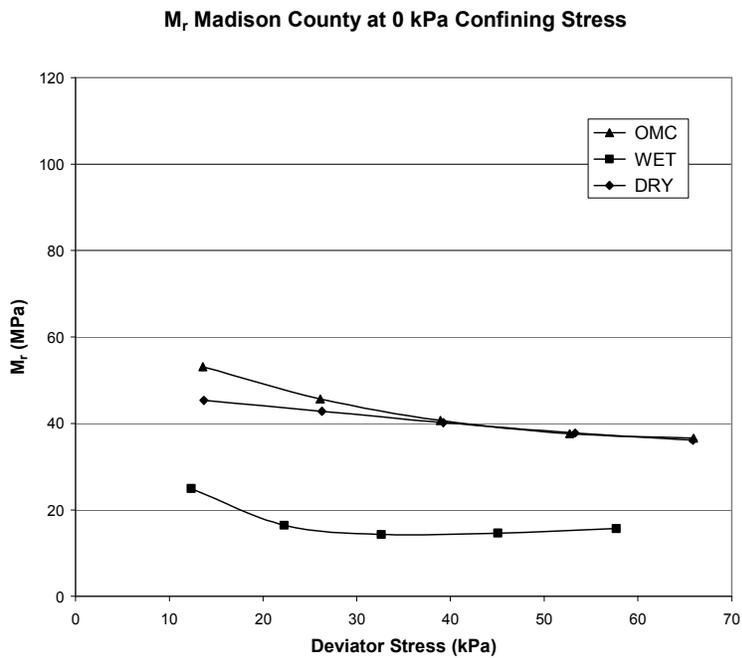


Figure 6.10 M$_R$ test results for MAD 70 at 0 kPa Confining Stress

**M$_r$ Wayne 30 Station 2 at 41 kPa Confining Stress**
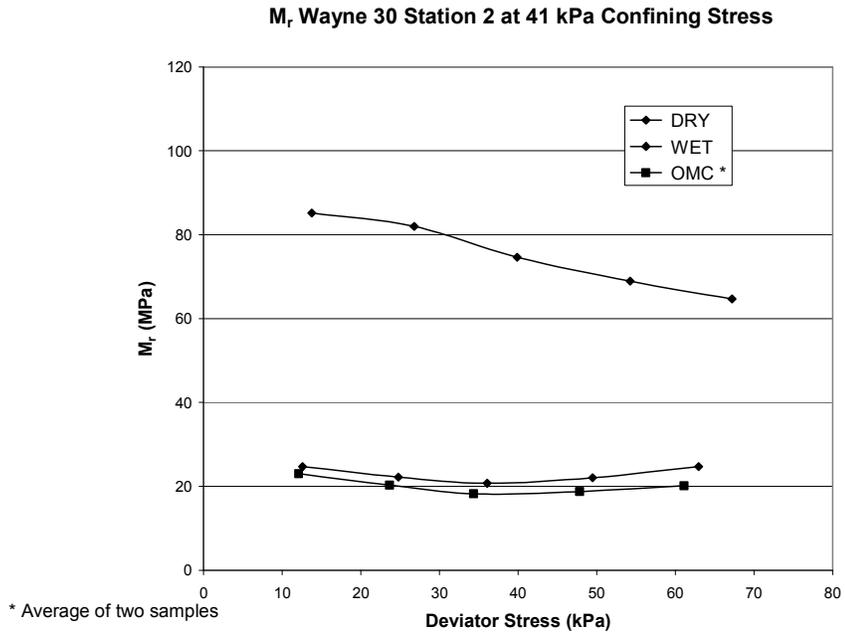


Figure 6.11 M$_R$ test results for WAY 30 Station 2 at 41 kPa Confining Stress

**M$_r$ Wayne 30 Station 2 at 21 kPa Confining Stress**
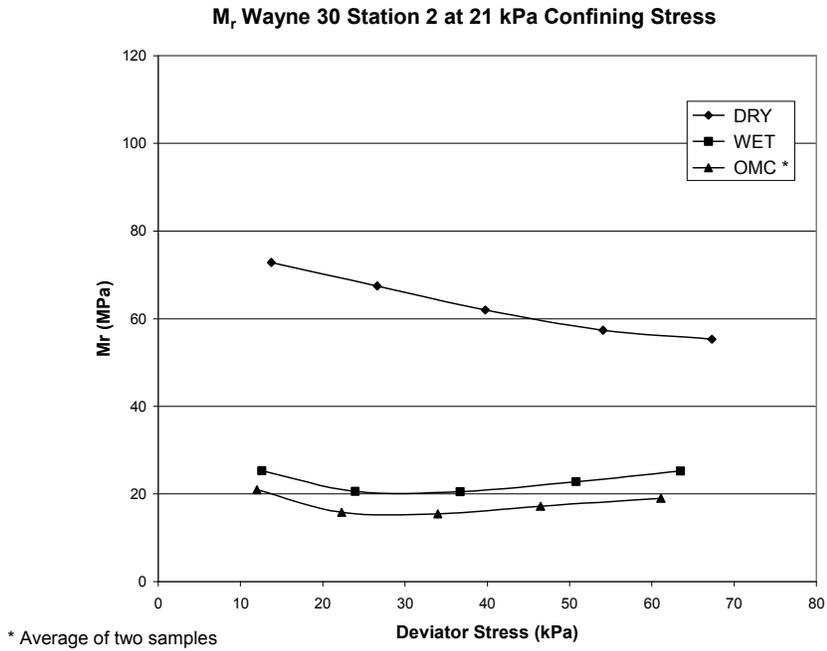


Figure 6.12 M$_R$ test results for WAY 30 Station 2 at 21 kPa Confining Stress

**M$_r$ Wayne 30 Station 2 at 0 kPa Confining Stres**

* Average of two samples
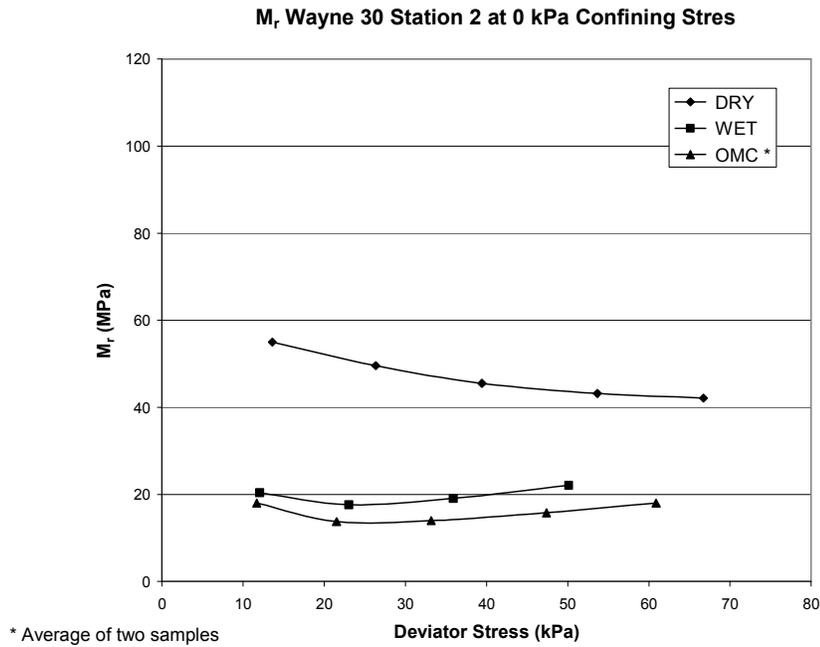
Figure 6.13 M$_R$ test results for WAY 30 Station 2 at 0 kPa Confining Stress

As shown in Figures 6.8 through 6.13, M$_R$ increased with an increase in confining stress. At constant confining stress, M$_R$ gradually decreased with increasing deviator stress. This trend was observed and has been reported by other researchers (e.g. Seed, et al. (1962), Fredlund, et al. (1977), Drumm, et al. (1990), Li and Selig (1994), Pezo and Hudson (1994), Lee et al. (1995), Mohammad, et al. (1999)) as well as being observed in the earlier OSU tests and described in our previous project reports.

The modulus generally decreased with increasing moisture content; however for WAY 30 Station 2 the curves, the measured values for M$_R$ at OMC and for M$_R$ at WET conditions were similar at zero confining stress. The measured modulus at the design optimum condition was lower than for the wet of optimum condition at 0 and 21 kPa confining stresses, highlighting the sensitivity of the modulus to slight variations in moisture content and density. Actual sample moisture contents and dry densities are shown in Table 6.5.

| Sample Location | Sample ID | $w$ target (%) | Max. Dry Density target (g/cm³) | $w$ actual (%) | Dry Density (g/cm³) |
|---|---|---|---|---|---|
| W30ST1 | DRY S2 | 12 | 1.89 | 12.64 | 1.92 |
| | OMC S2 | 14 | 1.928 | 14.93 | 1.86 |
| | OMC S3 | 14 | 1.928 | 14.92 | 1.9 |
| | WET S3 | 16 | 1.877 | 16.61 | 1.82 |
| MAD | DRY S2 | 11 | 1.886 | 11.94 | 1.92 |
| | OMC S1 | 13 | 1.941 | 12.86 | 1.93 |
| | WET S1 | 15 | 1.915 | 14.82 | 1.89 |
| W30ST2 | DRY S1 | 12.5 | 1.882 | 13.01 | 1.89 |
| | OMC S1 | 14.5 | 1.918 | 14.72 | 1.88 |
| | OMC S2 | 14.5 | 1.918 | 15.21 | 1.83 |
| | WET S1 | 16.5 | 1.82 | 15.51 | 1.82 |

Table 6.5 Design and Actual Soil Sample Moisture Contents and Dry Densities

6.4 Summary

Additional resilient modulus tests were performed on soil samples retrieved from three locations where field tensiometers were installed (Sections 4 and 5). General trends similar to those observed during earlier testing were observed.

# 7 RESILIENT MODULUS NEURAL NETWORK MODELS

The artificial neural networks developed in this research program were created using six principal parameters. The six values were: confining stress (kPa); deviator stress (kPa); unconfined compression stress (kPa); plasticity index, liquid limit, and the difference between actual sample water content (*w*) and the optimum moisture content (OMC). These parameters were identified in the extensive laboratory testing program (presented in detail in our previous reports) as having the most significant influence on the value of the resilient modulus. The program was trained until the neural networks were able to reproduce the resilient modulus vs. deviator stress laboratory curve and predict resilient modulus values within a small error (high correlation coefficient) for all three soil types (A-4, A-6 and A-7-6). Examples of comparisons between measured data and predicted values for the Resilient Modulus are presented in Figures 7.1 (A-4), 7.2 (A-6) and 7.3 (A-7-6) for the three soil types examined.
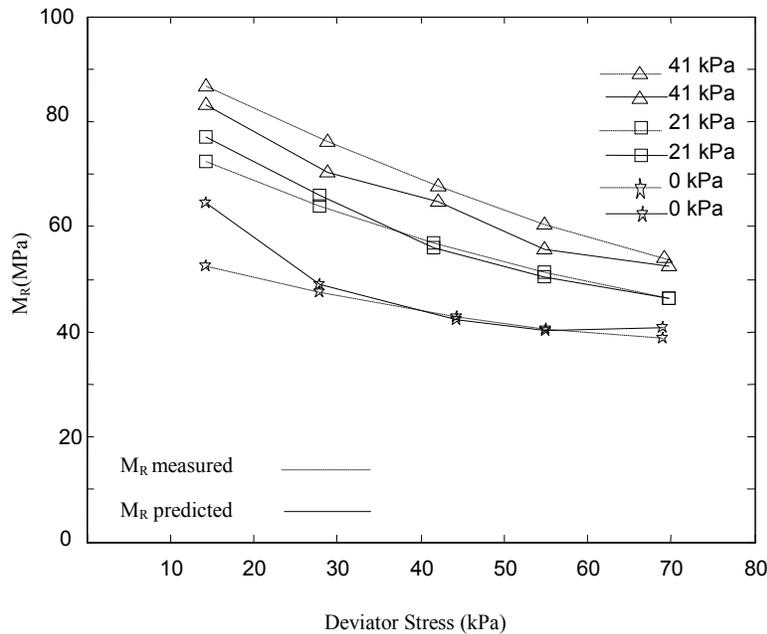


Figure 7.1 $M_R$ vs. Deviator Stress, A-6 Soil
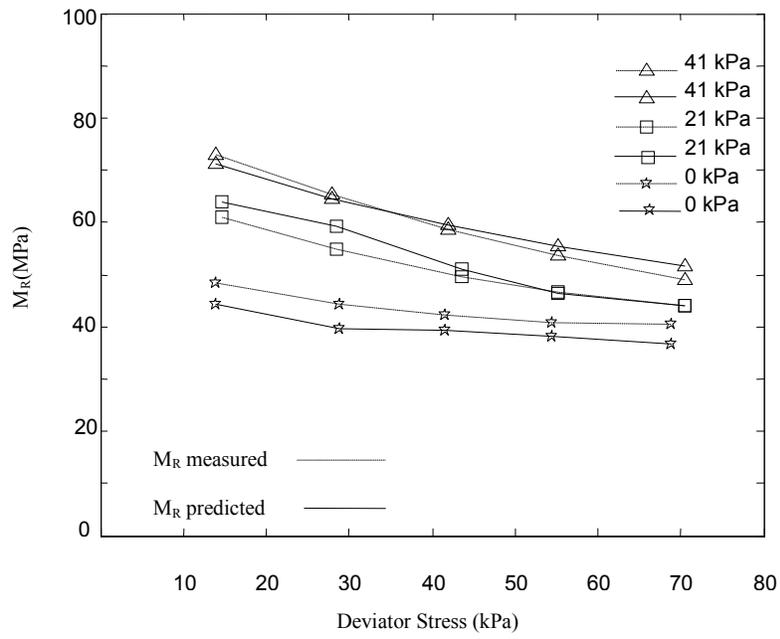
Figure 7.2 $M_R$ vs. Deviator Stress, A-4 Soil
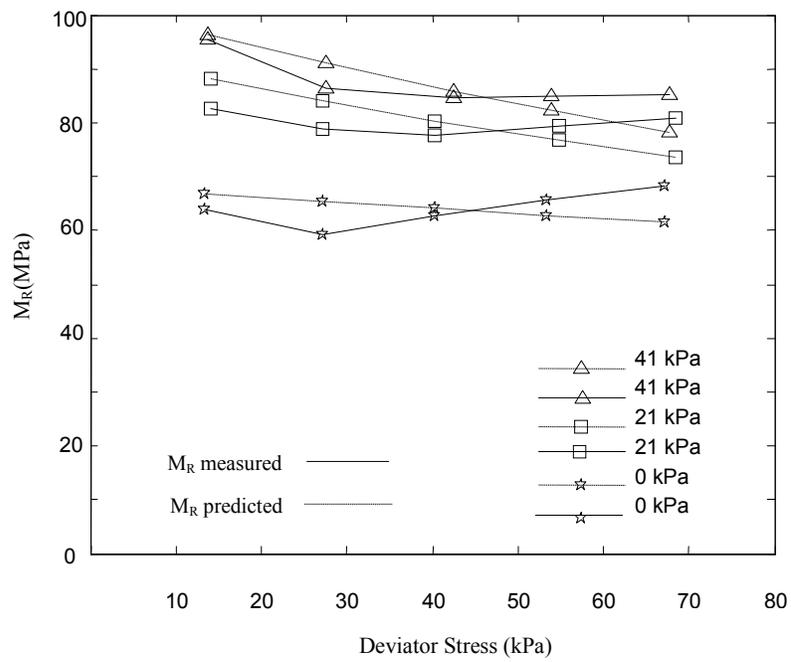


Figure 7.3 $M_R$ vs. Deviator Stress, A-7-6 Soil

Even the predictions of the A-7-6 soil moduli show quite good correlation with the observations in spite the fact that the A-7-6 data set was much smaller than were the A-4 and A-6 data files.

The present study improves on the correlations between the results of commonly used laboratory tests and the resilient modulus. Given that neural networks do identify patterns and associate input values with output target values, it can be used to estimate $M_R$ for samples that were not included in the training process. One of the most important advantages of neural networks is that they recognized the nonlinear behavior of $M_R$ with respect to its inputs and can without difficulty accommodate new data additions. Since only the Ohio soil samples were used to train the network, it is useful to evaluate the performance of the neural network model with soils that were not used in the training process. In the present study, tests conducted at the University of Mississippi and at Purdue University were evaluated.

As seen in Figure 7.4, the network is capable of successfully predicting the resilient modulus of Mississippi study soils accurately, with a correlation coefficient of 0.963.
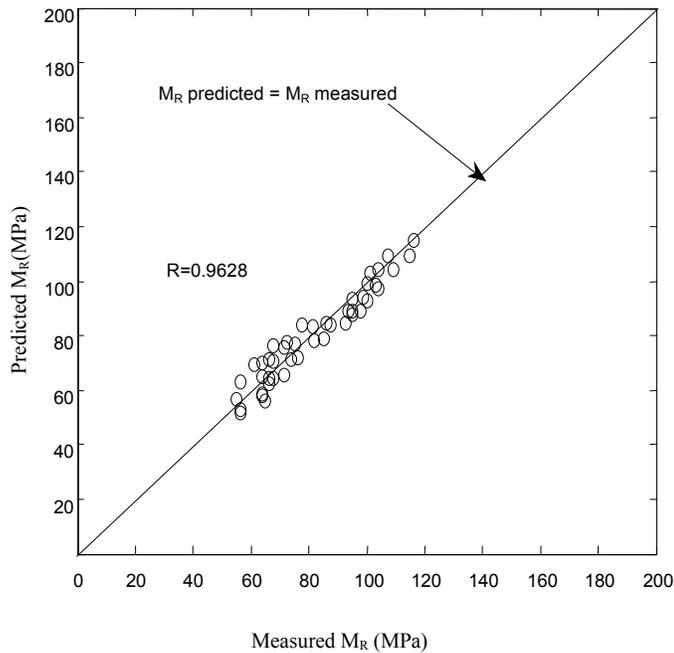


Figure 7.4 Predicted vs. Measured $M_R$ University of Mississippi Test Soils

Figure 7.5 shows the predictions for the Purdue study soils were not as accurately made. This inability to accurately predict the behavior of both the Mississippi and Purdue soils equally well points to the fact that $M_R$ is very sensitive to the differences in testing procedures and test equipment (Mohammad et al. (1994), Durham et al. (2003)). The Ohio and Mississippi soils were tested following the current T294-94 (SHRP Protocol P46) testing procedures, but in the case of the Purdue soils, the $M_R$ laboratory tests were performed using an earlier (AASHTO T274-82) procedure and a special compaction method design for the particular project.
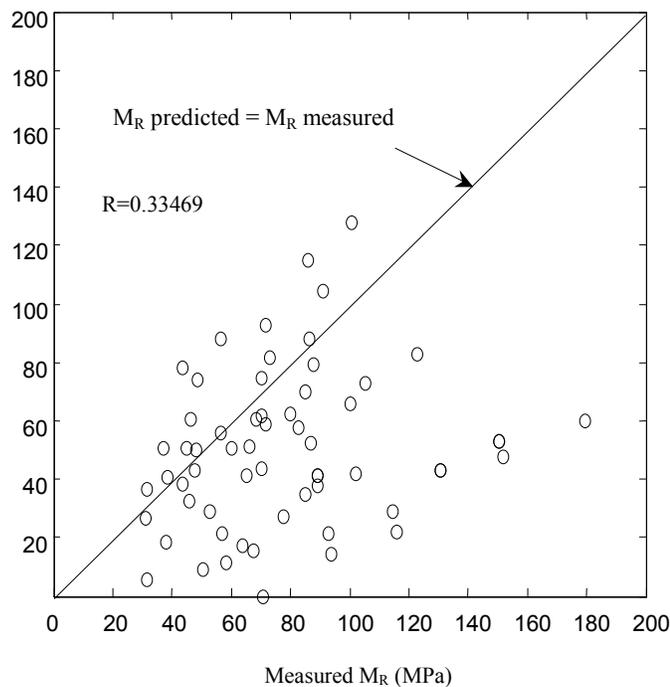


Figure 7.5 Predicted vs. Measured $M_R$ Purdue Test Soils

Clearly, consistent testing procedures and preparation are required for a reliable model of modulus behavior to be useful. The Neural Network method developed in this study is capable of predicting with high precision an appropriate value for the Resilient Modulus for different cohesive soils provided the soils are tested according to current standards.

## 8 RESILIENT MODULUS PREDICTION MODEL

### 8.1 Introduction

The goal of this study was to develop an interface package to be used for resilient modulus ($M_R$) prediction. In this section a numerical program developed according to the algorithms described in Section 4 is presented. Since some required input parameters may not be directly measured but can be calculated from other parameters, we designed a model capable of assisting the user in the development of the input data set required to execute the model. Figure 8.1 shows the input screen of the $M_R$ prediction model.

### 8.2 Input Command Controls for Data Entry

The topmost three input boxes (percent passing the #200 sieve ($P_{\#200}$), liquid limit (LL), plasticity index (PI)) are used to determine soil type. Alternatively, if these three inputs are unknown, soil type (A-4, A-6 or A-7-6) can be specified. The next two lower boxes accept data (Maximum Dry Density and % Optimum Moisture Content) from the Standard Proctor test. The next four boxes are application specific soil values (percent compaction, percent moisture content, soil unit weight, dry unit weight) that typically would be either measured or specified. Since not all these inputs are independent, the program is designed to calculate those values not specified, provided enough information to do so has been entered. Data from a specific gravity test should be entered if the test has been performed. However, since a direct measure of this parameter is typically made less commonly than the other inputs, the program will calculate the specific gravity ($G_s$), based on the other input values entered.

The range of values measured for each input parameter in the database during the extensive laboratory detailed in our 1998 and 2004 studies is given to the left of the corresponding input box. The reader should refer to those earlier reports and section 3 of this report for a list of materials studied and tests performed. Although a value outside the data range specified can be entered, the color of the input box will change to alert the user. The final inputs are the unconfined compressive strength, the design confining and deviator stresses. When all these inputs have been provided, a calculation of resilient modulus is made.

### 8.3 Additional Features and Functions

If the $P_{\#200}$, LL, and PI, data are provided, they can also be used to estimate the CBR based upon either ODOT or ME-PDG guidelines. The CBR results display in window screens as shown in Figures 8.2, 8.3 and 8.4. Figure 8.5 displays an estimate of

the graph used to determine the optimum moisture content and maximum density using a one point Proctor test. Figure 8.6 shows the page where the one point Proctor information is entered.

As stated previously, several neural networks were developed specifically to calculate the unconfined compressive strength from classification and compaction moisture and density tests. To predict a design value for the unconfined compression from the other inputs, the user should click on the "Estimate" button located beneath the $q_u$ input box. A range of values for $q_u$ will be returned. With all input information either entered or calculated, values for $M_R$ will be calculated when the "Predict Soil $M_R$" button is clicked. If any of the inputs were given as a range of values, a range of moduli consistent with the observed terms recorded in the database will be returned.
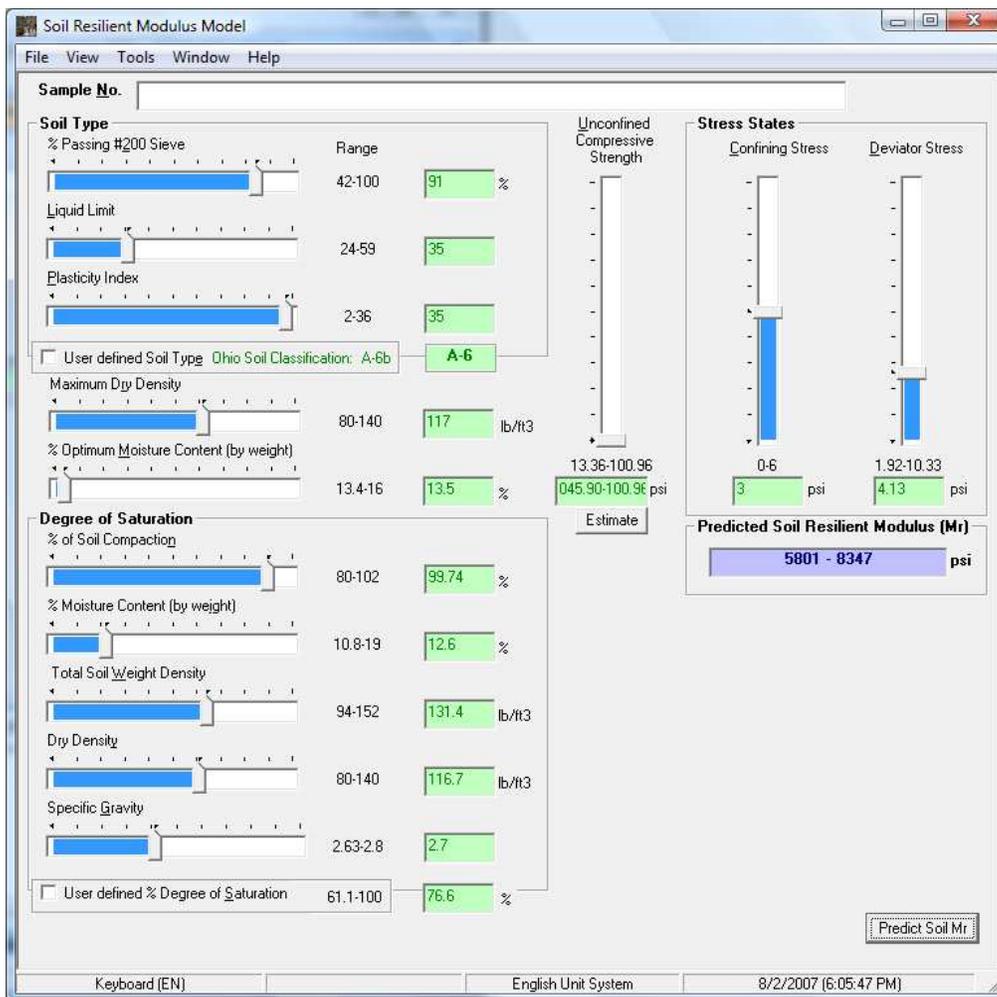


Figure 8.1 The main window screen for $M_R$ prediction
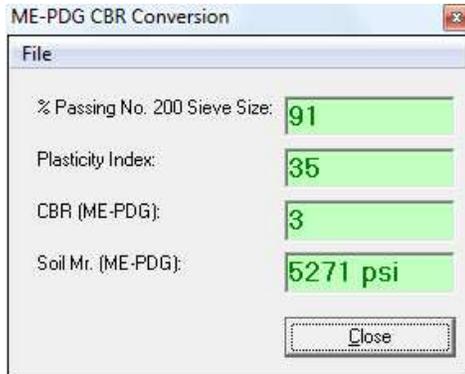
Figure 8.2 Window screen for CBR and $M_R$ prediction according to the ME-PDG model
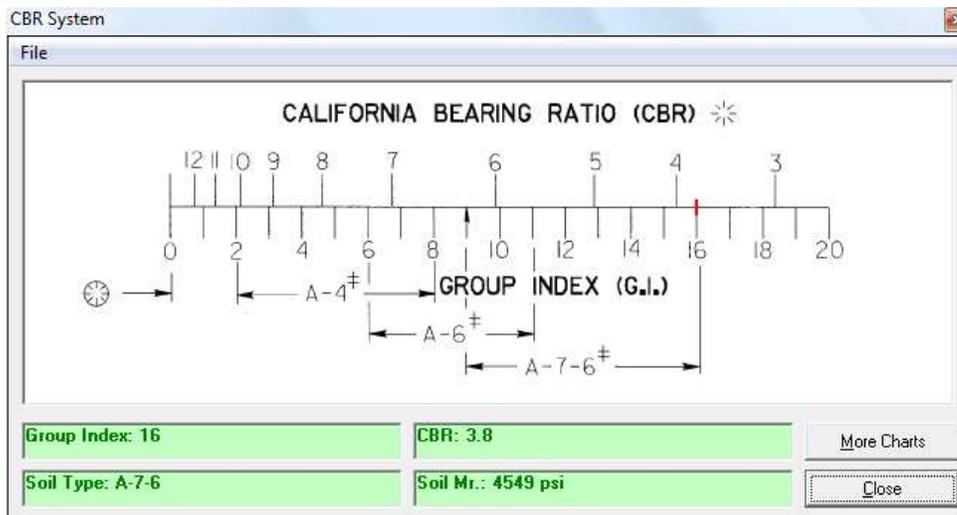


Figure 8.3 Window screen for CBR and $M_R$ prediction according to ODOT [ODOT, 1999]
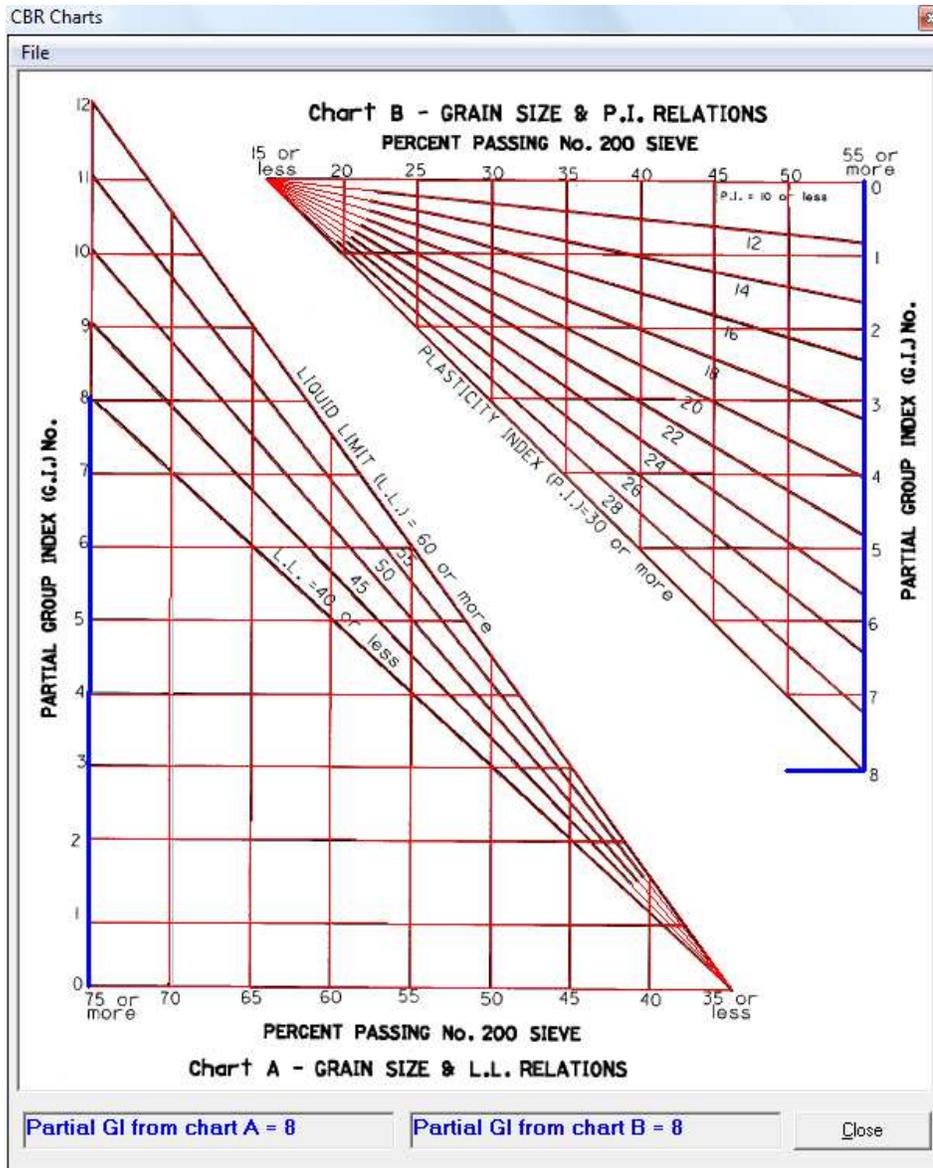
Figure 8.4 Charts to determine Group Index for Ohio soils from a CBR

WET DENSITY CURVES

TYPICAL
MOISTURE
DENSITY
CURVES
SET "C"
MAY, 1949

PREPARED BY THE OHIO
STATE HIGHWAY TESTING
AND RESEARCH LABORA-
TORY FROM RESULTS OF
TESTS ON 10,000 OHIO
SOIL SAMPLES

| CURVE | MAX. DRY WT. LBS. PER CU. FT. | OPTIMUM MOISTURE |
|---|---|---|
| A | 141.8 | 6.6 |
| B | 139.1 | 7.2 |
| C | 136.3 | 7.9 |
| D | 134.1 | 8.5 |
| E | 132.0 | 9.0 |
| F | 129.3 | 9.7 |
| G | 126.6 | 10.5 |
| H | 124.2 | 11.2 |
| I | 121.7 | 11.9 |
| J | 119.3 | 12.7 |
| K | 117.0 | 13.5 |
| L | 114.6 | 14.6 |
| M | 112.0 | 15.8 |
| N | 109.6 | 16.9 |
| O | 107.1 | 18.1 |
| P | 104.7 | 19.2 |
| Q | 102.4 | 20.3 |
| R | 99.9 | 21.5 |
| S | 97.4 | 22.7 |
| T | 94.6 | 24.4 |
| U | 92.1 | 25.8 |
| V | 89.9 | 27.4 |
| W | 87.5 | 29.5 |
| X | 85.0 | 30.5 |
| Y | 83.0 | 31.5 |
| Z | 81.1 | 32.5 |

134.7 lb/ft³

TOTAL WT. POUNDS PER CUBIC FOOT

WET
WEIGHT
CURVES

MOISTURE–PERCENT OF DRY WEIGHT

13.1%

Figure 8.5 Ohio Typical Soil Moisture vs. Density Family Curves
[ODOT, 2002]

Figure 8.6 Optimum moisture content using one point proctor testing
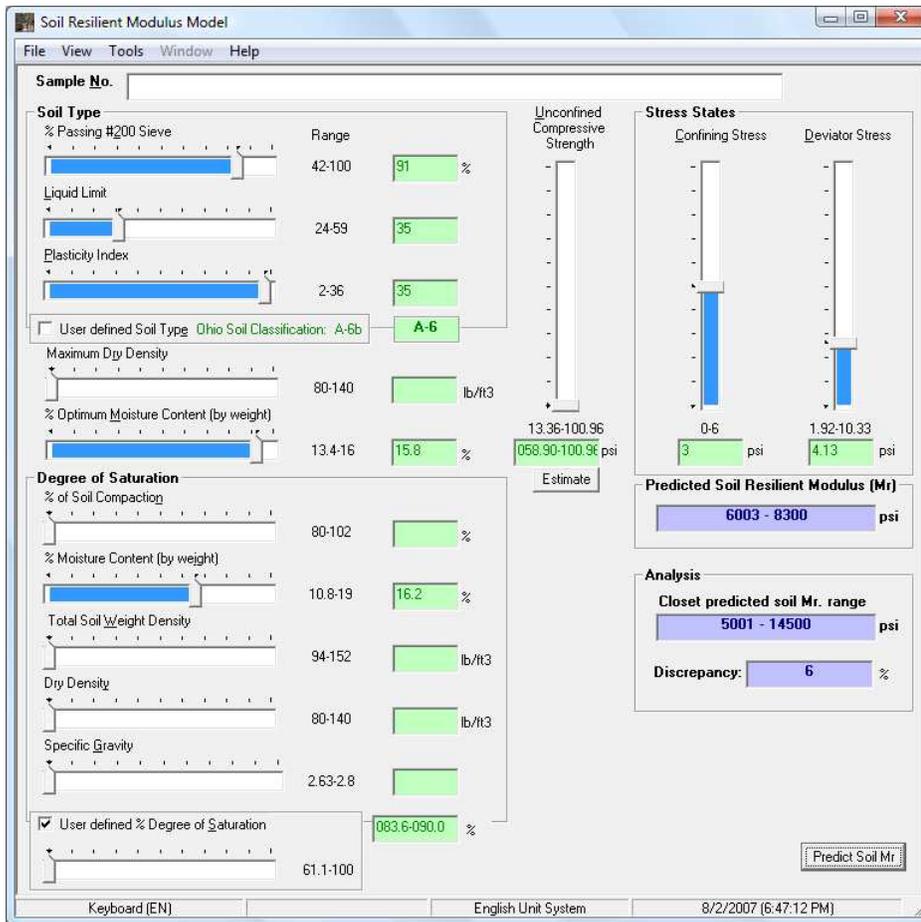
Figure 8.7 The main window screen with a predicted $M_R$ range

## 8.4 Summary

Three distinct research programs were performed and discussed in this report. Monitoring of the environmental instrumentation for the pavements at the DEL 23 LTPP research site begun in 1995 was completed. Measurement of volumetric water content (TDR) continued throughout the study period but temperature and frost depth data could only rarely be collected due to repeated failures of the sensors and/or collection systems.

A research program to monitor the location of the groundwater under highway pavements that began with three locations under the LTPP pavements and was extended to additional sections at the DEL 23 site and at other locations across the state was completed. The measurements taken over the duration of the project clearly showed that the soil under the pavement sections studied became saturated as the water tables rose. In most locations saturated conditions up to the base layer (none of the instruments were installed in the base so the maximum height of the water table could not be determined by direct measurement) within a year of construction. It is reasonable to conclude that saturated conditions typically exist for much of the life of the pavement.

In the third activity a model for predicting the resilient modulus from static soil properties was developed for compacted cohesive subgrade soils typical of those found in Ohio. A laboratory program designed to develop a database sufficient to establish relationships between dynamic soil behavior and static properties was conducted.

The development of the mathematical model is based on the implementation of artificial neural networks (ANNs). One advantage to using ANN algorithms for regression analysis is that they are flexible and based on mathematical applications without strict statistical boundaries. Once required input parameters and targeted parameters are determined and proper ANN algorithms are set, the algorithms are capable of handling complex problems. The ANNs developed in this study were incorporated with multilayer back-propagation (supervised learning) algorithms. Further exploration using different ANN algorithms with improved overall prediction and a better fit to the nature of the problems should be encouraged.

The database could be strengthened with additional test results. Although nearly 800 $M_R$ tests were performed, there are only about 80 soil samples in the database for predicting $q_u$. In addition, even though our field data show that saturated conditions can be expected in most pavement systems in Ohio, the number of tests performed on saturated samples is not sufficient to provide seasonal $M_R$ values for the ME-PDG model as required. The development of ANNs for soil property prediction with expediting algorithms capable of handling small data sets should be explored. Another possible approach would be to use artificial neural network algorithms to determine the 3 regression coefficients ($k_1$, $k_2$, and $k_3$) required in the input Level 1 of the ME-PDG model for $M_R$ prediction. The same ANN concept can be applied to aggregated or coarse-grained soils which are key materials for the base layers of pavement structure.

# 9 IMPLEMENTATION

Subsurface soil data collected at the DEL23 site over the duration of the current project, combined with the data from our two previous projects, have provided the environmental background information for researchers studying pavement performance at the Ohio LTPP site. Over the duration of the projects, much of the thermal and resistivity instrumentation failed but the devices recording the changing groundwater conditions continued to provide useful information for the full duration of the projects. The pore pressure instrumentation installed at the DEL23 and other sites across Ohio documented a significant rise in groundwater levels over time under virtually all monitored highway sections. Recognition that high water levels are typical under pavement sections throughout the state should impact the design of new and repaired pavements across Ohio. The method presented should replace current procedures for most A-4, A-6 and A-7-6 soils.

The numerical method presented in this report will calculate the resilient modulus of cohesive soils for use in pavement design based on the results of nearly 1000 laboratory dynamic resilient modulus tests. Because the data base behind the numerical methods employed in the model is so extensive, comparison of predicted moduli with laboratory measured values is very good even when only classification test results and static soil properties are used as inputs. Provided current ASTM standard procedures are followed, good agreement between measured and predicted moduli was maintained even for tests conducted by other agencies on soils with different geologic origin and from other parts of the country.

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11.1 APPENDIX A

RESILIENT MODULUS USERS GUIDE

Department of Civil and Environmental Engineering and Geodetic Science
The Ohio State University


Soil Resilient Modulus Determination, version: June 22, 2009


This is a program to estimate soil resilient modulus for three different cohesive soils
commonly found in Ohio: A-4, A-6, and A-7-6.


=====================================================================
Installation
1) On the installation package of this program, look for the "Setup.exe" file.
2) Double-click on the "Setup.exe" file and follow the installation process.


=====================================================================


Introduction
1) Go to the directory where you have installed this program
2) Double-click on the "Soil Resilient .exe" file to run the program

Data Entry

1) Enter the information in the active input boxes.
   **Sample No**.
       Here enter any identifying information you want to provide
   **Soil Type**
       *% Passing #200 Sieve*
       *Liquid Limit*
       *Plasticity Index*
       The program will determine which soil type the sample represents
       (Currently A-4, A-6, A-7-6 are the soil types that can be analyzed)
       Alternatively the user can enter one of the three modeled soil types
       directly from a pull down menu.
   **Proctor Test Results**
       *Optimum Moisture Content (%)*
       *Maximum Dry Density*

*Total Max Density*

Values are entered as Unit Weights. Either Maximum Dry Density or Total Max Density is calculated from the other value when the Optimum Moisture Content is known.

## Degree of Saturation

*% of Compaction*

Value of compaction either required or achieved, given as a percentage of Standard Proctor density as obtained in ASTM D698

*% Moisture Content*

Measured or required in-place soil moisture content

*Total Density*

Measured or required in-place total unit weight

*Dry Density*

Measured or required in-place dry unit weight

*Specific Gravity*

Degree of Saturation will be calculated or can be supplied as input. If supplied, other inputs in this section are disabled

## Unconfined Compressive Strength

The soil strength as measured in an unconfined compression test is entered here. Alternatively, the unconfined compressive strength can be estimated from the supplied data using the program database and the neural network algorithms developed for predicting modulus.

## Stress States

*Confining Stress*
*Deviator Stress*

Enter test specific boundary conditions.

When all input values have been supplied or estimated the resilient modulus can be calculated by pressing bottom right (Estimate Soil Mr) button.
If any required inputs are missing, pressing the Estimate Soil Mr Button will generate a prompt to continue with data entry

You may use the active scrollbars when they are provided if you prefer.

You can select the system of units. Control +E for English units or Control +I for SI units, or from the View tab, select Unit System then select English or International units.

Under the Tools menu  and compare it to the model  estimate as would be obtained from the use ME-PDG or Ohio CBR for the given input values.


=====Copy screen function
1) On any window screen, go to the "File" menu bar and choose
   the "Copy Current Screen" option (shutter sound will be provoked indicating
   that the transaction is completed, the current screen will be captured
   in a clipboard).
2) Go to a word processor window or picture editor window and paste the
   clipboard to your working window.


======Optimum Moisture Content Estimator
This feature allows users to use one point proctor test
to estimate an optimum soil moisture content
Once you develop your optimum moisture content, click on the "APPLY" button
to transfer the data to the main screen.


On the "Optimum Moisture Content Estimator" window,

 Method 1:
 1.1) Provide information about the total wet soil weight, moisture % of soil
      dry weight, and % maximum dry soil density.
 1.2) If the % maximum dry soil density is greater or equal to 10,
      specific gravity of material retained on 3/4" sieve is also required to
      adjust for gravel factors

 Method 2
 2.1) Double-click on the "Show Graphic" button
 2.2) On the Typical Moisture Density Curve Set "C" window,
      place your mouse pointer (a cross shape) within a graphic area
      to get coordinates
 2.3) Back to the "Optimum Moisture Content Estimator" window,
      If the % maximum dry soil density is greater or equal to 10,
      specific gravity of material retained on 3/4" sieve is also required to
      adjust for gravel factors.

Method 3

3.1) Choose the "User defined maximum dry soil density" option,

3.2) Provide information on the % maximum dry soil density and
the maximum dry soil density

3.3) If the % maximum dry soil density is greater or equal to 10,
specific gravity of material retained on 3/4" sieve is also required to
adjust for gravel factors

Method 4

4.1) Choose the "User defined moisture density curve" option,

4.2) Provide information on the % maximum dry soil density and
the moisture density curve no.

4.3) If the % maximum dry soil density is greater or equal to 10,
specific gravity of material retained on 3/4" sieve is also required to
adjust for gravel factors

=================================================================

Disclaimer:

This computer program was developed by Department of Civil and Environmental
Engineering and Geodetic Science, The Ohio State University.  This software has been
carefully tested on multiple systems at the University but may not work on every
computer.

The soil data used to develop this program did not include all possible soils that might be
encountered. Therefore the calculated values should not be used for specific purposes
without verification by a professional qualified to verify the applicability of such data or
information.

The University may not be held liable for any damages, direct or consequential, which
may result from the use of this program.