A Tool for Estimating Impact of Construction Quality on Life Cycle Performance of Pavements

Research Report 0-4046-4

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16. Abstract

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The implementation of an effective performance-based construction quality management requires a tool for determining impacts of construction quality on the life-cycle performance of pavements. This report present the final efforts in the development of a statistical-based algorithm that reconciles the results from several pavement performance models used in the state of practice with systematic process control techniques. Guidelines for the short- and long-term implementation of this methodology are included in this report.

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by

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ABSTRACT

Almost every constructed road develops distresses randomly in different subsections of the pavement. One reason for the random development of distress is the variability in construction quality. As such the goal in this project is to devise a tool that can be used to identify and minimize variability in material properties that impact the performance of the pavement to ensure a performance period compatible with the expected life of the pavement. With that framework, structural models that predict performance of pavements and material models that relate construction parameters to primary design parameters were identified. Finally, a statistical algorithm that relates the impact of each construction parameter to the performance of a pavement is incorporated into the algorithm.

The implementation of an effective performance-based construction quality management requires a tool for determining impacts of construction quality on the life-cycle performance of pavements. This report present the final efforts in the development of a statistical-based algorithm that reconciles the results from several pavement performance models used in the state of practice with systematic process control techniques. Guidelines for the short- and long-term implementation of this methodology are included in this report.

EXECUTIVE SUMMARY

The ability of a flexible or rigid pavement to perform adequately throughout its design life is one of the biggest challenges that transportation agencies face. One factor that has a large impact on the performance of a pavement is the quality of construction. The implementation of an effective performance-based construction quality management program is one way of ensuring that pavements are meeting their expected service life. As a part of that program a tool for determining impact of construction quality on life-cycle performance of pavements is required.

Ideally, if a pavement section is designed with the same cross section and constructed with the same materials, its performance should be uniform throughout the section. This is not the case in the real world. Almost every constructed road develops distresses randomly in different subsections of the pavement. One reason for the random development of distress is the variability in construction quality. As such the goal in this project is to devise a tool that can be used to identify and minimize variability in material properties that impact the performance of the pavement to ensure a performance period compatible with the expected life of the pavement. With that framework, structural models that predict performance of pavements and material models that relate construction parameters to primary design parameters were identified. Finally, a statistical algorithm that relates the impact of each construction parameter to the performance of a pavement is incorporated into the algorithm. Guidelines for the short- and long-term implementation of this methodology are included in this report.

IMPLEMENTATION STATEMENT

At this stage of the project the tools developed can be used for limited implementation. The software has undergone major changes to increase its flexibility and expand its ability to identify and minimize variability in material properties that impact the performance of the pavement to ensure a performance period compatible with the expected life of the pavement. The software is called Rational Estimation of Construction Impact on Pavement Performance (RECIPPE). It can be used to reconcile the results from existing pavement-performance models with statistical process control techniques and uncertainty analysis methods, to determine project-specific parameters that should be used in construction quality management. Several options for the implementation of the software are provided.

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CHAPTER ONE - INTRODUCTION

The quality of construction is a very important factor in the life-cycle performance of flexible pavements. This is particularly true of the individual characteristics of construction and their relative effect on life-cycle performance of the pavement. It is crucial to determine both what these characteristics are and, to what degree their variability from the desired value affects the life-cycle performance of pavements. Knowing this will enable the transportation agencies to apply its ever increasingly limited resources (inspection forces) in the most effective manner. Therefore, the goal of this research was to identify construction parameters that have the greatest effect on the life-cycle performance of the pavement. In the long term, the results of this research should enable TxDOT to write more effective performance-based specifications for construction of pavements and determine the cost effectiveness of innovations in construction practices. This research was carried out in three phases.

The first phase consisted of determining the characteristics of construction, which have a significant effect on the life-cycle performance of pavements, and whether these characteristics are observable and measurable.

The second phase consisted of the prediction of how the variability of these characteristics of construction affects the life-cycle performance of pavements by using mechanistic analysis. The mechanistic analysis should enable the engineers to predict the life-cycle performance of the pavement as the characteristics are varied.

The third phase consisted of field measurements to verify the predictions of the second phase. A list of characteristics of construction and the methodology to measure and analyze these characteristics available to TxDOT were developed.

The first two years of this project, which are documented in Research Report 0-4046-1 (Abdallah et al., 2004a) were focused on addressing the following items:

a) Information search on existing mechanistic models and ways that they can be used in developing an algorithm to relate the impact of construction parameters to performance was carried out. After a national search, several material models were identified, and feasible models were selected. Several popular and well-established performance-based models were also selected.

b) A probabilistic analysis tool was developed. The probabilistic approach differs from a deterministic approach by explicitly accounting for the variability of a parameter. A random parameter can take a range of values and can be represented by different types of probability distributions. The Monte Carlo simulation method, a common probabilistic method for simulating and accounting for the variability of a parameter, was used. Since many parameters are used in the analysis, the two-point mass method (TPM, Rosenblueth, 1981) was combined with the Monte Carlo method to accelerate the process. The TPM method can be used to approximate mean and standard deviation of random variables. The detail of both methods is provided in Chapter 2 of Report 0-4046-1 (Abdallah et al., 2004a).

c) Once the models were selected and the flow of probabilistic algorithm was defined, a prototype algorithm was developed. Figure 1.1 shows the general flow of information used in the mechanistic algorithm with the probabilistic methods. The detail and a case study of how to use the program were also provided in (Abdallah et al., 2004a).

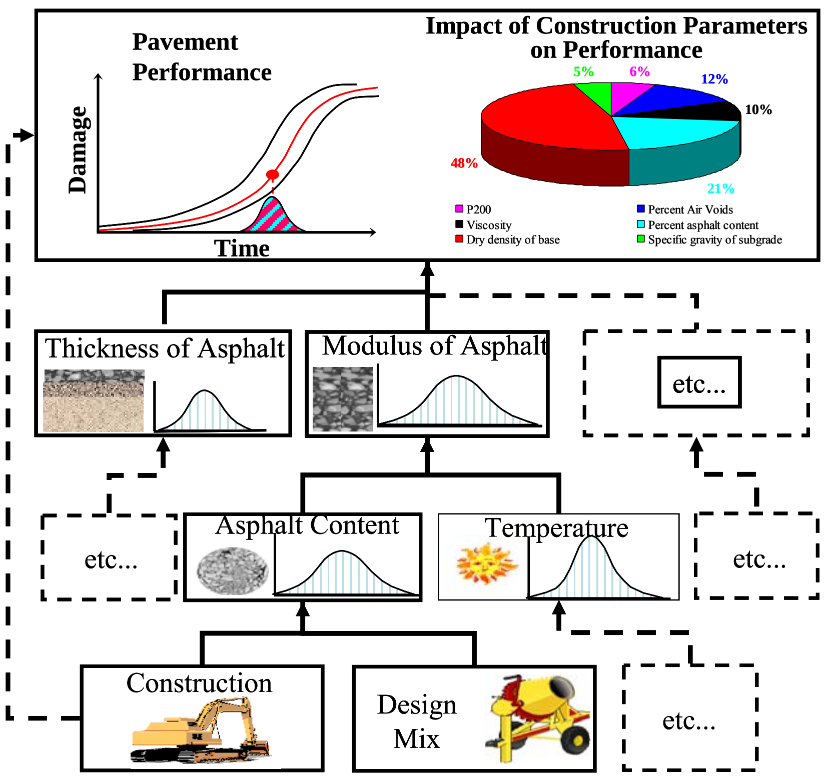


Figure 1.1 - Flowchart Depicting the Process of Utilizing A Probabilistic Approach in a Mechanistic Analysis

d) The mechanistic models selected provide a number of parameters that are used as a measure of construction practices. To optimize the process, a sensitivity analysis was conducted to primarily identify the relative importance of construction parameters on performance indicators. The results of this study, as presented in Abdallah et al. (2004a), provided an indication of important parameters for pavements with different traffic levels.

e) Based on results of the sensitivity study, a search to document methods on measuring important parameters was carried out. The document was embedded into software package RECIPPE. In that manner, the users can easily access the different ways to measure any given parameter. Another advantage of including the document into the program is that when new parameters are added, the document can be easily amended or updated. This document is included in Appendix A of Research Report 0-4046-2 (Abdallah et al, 2004b).

The third year of the research effort under this project focused on developing a document for validation using few of construction parameters and demonstrating the validation process using selected parameters. The details of these tasks were documented in Research Report 0-4046-2 (Abdallah et al, 2004b). The efforts are summarized below:

a) A validation of the algorithm to quantify the impact of construction parameters on performance is the initial step before being able to utilize RECIPPE with confidence. Three types of models make up the mechanistic algorithm developed: a) the material models, b) the structural models and c) the performance models. The material models were calibrated with information from existing databases and from field data collected at several sites in Texas. The structural and performance models incorporated into the algorithm are well-established. The structural model is based on a nonlinear model using equivalent linear algorithm. The equivalent linear model was developed under TXDOT Project 0-1780 (Ke et al., 2000, and Abdallah et al., 2003). The calibration and validation of these models are outside the scope of this project. Research Report 4046-2 (Abdallah et al, 2004b) provides the validation strategy to calibrate and validate the material models that are being incorporated into RECIPPE. The efforts in extracting data from the Long-Term Pavement Performance (LTPP) database for the asphalt-concrete (AC) layer material model were discussed. The protocol for targeting sites and collecting data for base and subgrade material models were presented. The calibration of the AC material model using data extracted from LTPP database for Texas sites was also presented in that report.

b) The probabilistic process to obtain the variability of performance based on the uncertainty in construction parameters using mechanistic analysis was also validated. Two techniques were used in the probabilistic process. The advantages and disadvantages of each technique and a comparison of their effect on producing the Impact Chart (a chart used to identify significant parameters) were documented in that report.

c) The calibration of the AC material model using data collected from Texas sites was performed in three different ways. The first method was based on least squares single variable calibration. The second equation was based on modifying the existing coefficients of the current Witczak equation. The final approach was to develop a new model using similar parameters used by the Witczak equation. Summary of the results are presented in Research Report 0-4046-2 (Abdallah et al, 2004b).

d) A case study showing a limited implementation of the validation process was also presented in Research Report 0-4046-2 (Abdallah et al, 2004b). The validation process is presented by demonstrating the impact variability of one construction variable on the variability of performance.

The fourth year of the research effort under this project focused on adjustments to be made to the prototype of RECIPPE to provide optimal results. This includes:

a) enhancing the reliability analysis process,
b) automating the optimization algorithm,
c) incorporating a sampling frequency algorithm (including control charts),
d) incorporating a cost allocation algorithm and
e) incorporating a cost allocation equation.

These efforts also included replacing the programming platform from MS Excel to Borland C++.

In the fourth year of the project, new material models were developed and the existing models were calibrated. Data from sites collected throughout the research efforts of this project and from databases of previous research such as 0-1336 were used to calibrate existing models or to develop new base and subgrade material models. The outcomes of the fourth year efforts of this project were documented in Research Report 0-4046-3 (Haggerty et al., 2005).

The remaining Tasks of this project are addressed in this report.

ORGRANIZATION OF REPORT

Chapter 2 provides background on the methodology that illustrates the use of construction parameter variability to estimate variability on pavement performance. Also included in Chapter 2 is the description of the methodology used in RECIPPE in pre-construction mode to identify significant impacting parameters on variability of pavement performance, and in post-construction mode, which provides inspectors with tool for quality control.

Chapter 3 focuses on presenting the models for pavement performance and focusing on the material models that were identified in the literature and that are incorporated into the software. The validation of material models developed and calibrated under this project is also presented. The last part of the chapter discusses the flexibility of RECIPPE to incorporate both new performance and material models.

Chapter 4 covers the strategy to utilize RECIPPE for quality management. Several scenarios are presented that illustrate the input level for RECIPPE and recommendation of which level in most suitable for analysis.

Finally, Chapter 5 contains the summary, conclusion and future recommendations for this project.

CHAPTER TWO - BACKGRAOUND

METHODOLOGY

The methodology developed under this project provides a link between construction and performance. Figure 2.1a provides a conceptual representation of the methodology starting from the center, or inner circle and moving to the outer circle. The three circles presented in the figure represent the main features in the methodology. The process starts from construction parameters, which is represented by the inner circle. These parameters are used to estimate the layer moduli via material models for the different layers of a pavement system. The material characteristic models, represented by the middle circle, are the links between the construction and pavement performance. Pavement performance is represented by the outer circle, which is based on the layer moduli and other pavement properties so that the pavement system performance can be determined.

In Figure 2.1b the process is further clarified. The core of this methodology is based on mechanistic analysis. The structural model is based on a nonlinear model using equivalent-linear algorithm. The equivalent-linear model was developed under TXDOT Project 0-1780 (Ke et al. 2000, and Abdallah et al., 2003). The structural model, designated as *(1)* in Figure 2.1b serves as the engine that performs all numerical calculations such as determining the nonlinear layer moduli and appropriate stresses and strains in the pavement analysis process. The next process illustrates the link of the inner circle and the middle circle *(2)*. Construction parameters are used in material models to determine the moduli of the layers. For example, the modulus of ACP is estimated using a model that incorporates as input construction parameters such as air voids, asphalt content, asphalt viscosity, etc. The last step illustrated in the process shows the link between the middle circle, material models, and the outer circle, performance models *(3)*. This step depicts the process of estimating the critical strains based on the layer properties (thickness, modulus, etc…) to determine performance of the pavement using the structural model. The process described thus far allows the estimation of pavement performance based on construction parameters. As such, this analysis only represents a deterministic analysis. The uncertainties that are associated with the input parameters are not accounted for. However, engineering measurement associated with a construction parameter demonstrates a certain variation. Therefore, a probabilistic approach is a more rational approach and was incorporated into the process.

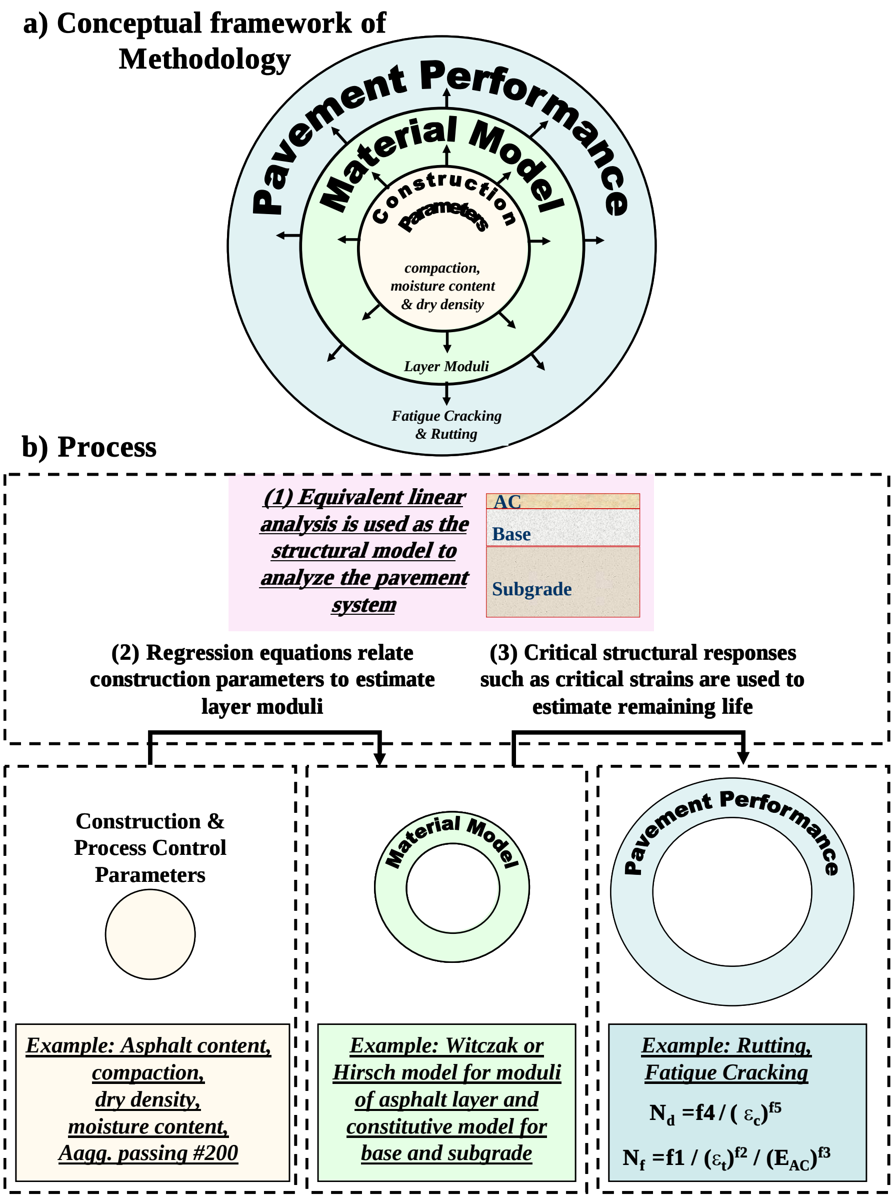


Figure 2.1 - Conceptual Framework of Methodology and Process for Determining Pavement Performance from Construction Parameters

Probabilistic Approach and Generation of Impact Chart

In this research project, for practical consideration, all input parameters are assumed to be normally distributed. Once variability of input parameters is incorporated into the system, performance outputs will also retain variability. By accounting for variability in the analysis, the impact of construction variability on the variability of pavement performance is determined. This impact is estimated using an "impact chart". The impact chart compares the influence of each construction parameter on the remaining life. The probabilistic analysis employed in this project is based on two methods: 1) Monte Carlo Simulation and 2) Two Point Mass (TPM) Simulation.

Monte Carlo simulations technique randomly generates values to represent variables with uncertainty. For this case, the construction parameters are randomly created multiple times to simulate a continuous model. Similarly, the TPM simulation is used to approximate low-order moments of functions (e.g., mean and coefficient of variation, COV) for construction parameters (Rosenblueth, 1981). This is achieved by replacing continuously randomly-generated values with two discrete values.

The major difference between the Monte Carlo and TPM simulations is the number of iterations it takes to complete a simulation. With a Monte Carlo simulation, 500 simulations are considered adequate enough to model a normal distribution in this study (Abdallah et al., 2004a), while the number of iterations for TPM varies with the number of random variables represented by:

$$\text{Iterations}_{\text{TPM}} = 2^{\,Number\ of\ Random\,Variables} \tag{2.1}$$

For the algorithm developed in this research, two types of statistical analyzes are performed: 1) varying values for a single construction parameter and 2) varying all parameters at once. Figure 2.2 illustrates the concept of the simulation process. Any input parameter is described with a normal distribution represented by a mean and a coefficient of variation (COV). As illustrated in part one of Figure 2.2, each parameter is simulated individually and is processed through the system to determine its impact on the variation of pavement performance. This process is repeated for each parameter, and as such, for each construction parameter, the impact of that parameter can be determined.

The impact of each parameter does not account for the joint effect of all parameters impacting performance. Therefore, processing of all input parameters simultaneously through the system is required (the second part illustrated in Figure 2.2). The program developed in this project uses Monte Carlo simulation and TPM simulations in unison. The TPM simulations can be used to calculate the variance of the remaining life when one parameter is varied, and the Monte Carlo simulations can be used when all of the construction parameters are varied together.

The last part of the figure depicts the use of the impact values to develop the impact chart. To prioritize the significance of different construction parameters relative to one another, the approach described next is followed. When the simulation is carried out for a single construction parameter, it is possible to create pie charts showing how each parameter impacts the variability of a performance model with respect to the other construction parameters. The values that are entered into the pie charts are called normalized impact values, shown in Equation 2.2:

$$\mathbf{NIV_i} = \frac{\mathbf{COV_i}}{\sum_{i=1}^{n} \mathbf{COV_i}} \tag{2.2}$$

where *NIV* is the normalized impact value for construction parameter *i* and the COV_i is the coefficient of variation of the pavement performance model for construction parameter *i*. By

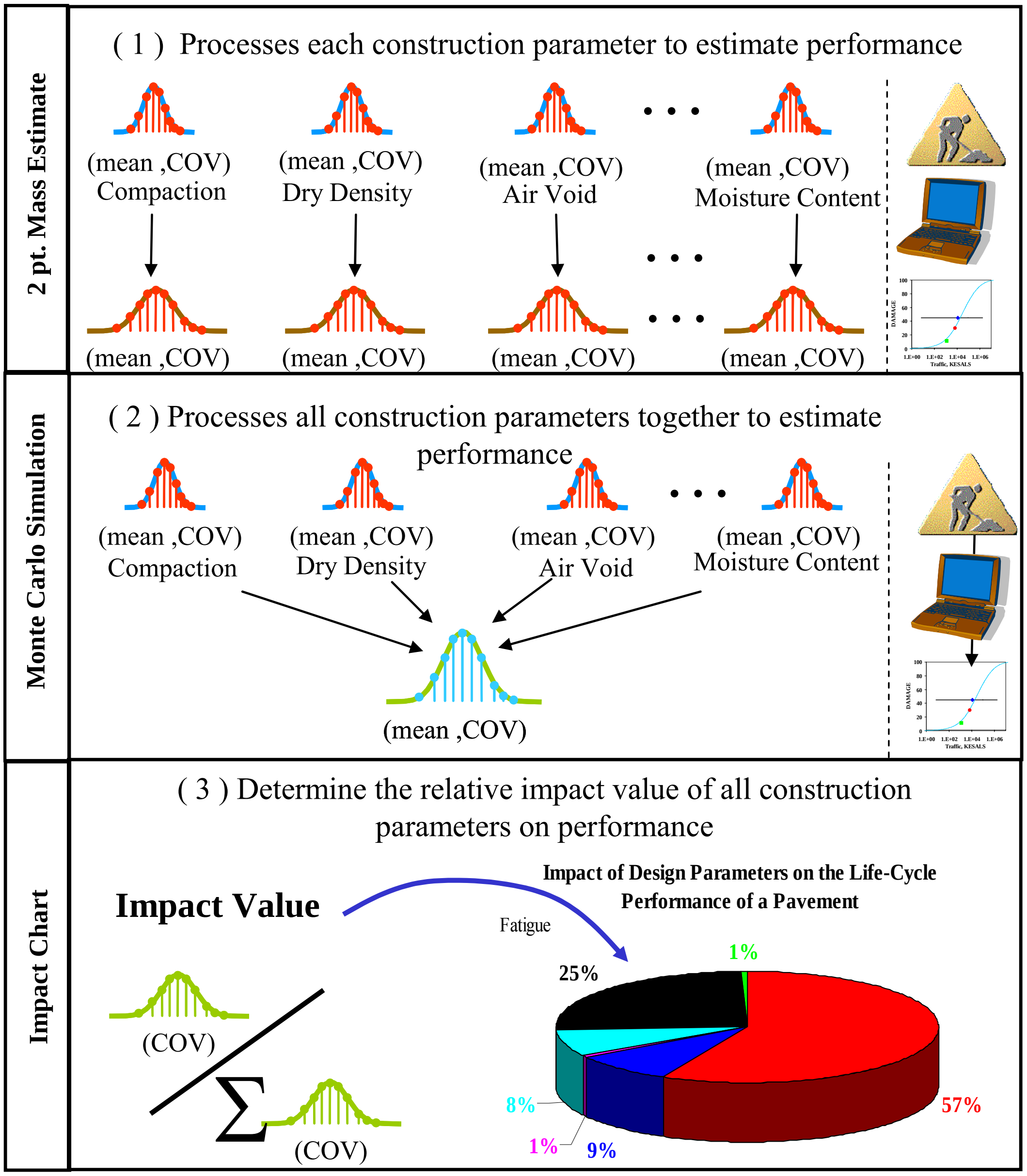


Figure 2.2 - Probabilistic Analysis Process used in Developing the Impact Chart

placing all of the *NIV*s in a pie chart, an impact chart can be created to identify significant construction parameters. The figure in the last part of Figure 2.2 is a representation of an impact chart, where each parameter is represented by an impact value. Parameters with large impact values indicate significant parameters and should be focused on in controlling performance. However, parameters with very low impact values indicate no significance, and resources for controlling variability should be focused elsewhere. If one is interested in changing the mean and COV of the performance indicator associated with these parameters, she/he should focus on reducing the COV for those parameters with significant impact values, therefore reducing performance variance.

Pre-Construction Process - Optimization Process to Identify Significant Parameters

The process presented thus far illustrates the procedure to determine the impact of construction variability on the variability of performance using the impact chart. The next step is to demonstrate the optimization process in the program.

Figure 2.3 illustrates the use of the impact chart to identify significant parameters through an optimization process. Initially, input information, as shown in Figure 2.3, is based on the mean and variance of each construction constituent found either in historical data or required specifications. These constituents are then simulated in the statistics-based algorithm by varying the inputs according to a normal distribution and using the simulated values in material models to estimate layer moduli. The results from the material models are then used to estimate pavement performance. The output is the pavement performance based on the input values and the performance variance based on the variability of the input. If the simulated pavement life meets the design specifications, the algorithm terminates and significant impact values are identified from the impact chart, and provided to those involved in the construction and inspection. If the variability in the performance is larger than specified, the COV values for parameters that are identified as significant are reduced, and the analysis is repeated. This process continues until the pavement performance specifications are met. The program provides means to adjust the number of significant parameters that are reduced, the increment of reduced variability after each iteration, and constraint of the minimum value of variability. The process is the pre-construction phase of this program. The next phase is post-construction.

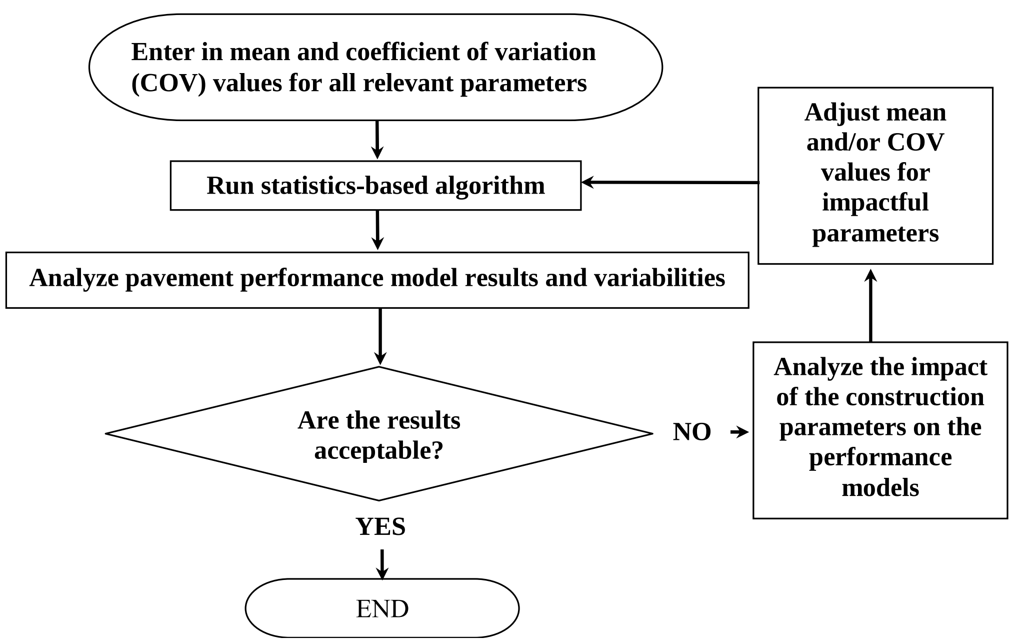


Figure 2.3 - General Flow of Optimization Process

Post-Construction Process - Quality Control Process

In pre-construction, the optimization process identifies the significant parameters for inspectors to focus on. Along with identifying significant parameters, the number of necessary samples for each parameter is determined based on the optimization process.

Number of Samples and Sampling Frequencies

The process of developing the number of samples based on the COV of each parameter is thoroughly documented in Research Report 0-4046-3 (Haggerty et al., 2005). Equation 2.3 represents the sample size equation used in the program.

$$n = \left(\frac{\left(Z_\alpha + Z_\beta\right) \times COV}{e} \right)^2 \tag{2.3}$$

where n is the sample size, e represents the tolerable error or tolerance, COV represents the coefficient of variation for an individual construction parameter, Z_α defines the normalized standard deviation value based upon the level of significant (α), and Z_β defines the normalized standard deviation value based upon the level of significant (β) found as the standard deviation divided by the mean.

For the purpose of this report, α and β are related to confidence level of the seller (contractor) and buyer (TxDOT), respectively. Zhang et al. (2001) presents definitions of those parameters as follows:

- Seller's Risk (α): The risk of rejecting "good" material. In highway construction this is associated with the risk of a contractor having good material rejected by the owner.
- Buyer's Risk (β): The risk of accepting "bad" material at reduced or full payment. In highway construction, this risk is associated with the owner's risk of accepting what is actually bad material.

The α-risk affects the contractor because it is probable that the agency may reject, what is in fact, acceptable work. The β-risk affects the agency because it is probable that the agency may accept, what is in fact, unacceptable work. The true meaning of risk is how much one is willing to lose in terms of dollars if an action is taken.

After determining the sample size, the testing frequencies can be determined. Zhang et al. (2001) shows example of two ways of determining testing frequency:

a) *Time-based testing frequency:* TF = daily production / sample size
b) *Quantity-based testing frequency:* TF = batch quantity / sample size

Once the testing frequency is determined, control charts can be used to provide quality control by the inspector.

Control Charts

Control chart is one way of conducting inspection. Control charts help identify instability and unusual circumstances in production processes. This implies that, based upon allowable variances, inspectors can randomly sample road specimens and determine whether or not the pavement, statistically, will be stable over time (in-control or out-of-control, respectively).

To assist in monitoring the important parameters during construction, the program provides control charts (CC) for the mean and COV of a specified parameter. The CC based on the mean has three limits: a) the center line (CL) defined by the mean and b) upper and lower control limits (UCL, LCL) defined by one deviation from the mean. The CC for the COV shows the trend of the QC variability with respect to the allowable COV value specified in preconstruction. Research Report 0-4046-3 (Haggerty et al., 2005) depicts the development, rules and examples of using control charts.

Cost Analysis

With the information that has been described, thus far, a quantitative value can be provided for inspection costs, which will be discussed in this section. Production expenditures, due to rehabilitation and maintenance, are intuitively calculated in a qualitative manner, because the basic concept of the program is to minimize variability thereby increasing the longevity of pavement.

The program estimates the minimum number of tests to be run for inspecting a single parameter. Hence, for each test run there is a corresponding cost, which can be related as a unit price (i.e. $10.00/Nuclear Density Gauge). If the unit price is known for each test to be run, then the total inspection costs can be found using a simple mathematical operation:

$$TotalCost_{inspection} = \sum_{i=1}^{m} C_i n_i \tag{2.4}$$

where C_i is the unit price for parameter i and n_i is the sample size for parameter i. Typical costs for some parameters of ACP, base and subgrade layers in Texas are shown in Table 1. These costs are estimated for the entire state of Texas. The program can modify this program if necessary.

Table 2.1 - Typical Inspection Tests & Costs for Texas Pavements

STANDARD		TEST	Unit	STATEWIDE AVG.		2 Year Avg.
				FY 2002	FY 2003	
Tex	103	Moisture Content	each	\$6.00	\$27.00	\$16.50
Tex	106	Plasticity Index	each	\$33.75	\$71.00	\$52.38
Tex	110, Pt1	Gradation	each	\$32.50	\$60.00	\$46.25
Tex	110, Pt2	Gradation	each	-	\$150.00	\$150.00
Tex	113	M-D Curve for Base	each	\$162.50	\$330.00	\$246.25
Tex	114	M-D Curve for Base	each	\$155.00	\$330.00	\$242.50
Tex	115	Nuclear Density	hour	\$31.50	\$37.50	\$34.50
Tex	116	Wet Ball	each	\$135.00	\$200.00	\$167.50

CHAPTER THREE - VALIDATION OF METHODOLOGY

The methodology developed to quantify the impact of construction parameters on performance needed to be validated. Since several algorithms encompass the methodology, several types of validation processes were carried out. The objective of the validating a process is to identify its effectiveness.

The sensitivity analyses, using the algorithms developed in this project, demonstrated the types of trends one can expect from the impact of the construction parameters on performance. These analyses were carried out by varying the COV of each parameter, and then computing the level of variability of performance indicators. In that manner, the relative sensitivity of construction parameters could be determined. The level of sensitivity or impact of parameters is detailed in the Research Report 0-4046-1 (Abdallah et al., 2004a).

PERFORMANCE MODELS

The three performance models investigated in the study were:

1) Permanent deformation in the ACP layer (Finn et al., 1984):

   ACP layers that are less than 6 in. thick

$$\log RR = -5.617 + 4.343 \log w_0 - 0.167 \log(N_{18}) - 1.118 \log \sigma_c \qquad (3.1)$$

   ACP layers equal to or greater than 6 in. in thickness:

$$\log RR = -1.173 + 0.717 \log w_0 - 0.658 \log(N_{18}) + 0.666 \log \sigma_c \qquad (3.2)$$

   where RR is the rate of rutting in micro-inches (1 μin. =10^{-6} in.) per axle load repetition, w_o is the surface deflection in mil (1 mil=10^{-3} in.), σ_c is the vertical compressive stress within the AC layer in psi, and N_{18} is the equivalent 18-kip single-axle load in 10^5 ESALS.

2) Permanent deformation in the subgrade (Huang, 1993):

$$N_d = f_4(\varepsilon_c)^{-f_5} \qquad (3.3)$$

   where N_d is the allowable number of load repetitions to prevent rutting, ε_c is the compressive strain at the top of subgrade and parameters f_4 and f_5 are design constants.

3) Pavement failure as a result of fatigue cracking (Huang, 1993):

$$N_f = f_1(\varepsilon_t)^{-f_2}(E_{ACP})^{-f_3} \tag{3.4}$$

where N_f is the allowable number of load repetitions to prevent fatigue cracking, ε_t is the tensile strain at the bottom of the ACP layer, E_{ACP} is the elastic modulus of asphalt-concrete layer (in psi), and parameters f_1 through f_3 are design constants.

Table 3.1 provide a list of coefficients for performance models in Equations 3.3 and 3.4. These models can be used in the mechanistic analysis developed for this project and can be incorporated into the program. The calibration and validation of these models are outside the scope of this project.

Table 3.1- Fatigue Cracking Model and Rutting Model Parameters used to Determine Remaining Life of a Flexible Pavement

Model	***Fatigue Cracking Model*** $N_f = f_1(\varepsilon_t)^{-f2}(E_{AC})^{-f3}$			***Subgrade Rutting Model*** $N_d = f_4(\varepsilon_c)^{-f5}$	
	f_1	f_2	f_3	f_4	f_5
Asphalt Institute	0.0796	3.291	0.854	1.365×10^{-9}	4.477
Shell	0.0685	5.671	2.363	6.15×10^{-7}	4.0
Shell (50% reliability)	-	-	-	6.15×10^{-7}	4
Shell (85% reliability)	-	-	-	1.94×10^{-7}	4
Shell (95% reliability)	-	-	-	1.05×10^{-7}	4
Illinois Dept. of Transportation	5E-6	3	-	3	-
Transport and Road Research Laboratory	$1.66*10^{-10}$	4.32	-	4.32	-
U.K Research & Road Research Laboratory (85% reliability)	-	-	-	6.18×10^{-8}	3.95
University of Nottingham	-	-	-	1.13×10^{-6}	3.571
Belgian Road Research Center	$4.92*10^{-14}$	4.76	-	3.05×10^{-9}	4.35
New Mechanistic Design Guide (MDG) (National Calibration Factors[1]) for top –bottom cracking $k^*_1 = \frac{1}{0.000398 + \frac{0.003602}{1+e^{(11.02-3.49h_{AC})}}}$ for bottom-top cracking, $k^*_1 = \frac{1}{0.000398 + \frac{0.003602}{1+e^{(15.676-2.8186h_{AC})}}}$ h_{AC} is thickness of ACP layer and C is laboratory to field adjustment factor	$0.00432k^*_1C$	3.9492	1	-	-

Note: constants are for US customary units

MATERIAL MODELS

As illustrated in Chapter Two, the methodology of the program depends on the material characteristics models and pavement performance models. Throughout the research of this project, several material models were identified that could be used in the program.

ACP Models

The material models selected for the ACP layer are summarized the Table 3.2. The Witczak 1982 model was first used in the study to determine the feasibility in the use of the methodology developed in this project. The other models were subsequently added to the software package RECIPPE.

Base and Subgrade Models

Several material models were discovered during the literature review phase of this project for the base and subgrade layers. Some of the models are summarized in Table 3.3. All these models can be generalized by the following constitutive model:

$$M_R = k_1 P_a \left[\frac{\theta}{P_a}\right]^{k_2} \left[\frac{\tau_{oct}}{P_a}\right]^{k_3} \tag{3.5}$$

where $\theta = \sigma_1 + \sigma_2 + \sigma_3$ = bulk stress; τ_{oct} = octahedral shear stresses; P_a = atmospheric pressure, and k_1, k_2 and k_3 are multiple regression constants evaluated from resilient modulus test data from equations developed from a regression procedure that relate the regression constants to construction parameters.

One of the biggest challenges in this study was finding regression constants that relate construction parameters. The first success in finding such parameters was from a study carried out for Georgia DOT. Santha (1994) presented equations for regression constants defined for both granular and cohesive soils. Those equations were used in most part of the research study and are set as the default values in the program. At the latter part of the study, regression equations from Minnesota and Indiana DOTs were found. The regression equations for the material model parameters are summarized in Table 3.4 and 3.5.

CALIBRATION OF MATERIAL MODELS

The above material models were calibrated using data collected from Texas sites. The detail and results of the calibration process are included in Research Report 0-4046-3. (Haggerty et al., 2005)

Table 3.2 - Summary of Material Models for ACP Layer

Witczak 1982 Model (Asphalt Institute, 1982)	$\log E_{AC} = 5.553833 + 0.028829 \frac{P_{200}}{f^{0.17033}} - 0.03476 V_V + 0.070377 \eta + 0.000005 t_p^{(1.3+0.49825 \log f)} P_{ac}^{0.5} - 0.00189 t_p^{(1.3+0.49825 \log f)} \frac{P_{ac}^{0.5}}{f^{1.1}} + 0.931757 f^{-0.02774} + \text{э}$ E_{AC} = dynamic modulus of AC mix (in psi), η = bitumen viscosity (in 10^6 poise) at 70°F, f = load frequency (in Hz), V_v = percent air voids in the mix by volume, P_{ac} = percent effective bitumen content by volume, and P_{200} = percent passing No. 200 sieve by total aggregate weight.
Witczak 1995 Model (Ayres and Witczak, 1998)	$\log \lvert E_{AC} \rvert = -1.249937 + 0.029232 P_{200} - 0.001767 (P_{200})^2 + 0.002841 P_4 - 0.058097 V_a - 0.808808 \frac{V_{beff}}{(V_{beff} + V_a)} + \frac{[3.871977 - 0.0021 P_4 + 0.003958 P_{38} - 0.000017 (P_{38})^2 + 0.00547 P_{34}]}{1 + e^{(-0.603313 - 0.31335 \log(f) - 0.393532 \log(\eta))}}$ E_{AC} = dynamic modulus of AC mix (in 10^5 psi), η = bitumen viscosity (in 10^6 poise) at 70°F, f = load frequency (in Hz), V_a = percent air voids in the mix by volume, V_{beff} = percent effective bitumen content by volume, and P_{200} = percent passing No. 200 sieve by total aggregate weight, P_4 = cumulative percent retatined No. 4 sieve by total aggregate weight, P_{34} = cumulative percent retatined No. 3/4 sieve by total aggregate weight, and $P_{3/8}$ = cumulative percent retatined No. 3/8 sieve by total aggregate weight.
Witczak Model 2000 (Witczak, 2003)	$\log \lvert E_{AC} \rvert = -0.261 + 0.008225 P_{200} - 0.00000101 (P_{200})^2 + 0.00196 P_4 - 0.03157 V_a - 0.415 \frac{V_{beff}}{(V_{beff} + V_a)} + \frac{[1.87 + 0.002808 P_4 + 0.00000404 P_{38} - 0.0001786 (P_{38})^2 + 0.0164 P_{34}]}{1 + e^{(-0.716 \log(f) - 0.7425 \log(\eta))}}$
Hirsch Model (Bonaquist, R., 2005)	$\lvert E^* \rvert_{mix} = P_c \left[4{,}200{,}000 \left(1 - \frac{VMA}{100}\right) + 3 \lvert G^* \rvert_{binder} \left(\frac{VFA\, x VMA}{10{,}000}\right)\right] + \frac{1 - P_c}{\left[\frac{\left(1 - \frac{VMA}{100}\right)}{4{,}200{,}000} + \frac{VMA}{3 VFA \lvert G^* \rvert_{binder}}\right]}$ $P_c = \frac{\left(20 + \frac{VFA\, x\, 3 \lvert G^* \rvert_{binder}}{VMA}\right)^{0.58}}{650 + \left(\frac{VFA\, x\, 3 \lvert G^* \rvert_{binder}}{VMA}\right)^{0.58}}$ VMA = Voids in mineral aggregates (%), VFA = Voids filled with asphalt (%), and $\lvert G^* \rvert_{binder}$ = shear complex modulus of binder (psi)

Table 3.3 - Summary of Material Models for Base and Subgrade Layers (Thompson et al., 1998)

K - Θ Model	$M_R = k_1 \theta^{k_2}$
Uzan Model	$M_R = k_1 \theta^{k_2} \sigma_d^{k_3}$ $\sigma_d = \sigma_1 - \sigma_3$ = deviator stress
Octahedral Shear Stress Model	$M_R = k_1 P_a \left[\frac{\theta}{P_a}\right]^{k_2} \left[\frac{\tau_{oct}}{P_a}\right]^{k_3}$
Itani Model	$M_R = k_1 P_a \left[\frac{\theta}{3}\right]^{k_2} \sigma_d^{k_{3a}} \sigma_3^{k_{3b}}$ where σ_3 = confining stress; k_{3a} and k_{3b} are multiple regression constants
UTEP Model	$M_R = k_1 \theta^{k_2} (\varepsilon_a)^{k_3}$ ε_a = induced resilient axial strain
UT-Austin Model	$M_R = k_1 \theta^{k_2} \sigma_3^{k_3}$ σ_3 = confining stress
Bilinear Approximation (Arithmetic Model)	$M_R = k_1 + k_{3a}(k_2 - \sigma_d)$ when $\sigma_d < k_2$ $M_R = K_1 + k_{3b}(\sigma_d - k_2)$ when $\sigma_d > k_2$

ACP Models

The Long-Term Pavement Performance (LTPP) database was used in the calibration process. The research effort was first focused on SPS sites and later expanded to other Texas sections. The required information extracted from the LTPP database was:

- Asphalt content
- Viscosity
- Percent of aggregate passing sieve #200
- Percent air voids
- Backcalculated layer modulus of the ACP

The backcalculated moduli were assumed as the desired modulus values and the modulus calculated from the other parameters were used to calibrate the models. The result of the calibration process showed:

$$E_{backcalculated} = 2.34 E_{Witczak} \tag{3.6}$$

Table 3.4 - Summary of Regression Equations for k-Parameters of Equation 3.5 Developed for GaDOT

Granular Soils	$Log(k_1) = 3.479 - 0.07MC + 0.24MCR + 3.681COMP + 0.011SLT + 0.006CLY - 0.025SW - 0.039DEN + 0.004\left(\frac{SW^2}{CLY}\right) + 0.003\left(\frac{DEN^2}{S40}\right)$ MCR represents the ratio of moisture content (MC) to optimum moisture content, COMP is the degree of compaction and SATU is the degree of saturation, S40 represents the percent passing sieve #40, SLT is the percent of silt, CLY is the percent of clay, SW is the percent of swell value, SH is the percent of shrinkage, DEN is the maximum dry density (in pcf) and CBR is the California bearing ratio
	$k_2 = 6.044 - 0.053OMC - 2.076COMP + 0.0053SATU - 0.0056CLY + 0.0088SW - 0.0069SH - 0.027DEN + 0.012CBR + 0.003\left(\frac{SW^2}{CLY}\right) - 0.31\frac{(SW + SH)}{CLY}$ OMC is the optimum moisture content
	$k_3 = 3.752 - 0.068MC + 0.309MCR - 0.006SLT + 0.0053SLY + 0.026SH - 0.033DEN - 0.0009\left(\frac{SW^2}{CLY}\right) + 0.00004\left(\frac{SATU^2}{SH}\right) - 0.0026CBR(SH)$
Cohesive Soils	$Log(k_1) = 19.813 - 0.045OMC - 0.131MC - 9.171COMP + 0.0037SLT + 0.015LL - 0.016PI - 0.021SW - 0.052DEN + 0.00001S40(SATU)$ PI and LL values, which stand for the plasticity index and liquid limit, respectively
	$k_2 = 0$
	$k_3 = 10.274 - 0.097 * MOIST - 1.06 * MCR - 3.471COMP + 0.0088S40 - 0.0087PI + 0.014SH - 0.046 * DEN$

Another attempt to calibrate the models was carried out by modifying the coefficients of the Witczak model. The new equation is as follows:

$$\begin{aligned}
&\log(E_{ac}) = 5.560 + 0.43\left(\frac{P_{200}}{F^{0.17033}}\right) + .004V_v \\
&+ 140.953\eta + 21.280t_p^{(1.3+0.49825\log(f))}P_{ac}^{0.5} \\
&- \frac{511.418}{f^{1.1}}t_p^{(1.3+0.49825\log f)}P_{ac}^{0.5}
\end{aligned} \tag{3.7}$$

Table 3.5 - Regression Equations of Material Models for Subgrade Layers Developed Based on Research of Transportation Agencies of Minnesota and Indiana

Minnesota DOT (Uzan Model)	Cohesive Soils	$k_1 = 5770.8 - 520.98DEN^{0.5} - 3941.8MC^{0.5} + 33.1PI - 36.62LL - 17.93P200$ MC is the moisture content, DEN is the maximum dry density (in pcf), P200 represents the percent passing sieve #200, PI and LL values stand for the plasticity index and liquid limit, respectively
		$k_2 = 5409.9 - 306.18DEN^{0.1} - 82.63MC + 0.033PI + 0.138SAND - 0.041LL$ SAND is the percent of SAND
		$k_3 = -5.334 + 0.000316DEN^3 + 9.686MC - 0.054PI + 0.046LL + 0.022P200$
Indiana DOT (Equation 3.10)	Fine-grained Soils	$Log(k_1) = 6.660876 - 0.22136OMC - 0.04437MC - 0.92743MCR - 0.06133DEN + 10.64862COMP + 0.328465SATU - 0.04434SAND - 0.04349SLT - 0.01832CLY + 0.027832LL - 0.01665PI$ MCR represents the ratio of moisture content (MC) to optimum moisture content (OMC), COMP is the degree of compaction and SATU is the degree of saturation, SLT is the percent of silt, CLY is the percent of clay, and SW is the percent of swell value
		$k_2 = 3.952635 - 0.33897OMC + 0.076116MC - 2.45921MCR - 0.06462DEN + 6.012966COMP + 1.559769SATU + 0.020286SAND + 0.002321SLT + 0.011056CLY + 0.077436LL - 0.05367PI$
		$k_3 = 2.634084 + 0.12447OMC - 0.09277MC + 0.366778MCR - 0.01168DEN - 1.32637COMP + 1.297904SATU - 0.01226SAND - 0.00512SLT + 0.00492CLY - 0.05083LL + 0.018864PI$

A third approach was carried to develop an independent regression equation for estimating the modulus of ACP using the data extracted from the LTPP database. The best equation was

$$\begin{aligned} E_{AC} &= -64342 + 169\ln(V_v)(t_p^{\,2}) + 1.25\left(e^{Pac}\right)\left(e^{P_{200}}\right) \\ &- 2.44\left(P_{200}^{\,3}\right)\left(e^{Vv}\right) - 7.38\times10^{-26}\left(\eta^3\right)\left(e^{t_p}\right) \\ &+ 109.7(f)\left(V_v^{\,3}\right) - 157.3\sqrt{t_p}\left(P_{200}^{\,3}\right) \end{aligned} \quad (3.8)$$

The performance of the three models is presented in Figure 3.1. Four sets of results are compared with the backcalculated layer moduli (depicted by the line of equality). The four sets of results are based on 1982 Witczak model, Equation 3.6 (linear calibration of Witczak model), Equation 3.7 (modified coefficients of Witczak model), and Equation 3.8 (a new nonlinear model). From the limited set of data used in the models development, the results of the new models show an improvement to the original Witczak model.

Few sets of data were set aside to test the validity of the models. The results of the models tested with data not used in calibration are presented in Figure 3.2. The original Witczak model showed consistent to those results shown in Figure 3.1. The modulus was under-predicted. The linearly calibrated model, although showed promise with calibrated data, still under-predicted the layer moduli as compared to the backcalculated moduli. On the other hand, Equation 3.7, with modified coefficients of the Witczak model, shows estimates of layer moduli on both sides of the equality line. The last model developed (Equation 3.8) over-predicted the layer moduli. With this limited database, the best behaved model from these results seems to be the model listed in Equation 3.7. This seems to suggest that if more data were available, the format of the Witczak equation could be used to develop a suitable model to predict the modulus of ACP layer. The 1995 and 2000 Witczak models and the Hirsch model were not used in calibration. The models were not identified at the time the research was carried out.

A few sections at a site in Euless, Texas were visited and data were collected to determine the accuracy of the ACP models (see Figure 3.3). The site was tested at three sections with 2 in. ACP and two sections with 8 in. ACP. The data collected at this site was part of a quality assurance-quality control (QA/QC) project of hot mix asphalt. The Portable Seismic Pavement Analyzer (PSPA) device was used to collect modulus data from the site. Also, the modulus values from the V-meter were obtained. The PSPA is a tool that is based on seismic technology and directly measures the modulus of ACP layer and the V-meter is a velocity measuring device that can also be used to directly estimate the elastic moduli of a core specimen. The modulus data from both methods were processed and the design moduliwere estimated based on Equation 3.9.

$$E_{Design} = \frac{\mathrm{E}_{\mathrm{seismic}}}{3.2(1.35 - 0.0078(\mathrm{t} - 32))} \qquad (3.9)$$

Cores and raw materials were retrieved from the site for laboratory testing to determine air voids, asphalt content, and gradation. The viscosity for PG64-22 was assumed at 5217 Poise and the temperature and frequency were set at 70^{o}F and 18 Hz respectively. Table 3.5 lists the values of the parameters used in the models. For this site no FWD data was collected, therefore, the design modulus results from the seismic test were used as a baseline for comparing estimated layer moduli from the ACP material models.

Figure 3.4 shows the results of the comparison. The two models that were closest to the desired results, were those estimated from the Witczak model and the model with the modified coefficients of the Witczak model. The remaining models failed to estimate the desired design moduli by either largely over-estimating or largely under-estimating the layer moduli. Again, the results seem to suggest that with a large enough database, the coefficients of the Witczak model could be determine to produce a reasonable material model for the ACP layer.

Table 3.6 - Laboratory Data for the Euless Test Sections

Air Voids, %	Asphalt Content, %	Percent Passing # 200	Percent Retained # 4	Percent Retained # 3/8	Percent Retained # ¾
7.8	4.2	4.2	44.9	26.0	3.1
4.5	4.4	4.1	58.9	38.4	8.3
13.7	4.4	3.1	42.8	24.4	2.3
11.0	4.4	4.2	47.5	26.3	0.6
9.6	4.3	3.4	41.2	23.5	1.2

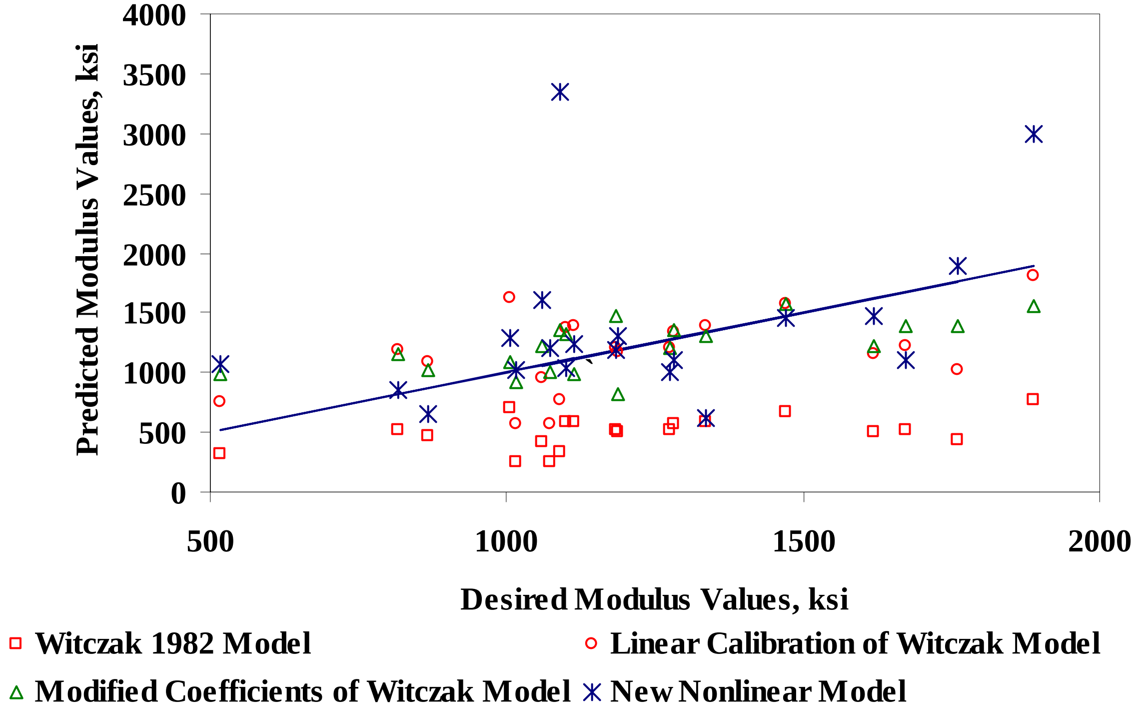


Figure 3.1 - Comparison of Results for the ACP Models with Data Used in Calibration

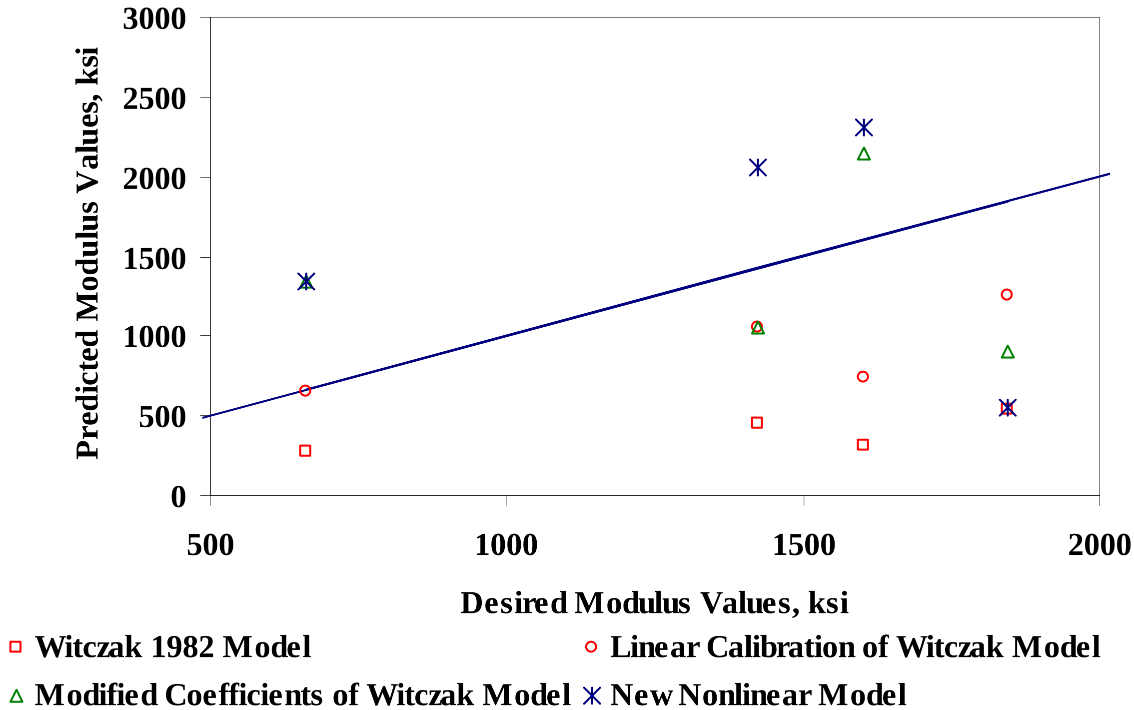


Figure 3.2 - Comparison of Results to Test ACP Models

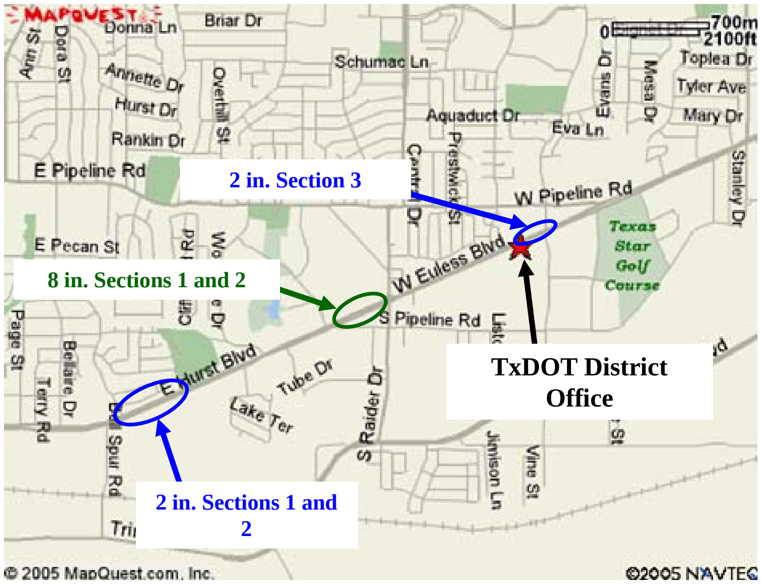


Figure 3.3 - Location of Site for Validation of the ACP Material Model

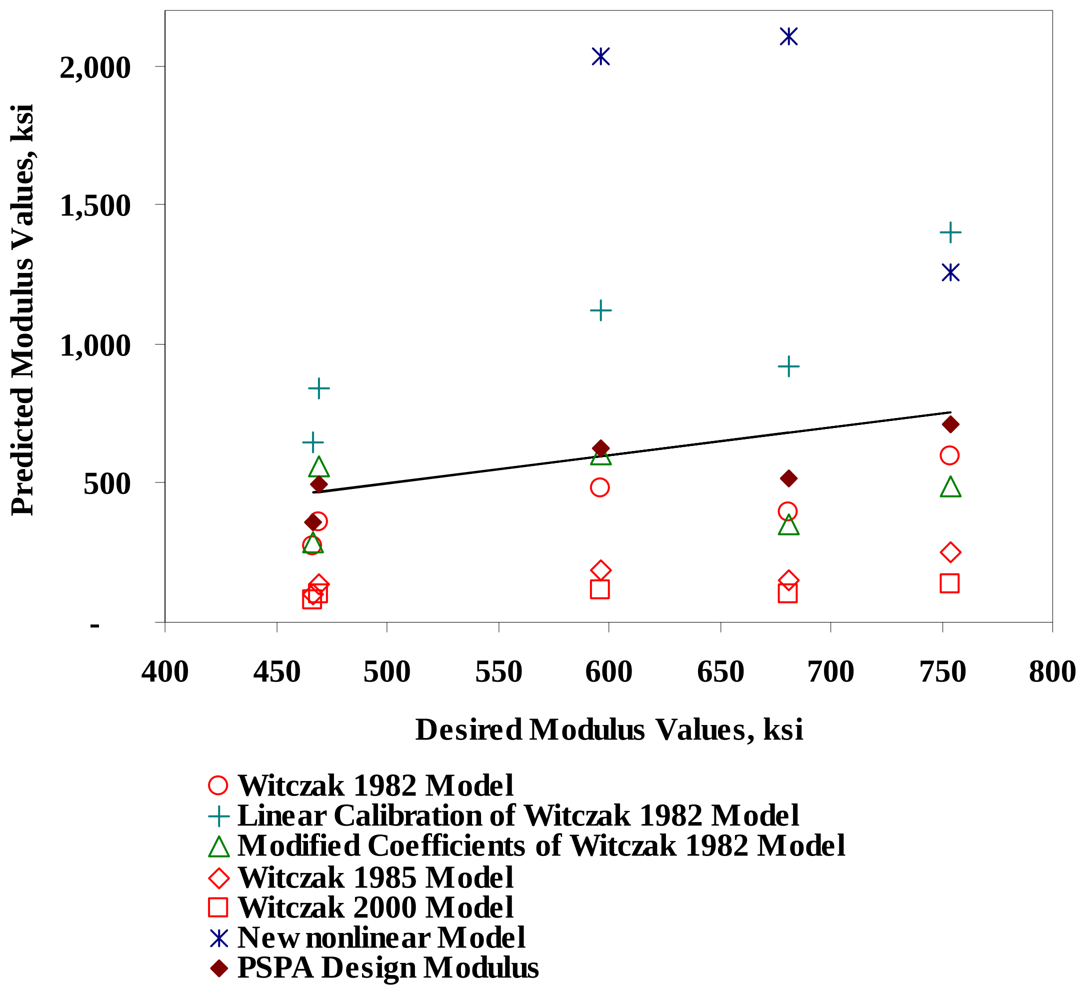


Figure 3.4 - Comparison of Results to Test ACP Models

Base and Subgrade Models

Since these empirical equations, listed in Table 3.3, were not developed based on section found in Texas, similar types of equations (estimating the k parameters based on construction parameters) were generated for pavement sections in Texas. Unfortunately, the LTPP database could not be used to for this task. The parameters required for base and subgrade materials were not comprehensively available in the LTPP database. As such a matrix of test sections that represents flexible pavements in Texas was developed. With the help of TxDOT personnel, a protocol was developed to allow for a comprehensive data collection scheme from Texas sites. Data were collected according to an adjusted guide schedule that specifies the frequency and location for gathering sample information for each required construction parameter. The adjustments to the guide schedule were developed by UTEP and TxDOT personnel for more practical testing frequencies. The protocol is includeded in Appendix A of Research Report 0-4046-3 (Haggerty et al., 2005). For the most part the protocol was followed. As a result, field and laboratory tests were performed on eleven sites. The eleven sites were located in six different counties, representative of the major climate differences of the environments found within the state of Texas. The location and pertinent information for the sites are also provided in Research Report 0-4046-3.

For this task, limited number of sections were identified and visited due to the time frame allocated. Data and raw materials were collected at each site and necessary laboratory test were carried out. Research report 0-4046-3 (Haggerty et al., 2005) contains the detail of the sites and data collection process. Since there was limited data, an innovative technique was used to populate the database using data from the limited sections. The process involved utilizing the values of the parameters collected from the sites and simulating hundreds of possible values for those parameters with similar attributes. To capture the attributes for each pavement layer, new values for each parameter were simulated considering their correlation to other parameters. The regression equations were then developed using the simulated data. The new regression equations are:

For base:

$$\begin{aligned} k_1 = {} & 52.84[\ln(DEN)](CLY) - \frac{8.21[\ln(OMC)]}{\sqrt{OMC}} + 0.418\left(\sqrt{MC}\right)\left(SLT^2\right) - \\ & 2.92(COMP)(CLY) - 1.11\left(\sqrt{S40}\right)[\ln(OMC)] + 18.21(CLY)\left(\sqrt{SLT}\right) \\ & + 98.35 \end{aligned} \tag{3.10}$$

$$\begin{aligned} k_2 = {} & \frac{-1.84[\ln(MC)]}{MOIST^2} + \frac{3.14\times10^{-4}\left(COMP^2\right)}{\sqrt{CLY}} - \frac{0.176[\ln(S40)]}{e^{SLT}} \\ & - 3.67\times10^{-5}\left(e^{CLY}\right)\left(MOIST^2\right) + \frac{0.442[\ln(SLT)]}{S40} \\ & - \frac{0.423[\ln(DEN)]}{\sqrt{CLY}} + 1.93\times10^{-5}\left(MOIST^3\right)\left(SLT^3\right) \end{aligned} \tag{3.11}$$

$$k_3 = 9.31\times10^{-4}\left(\sqrt{DEN}\right)\left(\sqrt{S40}\right)+1.44\times10^{-2}(MOIST)(CLY) - 4.83\times10^{-2}(MC)\left(\sqrt{SLT}\right)-\frac{0.182[\ln(COMP)]}{\ln(S40)}-\frac{2.22\times10^{-2}\left(\sqrt{S40}\right)}{CLY^3} - \frac{145.83\left(\sqrt{CLY}\right)}{e^{MOIST}}+\frac{2.03\left(e^{SLT}\right)}{e^{MC}} \tag{3.12}$$

For subgrade:

$$k_1 = 1453-\frac{1.52\times10^7[\ln(DEN)]}{COMP^3}-\frac{0.683\left(MOIST^3\right)}{PI^3}-\frac{133.9(COMP)}{\sqrt{COMP}} + \frac{104.7[\ln(S40)]}{LL}+\frac{1.25\times10^{39}\left(CLY^3\right)}{e^{COMP}}+\frac{42.21[\ln(SLT)]}{e^{MC}}- 7.897\times10^{-6}[\log(LL)]\left(CLY^3\right)-0.915[\ln(PI)][\ln(MOIST)] \tag{3.13}$$

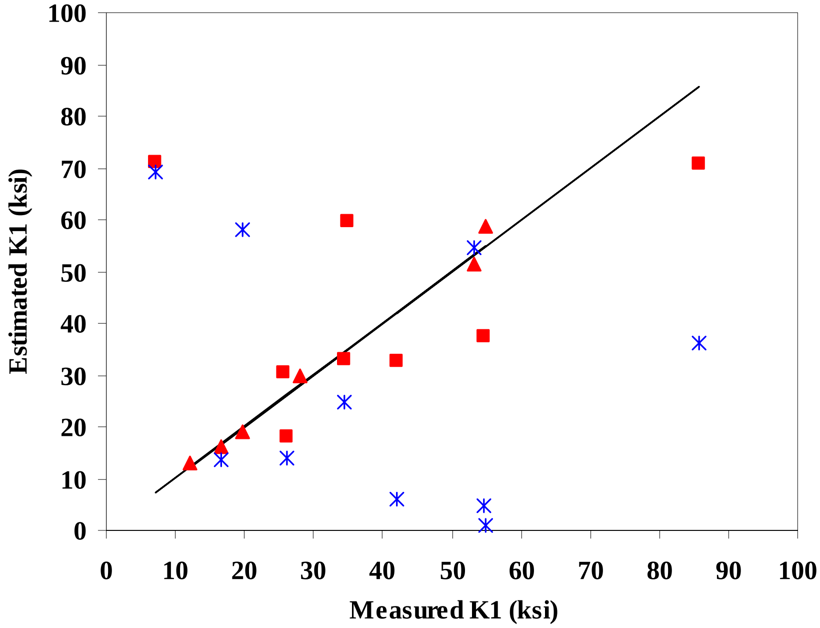
$$k_2 = 0 \tag{3.14}$$

$$k_3 = -3.06+\frac{1.48\times10^{42}(MOIST)}{e^{COMP}}-\frac{194.67(MC)}{LL^3}+5.65\times10^{-5}\left(COMP^2\right)[\ln(DEN)] + 1.05\times10^{-4}\left(\sqrt{CLY}\right)(DEN)-\frac{0.668\left(\sqrt{SLT}\right)}{MOIST}-\frac{8.29\times10^{41}(LL)}{e^{COMP}}+ \frac{0.033(PI)}{SLT}+6.04\times10^{-8}[\log(DEN)]\left(CLY^3\right) \tag{3.15}$$

The results of the equations for both base and subgrade material models are presented in Figures 3.5 through 3.9. The figure compared the desired values of k-parameters obtained from resilient modulus testing with three estimated results from regression models: a) data from the sites used in populating the database for developing the regression equations, b) data from sites collected for validating the models, and c) the results of the GADOT regression equations. Data for validating the models were based from two sources. Several ongoing projects that required similar laboratory testing was being carried out for five Texas bases and two subgrades. Also, two sites (one for the base and one for the subgrade) were visited for the purpose of validating the models.

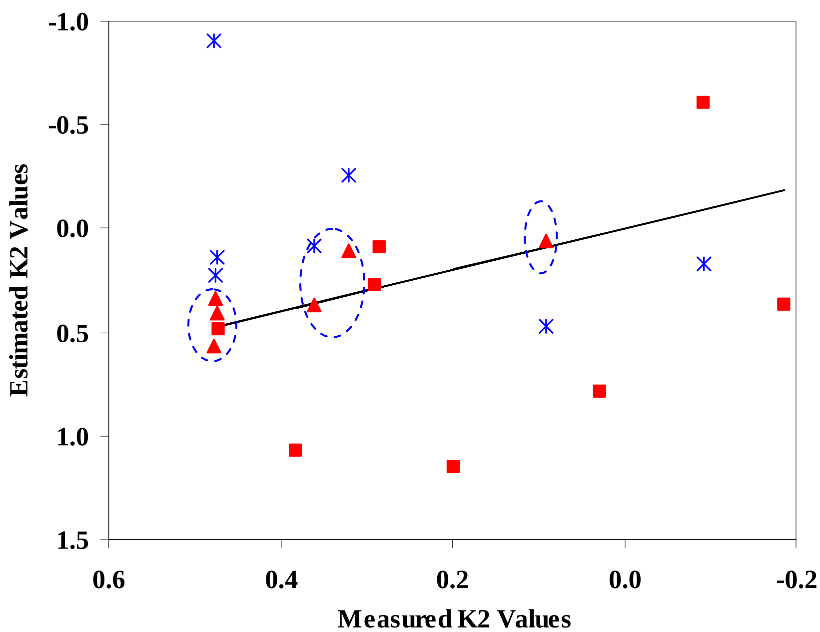
Figure 3.5 compares the results for the parameter k_1. The line of equality represents the target values estimated using the resilient modulus laboratory test. The results show that the new regression model (represented the results with by the symbols "square" and "triangle") was a better predictor of k_1 than the results of the GaDOT regression model. The GaDOT underestimated the k_1 parameter in most cases. This is because the new model was developed and tested "validated" with empirical data from sites across Texas.

Figure 3.6 compares the results for the parameter k_2. The results show that the new regression model estimated well the data that was used on developing the model. However, the validation results were generally overestimated. This is contradictory to results of the parameter k_1. But a closer look at the data used to populate the database and development of the model shows that the data seems to be clustered in three zones (highlighted by the dashed-circles). This permits a narrow range for model development. This suggests the need to expand the database to cover the



▲ Data used in populating the database & developing regression equations
■ Data for validating the regression equations
✳ Results of the GaDOT regression equations

Figure 3.5 - Comparison of Results from Different Base Layer Models for Parameter k_1



▲ Data used in populating the database & developing regression equations
■ Data for validating the regression equations
✳ Results of the GaDOT regression equations

Figure 3.6 - Comparison of Results from Different Base Layer Models for Parameter k_2

range of parameter k_2. The GaDOT model results are also compared in the figure, and as expected the results are not well estimated. In some cases, the estimated values were negative.

Figure 3.7 compares the results for the parameter k_3. The results of the new regression model were generally underestimated. Similarly to reasoning for improving the parameter k_2, an expansion of the database range would improve the model predictions. Again, the GaDOT model does not estimate satisfactorily the values of the parameter k_3.

Figures 3.8 and 3.9 compare the results for the k_1 and k_3 parameters for the subgrade, respectively. The results of both models show similar outcomes. The models seem to estimate the k-parameters very well for data used to develop the models. However, the database for the subgrade was very limited and as the results indicate, a much larger sample needs to be used for developing better regression models.

The overall process of developing and validating the new regression equations showed the need to have a large database. In certain cases, where the range of output used for developing a model was wide and evenly spread, the models behave well. In other cases, the output was clustered which led to poor model predictions when being validated. In both instances, the process of developing the model, by means of populating the database, seemed promising and in the future when more data is collected and tested better models can be easily developed. In this project the goal of generating a large database was hoped for, but under the time constraints was not fulfilled.

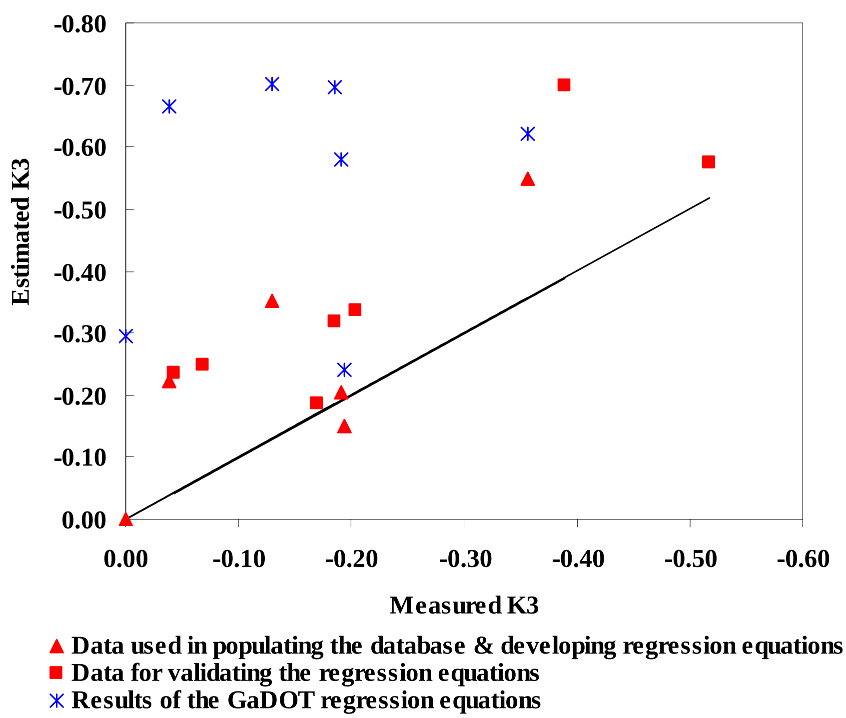
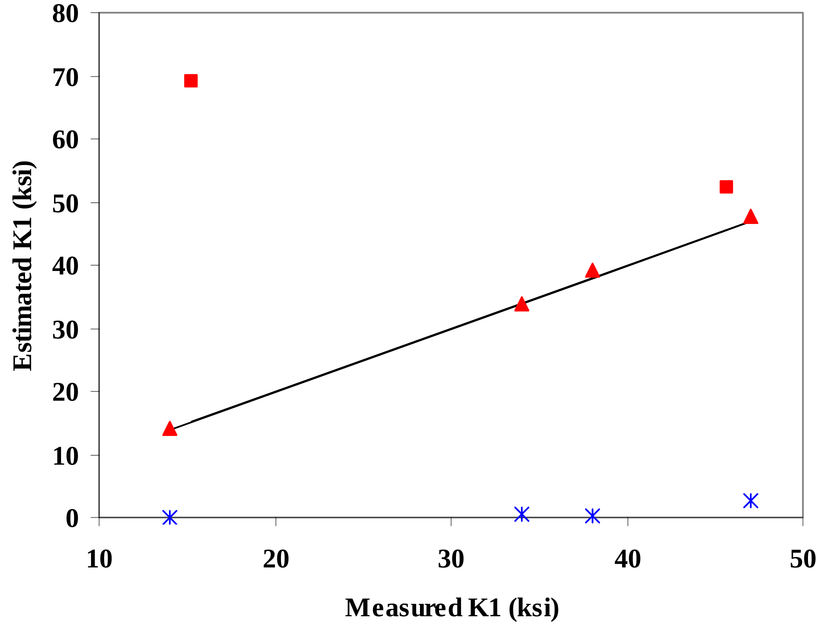
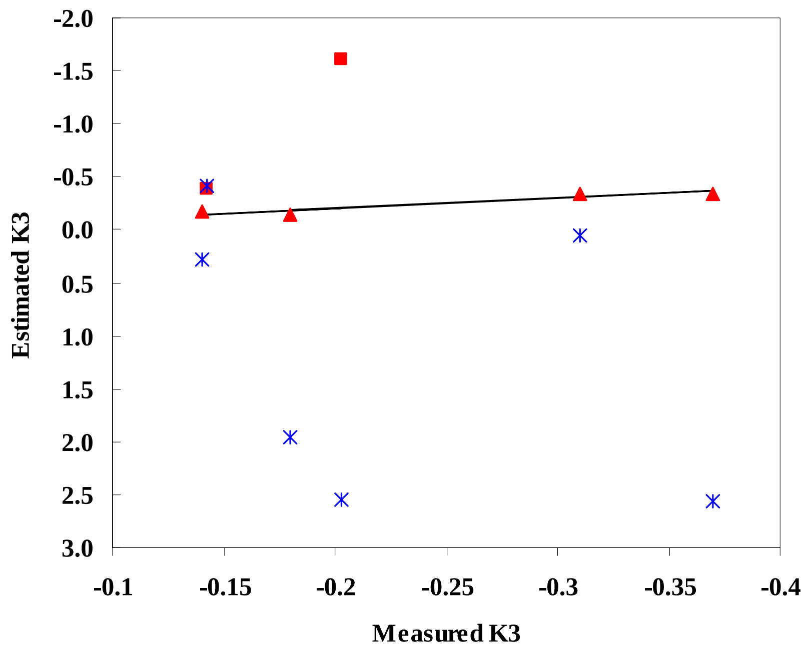


Figure 3.7 - Comparison of Results from Different Base Layer Models for Parameter k_3



▲ Data used in populating the database & developing regression equations
■ Data for validating the regression equations
⋇ Results of the GaDOT regression equations

Figure 3.8 - Comparison of Results from Different Subgrade Models for Parameter k_1



▲ Data used in populating the database & developing regression equations
■ Data for validating the regression equations
⋇ Results of the GaDOT regression equations

Figure 3.9 - Comparison of Results from Different Subgrade Models for Parameter k_3

CHAPTER FOUR - STRATEGY TO UTILIZE RECIPPE FOR QUALITY ASSURANCE

The methodology presented in this research provides a means of assessing construction consistency for a flexible pavement system. Thus far, the methodology and the algorithms were discussed and documented. Also, material model development, calibration and development were presented. To assist in utilizing RECIPPE, a strategy is provided in this chapter.

The main purpose of this research was developing a tool to ultimately optimize effectiveness of inspection and testing resources during construction given TxDOT limited resources by:

1. Estimating if variability of construction parameters meets the owner's expectations for a reasonably uniform pavement life.
2. Identifying the construction parameters to focus on during construction inspection, in order to reduce pavement life variance and increase reliability.
3. Tracking and identifying out of control procedures during construction.
4. Improving construction practices through process control.

Figure 4.1 outlines the overall purpose of RECIPPE. The first part of the figure shows a representation of pavement performance. As depicted in the figure, pavement performance can be specified based on level of damage with time. Therefore, for a certain specified time period, a pavement is designed to withstand a certain level of damage caused be traffic loading and environmental factors. However, due to inconsistencies in construction practices along the length of the pavement, the pavement quality varies from one section to the next, and as a result damage is accumulated faster than estimated in the inferior sections, and therefore, the life of the pavement is shortened.

The primary objective for this research was to develop a tool to minimize variability of performance to ensure that pavement life is achieved based on design specification (listed in the right side of Figure 4.1). To address this objective, the strategy was to develop a tool that can be used to identify and track pavement properties for quality control. In this case, pavement properties are the layer thickness and layer moduli. These parameters are the main components used in estimating the pavement performance. For each of these parameters, certain variability exists, and depending on the pavement system, these parameters can contribute differently to performance. This means that by identifying which of these parameters is found significant and by controlling the variability of those parameters, variability of performance can be managed.

To address this strategy and meet the objective, RECIPPE was developed to identify significant pavement properties and provide a process control tool for quality assurance.

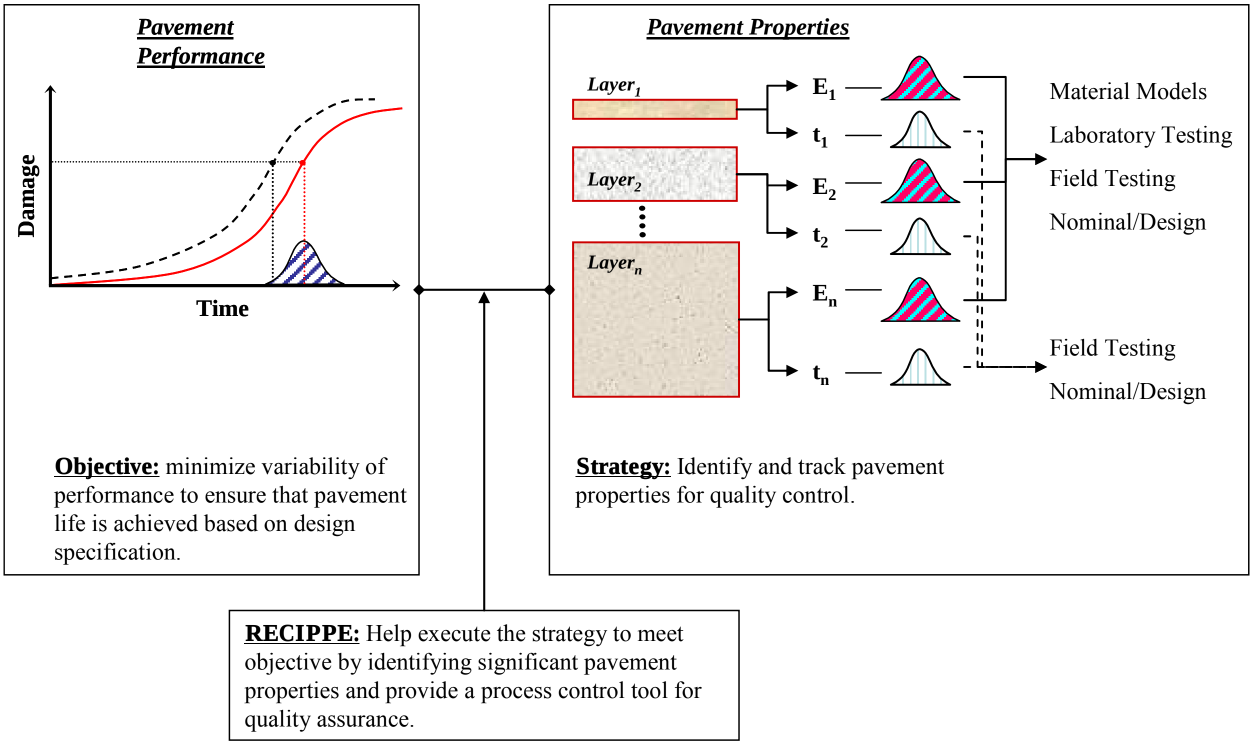


Figure 4.1 - Process of using RECIPPE to Ensure Uniform Pavement by Monitoring Pavement Layer Information

In order to present different ways that RECIPPE can be utilized, it is beneficial to first summarize the different types and levels of input that can be incorporated into the program. Table 4.1 provides a summary of inputs categorized by levels according to the type of data used. In this table the input levels are divided into three categories for each of the pavement layer properties. Level 1 is designated for design values. This is data that is easily obtainable and requires neither field nor laboratory efforts. This type of input is best used when no other information is provided or to supplement the input to RECIPPE since pavement layer information for all layers is required to carryout the analysis. Level 2 and Level 3 inputs require field and laboratory measurements. Both these levels of input are necessary when a significant pavement property is identified. In most cases, Level 2 input indicate direct measurements of layer property and Level 3 input requires the use of material models that is based on construction parameters to estimate layer properties.

For the layer thickness, the ACP layer can be measured from cores and or Ground Penetrating Radar (GPR), and the base and subgrade layer can be measured form cores or Dynamic core penetrometer (DCP). For the ACP modulus the information can be provided based on V-meter test using cores and or PSPA field measurements (Level 2) and material model such as those presented in Table 3.2. Finally, the base and subgrade modulus can be measured using devices such as the Dirt Seismic Pavement Analyzer (DSPA) or an equivalent system in the field and or laboratory testing such as resilient modulus with in-situ material from the field (Level 2). The DSPA is one tool that can be used for quality control to measure the elastic moduli of base and subgrade layers. For Level 3 input, material models, such as those presented in Figures 3.3 through 3.5, can be used for estimating the layer moduli.

Table 4.1 - Input Levels for Estimating Pavement Layer Properties

Material Property	Input	Type of Data	Methods
ACP Thickness	Level 1	Design	Nominal
	Level 2	Measured	Cores
	Level 3		GPR
Base and Subgrade Thickness	Level 1	Design	Nominal
	Level 2	Measured	Cores
	Level 3		DCP
ACP Modulus	Level 1	Design	Nominal
	Level 2	Measured	Cores (V-Meter)
			PSPA
	Level 3	Material Model	Construction parameters such as Gradation and volumetric information
Base and Subgrade Modulus	Level 1	Design	Nominal
	Level 2	Measured	DSPA
		Material Model	DSPA and assumed material parameters
		Measured & Material Model	DPSA & Resilient Modulus
	Level 3	Material Model	Construction parameters such as Gradation and volumetric information

RECIPPE is separated into two phases: pre-construction and post construction. Figure 4.2 is a flowchart of the progression of utilizing different levels of inputs in RECIPPE. For the pre-construction phase, a dry-run can be initially carried out based on Level 1 input. Level 1 input is based on the pavement system design values with their associated variability, which can be assumed base on experience and or historical information. Based on results of the dry-run, significant pavement parameters can be identified. This allows users to decide on the input levels to use when stating the analysis is pre-construction mode. Level 1 inputs can be used for the parameters not found significant. The inputs for the more significant parameters can be measured based on the Levels 2 and 3 protocols. Once the levels of inputs are defined, RECIPPE can be processed in pre-construction mode followed by post-construction mode.

In the post-construction phase, the parameters that are identified as significant are used to determine a set of sampling frequencies for inspectors to use in control charts to ensure quality of the construction process in an optimized manner.

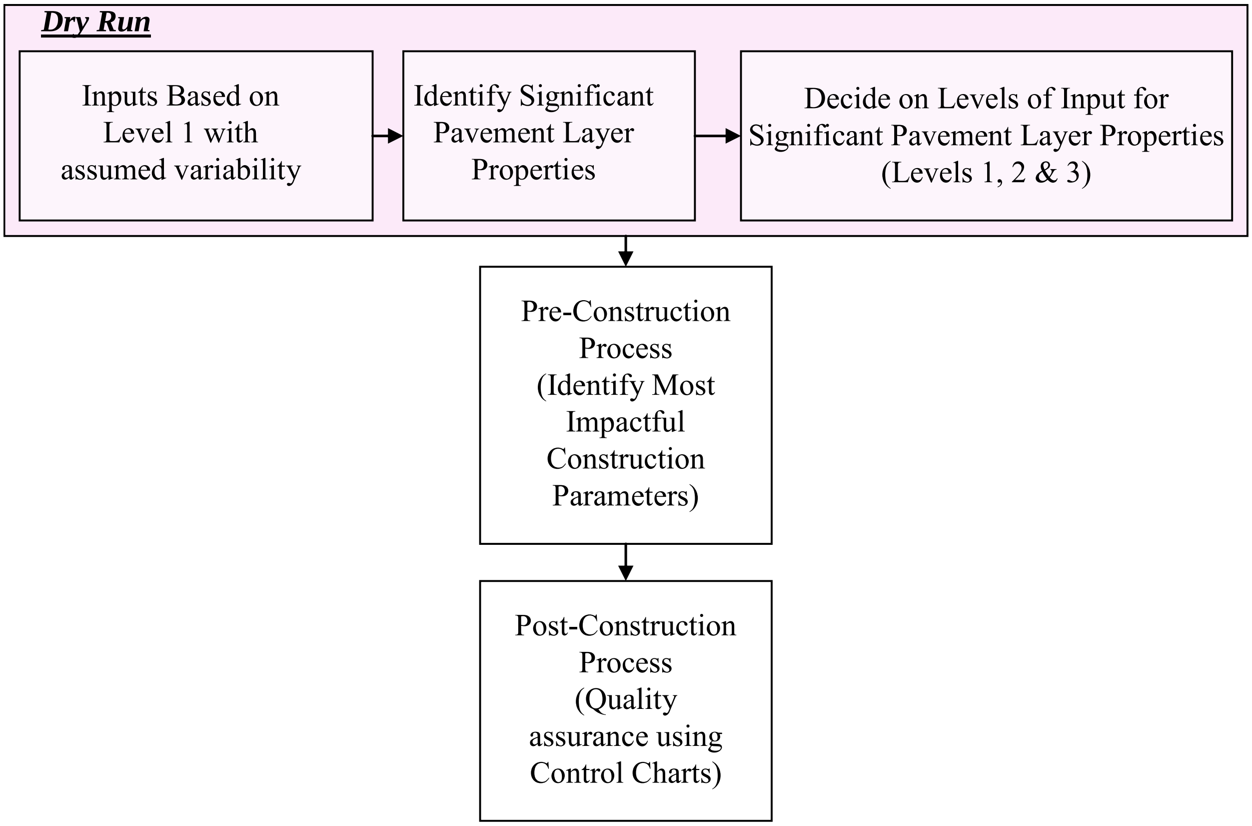


Figure 4.2 - Flowchart of RECIPPE to Ensuring Uniform Pavement Construction

Three general scenarios are presented to illustrate how RECIPPE can be used at different stages and with different levels of input. Table 4.2 presents a general scenario for a pavement where the subgrade layer properties were identified as significant. The information in the table presents the levels of input for the layer moduli. For this scenario, the input to the RECIPPE for the top layers can be provided as Level 1 input. However, the input for the subgrade layer moduli can be provided either based on Level 2 input or Level 3 input. Based on Table 4.2, Level 2 input could be a direct field measurement using a device such as the DSPA. This would measure the elastic modulus of the layer and thereby uses the linear elastic algorithm in the program for the subgrade layer. The other Level 2 option is to combine the field measurements from DSPA with laboratory tests such as the resilient modulus test that is used for determining the k-parameters of the nonlinear model. The modulus from the DSPA can be used to calculated k_1 and the results of the resilient modulus for k_2 and k_3 parameters. This allows the constitutive model listed in Table 4.2 as the material model for the analysis. The last input level is Level 3, which requires the use of constitutive models that uses regression equations to estimate the k-parameters. These regression equations are functions of construction parameters. Chapter 3 provides a list of regression equations from various regions in the country that can be used to estimate the k-parameters. Also, Equations 3.12 through 3.14 developed under this project with a limited database can be used for Level input. At the present time, due to the lack of comprehensive models for Texas, it is not recommended to use Level 3 input.

Table 4.2 - Input Levels of Design Parameters for Subgrade Layer

<table>
<tr><th>Parameter</th><th>Input</th><th>Material Type</th><th>Methods</th></tr>
<tr><td>Thickness</td><td>Level 3</td><td>-</td><td>Cores</td></tr>
<tr><td rowspan="4">Modulus</td><td rowspan="3">Level 2</td><td>Linear Elastic</td><td>DSPA used in the field for quality control to measure layer moduli directly</td></tr>
<tr><td rowspan="2">Nonlinear based on Constitutive Model
$M_R = k_1 P_a \left[\frac{\Theta}{P_a}\right]^{k_2} \left[\frac{\sigma_d}{P_a}\right]^{k_3}$</td><td>- DSPA is used to Estimate k_1
- k_2, and k_3 are assume from literature based on material quality</td></tr>
<tr><td>- DSPA is used to Estimate k_1
- Resilient Modulus performed in the laboratory on in-situ material to determine k_2, and k_3</td></tr>
<tr><td>Level 3</td><td>Nonlinear based on Constitutive Model
(same as equation in Level 2)</td><td>k_1, k_2, k_3 are estimated based on regression equations that are functions of construction parameters</td></tr>
</table>

Note: 1) ACP and Base layer information are based on design values.

The next scenario is for a pavement system where base layer properties were identified as significant. In this case, the input to RECIPPE for the top layer can be provided as Level 1 input, and input to the subgrade layer could be the results from scenario one represented as a mean and standard deviation. For the base layer moduli (significant parameter) information from either Level 2 input or Level 3 input can be used. The information in Table 4.3 presents the levels of input for both the layer thickness and the layer moduli. The two main properties for the base layer are the thickness and layer moduli. For the base layer thickness, the monitoring tool can either be to measure cores directly (Level 2) or DCP field testing (Level 3).

Based on Table 4.3, Level 2 input for the base layer moduli is similar to the Level 2 input for the subgrade layer. This can be a direct field measurement using DSPA (or an equivalent device) or a combined field measurements from DSPA and laboratory tests using the resilient modulus results. Also, Level 3 input is same as that presented in for Level 3 input of the subgrade layer, which is to use regression equations to estimate the k-parameters of the constitutive model.

The last scenario presented involves an analysis where ACP layer properties were identified as significant. Input levels for the top layer are summarized in Table 4.4. The thickness of the top layer can be monitored either by cores or GPR, which are designated as Levels 2 and 3, respectively. For the layer moduli Level 2 input, two options are presented: a) V-meter measurements of cores to estimate layer moduli directly and b) direct measurement of the modulus in the field using the PSPA or an equivalent system. For Level 3 input the material models listed in Table 3.2 can be selected to estimate the layer moduli based on construction parameters. The input for the lower layers in this scenario can be provided as Level 1 input. If any parameter of the lower

Table 4.3 - Input Levels of Design Parameters for Base Layer

Parameter	Input	Material Type	Methods
Thickness	Level 2	-	Cores
	Level 3		DCP can be used to estimate thickness value
Modulus	Level 2	Linear Elastic	DSPA used in the field for quality control to measure layer moduli directly
		Nonlinear based on Constitutive Model $M_R = k_1 P_a \left[\frac{\Theta}{P_a}\right]^{k_2} \left[\frac{\sigma_d}{P_a}\right]^{k_3}$	- DSPA is used to Estimate k_1 - k_2, and k_3 are assume from literature based on material quality
			- DSPA is used to Estimate k_1 - Resilient Modulus performed in the laboratory on in-situ material to determine k_2, and k_3
	Level 3	Nonlinear based on Constitutive Model (same as equation in Level 2)	k_1, k_2, k_3 are estimated based on regression equations that are functions of construction parameters

Note: 1) ACP layer information are based on design values.
2) Subgrade layer information is based on either design values or actual field data estimated in Scenario 1 from either level 2 or level 3 inputs.

layers was found significant, then the statistics from that analysis can be incorporated into this scenario.

As demonstrated from the three scenarios presented, RECIPPE can be used at different stages of a construction project and at different levels of input to monitor variability of construction. At this stage of the program, a combination of Level 1 and Level 2 inputs are recommended in the analysis until more elaborate material models can be developed and calibrated for Texas. However, Level 3 inputs provided in the program should be investigated further since for that level, construction parameters can be related directly to performance. A user's guide for RECIPPE is included in Appendix A. Also, a training web site located at http://ctis.utep.edu makes available training modules for the program.

Table 4.4 - Input Levels of Design Parameters for ACP Layer

Parameter	Input	Material Type	Methods
Thickness	Level 2	-	Cores
	Level 3		GPR
Modulus	Level 2	Linear Visco-elastic	V-Meter to measure layer elastic moduli directly from cores Lab testing to determine the viscous properties of the material
			PSPA used in the field for quality control to measure layer moduli directly Lab testing to determine the representative viscous properties of the material
	Level 3	Linear Visco-elastic (Material Model such as regression equations based on Master Curve)	Construction parameters such as Gradation and volumetric information

Note: 1) Base and subgrade layer information is based on either design values, level 1input, or actual field data estimated in Scenarios 1 and 2 from either level 2 or level 3 input.

CHAPTER FIVE - SUMMARY AND CONCLUSION

SUMMARY

The goal of this project was to develop a rational algorithm that can be used in practice for the quality control of construction of pavements. As such, a method was developed, which for a given project, will guide TxDOT personnel to determine what parameters would significantly impact the performance, what parameters will moderately impact and those that are of small importance. The level of acceptable deviations from the target design value for each parameter is established based on quantification of the variability of the construction parameters introduced by: (a) the construction processes, (b) the material properties, (c) the models used to predict pavement performance and those used for data analysis, and (d) the resolution of the procedures used in the field for quality control.

The software developed utilizing the algorithm is called Rational Estimation of Construction Impact on Pavement Performance (RECIPPE). It can be used to reconcile the results from pavement-performance models used in the state of practice, or those widely accepted by state agencies, with statistical process control techniques and uncertainty analysis methods, to determine project-specific parameters that should be used in construction quality management.

This is the fourth report in this project. The first report introduced the algorithm and the link between the construction processes and performance parameters. The second report provided a limited validation of the methodology. The third report focused on presenting the enhanced features of the program RECIPPE and the calibration and development of the material models. This report discusses the final phase of the project. The validation of the models is presented and the application of RECIPPE based on different input levels is discussed.

CONCLUSIONS

RECIPPE presents a process that can be used in a practical manner to optimize pavement performance. Furthermore, the latest version of the process is versatile and avails complete modularity, which allows for new material and performance models to be inputted and/or calibrated as needed. Even though a limited number of sites were used to develop calibrated material models the results from RECIPPE and the methodology presented in this study is a step towards a more rational estimation of pavement remaining life from construction parameters.

The current RECIPPE program can be used to:

- Generate constructions parameter values that will meet owner's needs for pavement life
- Identify the construction parameters to focus on, in order to reduce pavement life variance and increase reliability
- Track and identify out of control procedures during construction
- Reduce sampling costs by optimizing the frequency of testing
- Create databases that can be used in future projects
- Lower variability of construction practices
- Perform quality control and/or quality assurance of construction practices
- Focus manpower on specific parameters and reduce costs

RECOMMENDATIONS FOR FUTURE STUDY

The proposed methodologies for predicting pavement performance, and their corresponding variations, have been completed and somewhat calibrated. The tools are deemed ready for shadow implementation. Shadow implementation would allow for RECIPPE to be validated by comparing its results to current methods. The results from the shadow implementation would provide the limitations/advantages of practically using the program in the real world.

Also, an additional cost/benefit analysis can be incorporated to show the life cycle cost analysis, based on the results from RECIPPE. To be specific, the present cost/benefit analysis concentrates on only the price of sampling and not the cost of future rehabilitation. Due to the fact that RECIPPE finds the amount of pavement that will withstand a set number of ESALs (in the form of the reliability), it could be expanded to find the amount of pavement that will not withstand a set number of ESALs. Hence, predicting how much pavement will need to be rehabilitated before the expected design life.

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APPENDIX A - RECIPPE USERS MANUAL

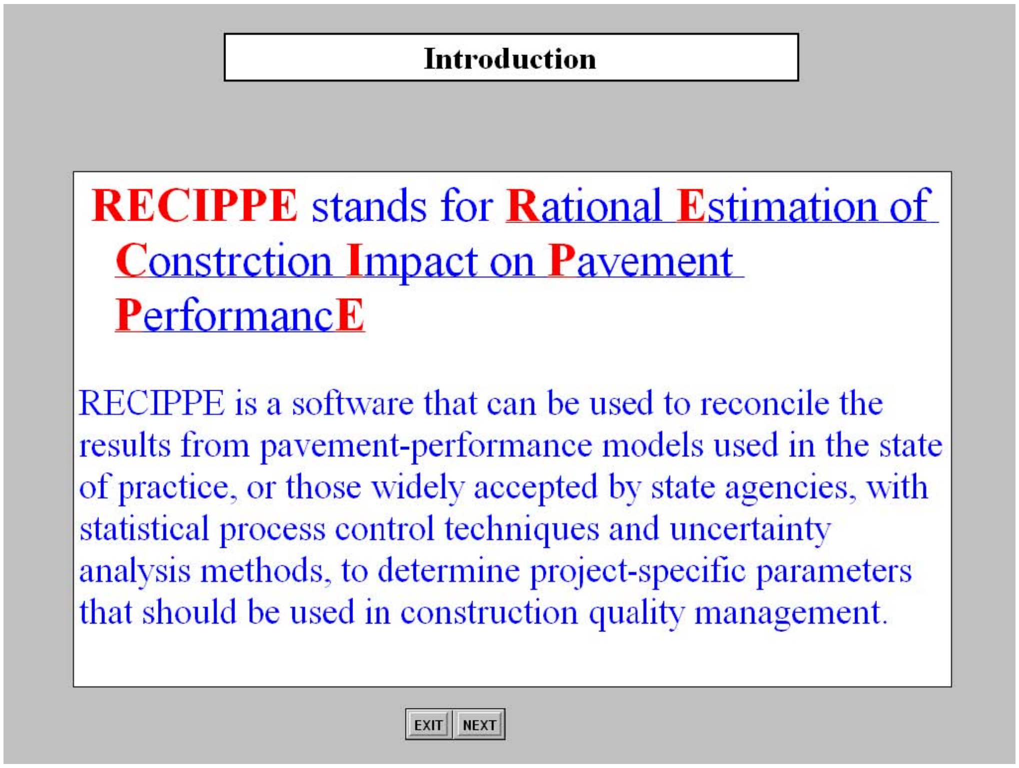
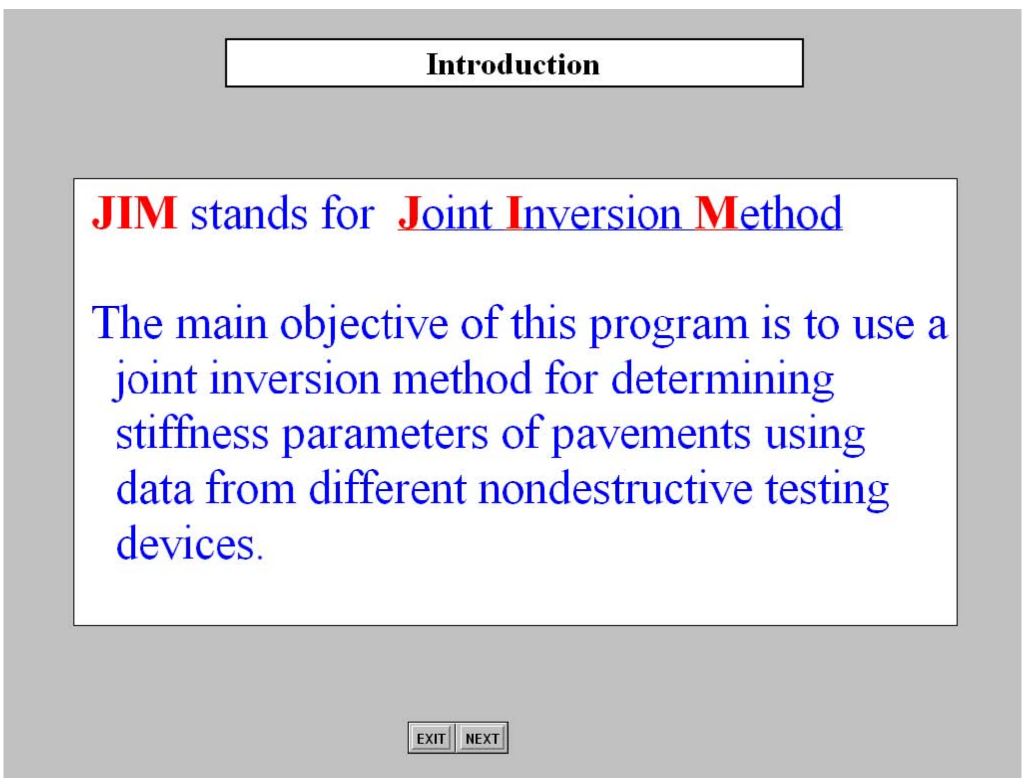


Figure A.1 - Slide 1 of Introduction



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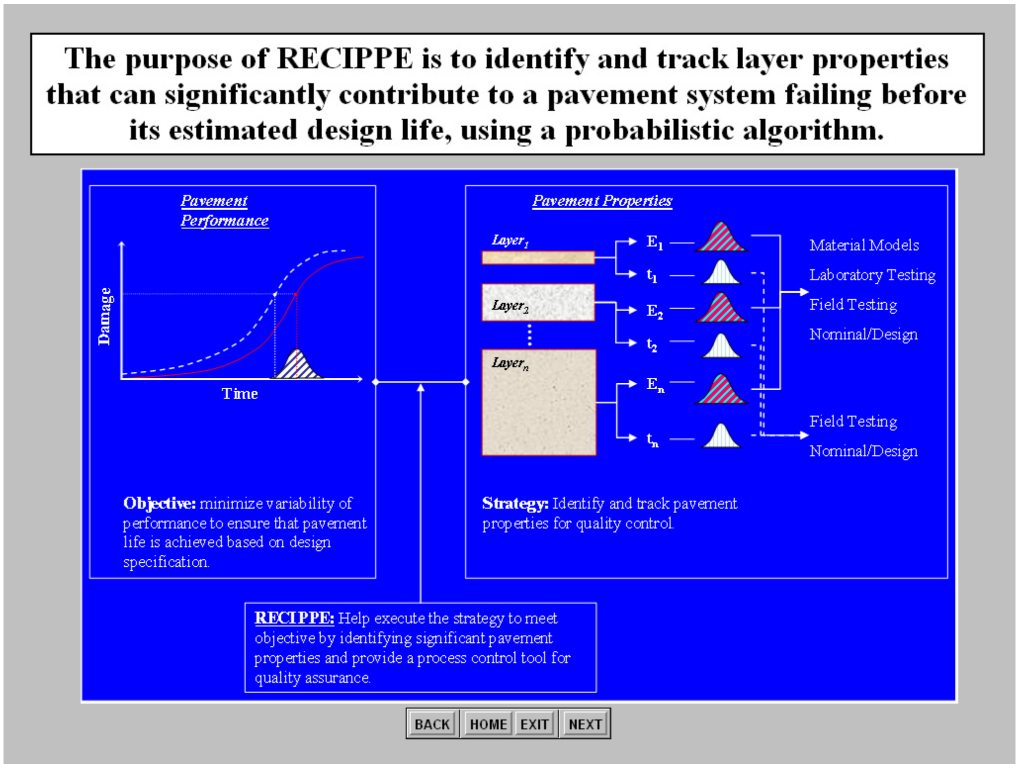

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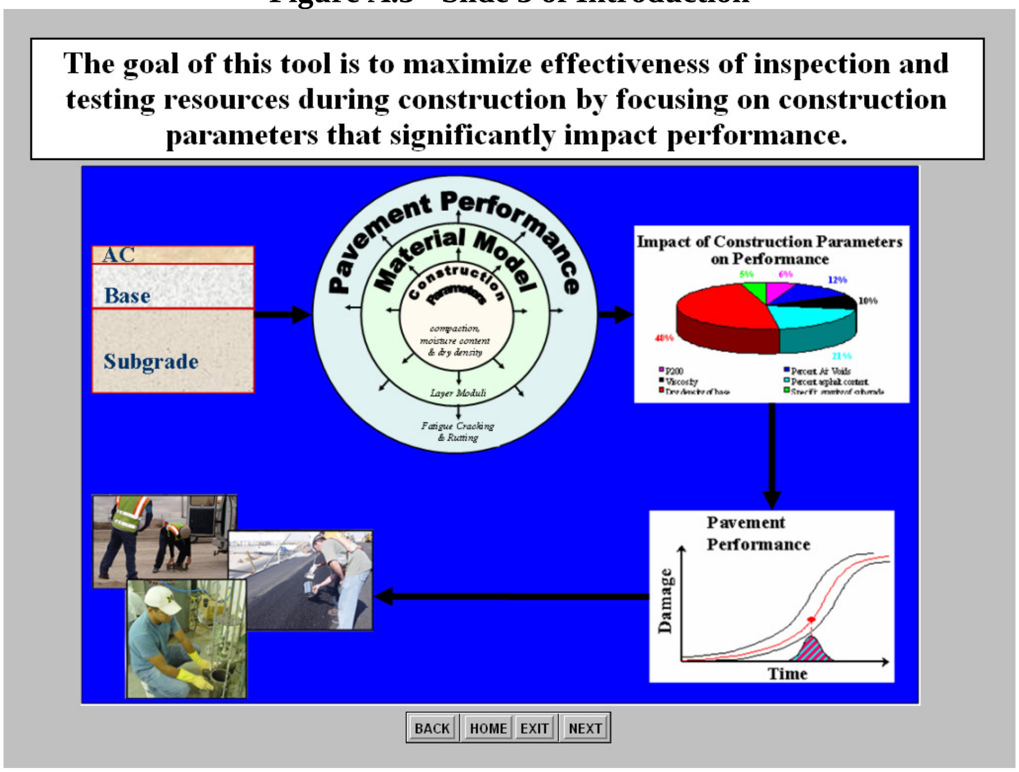

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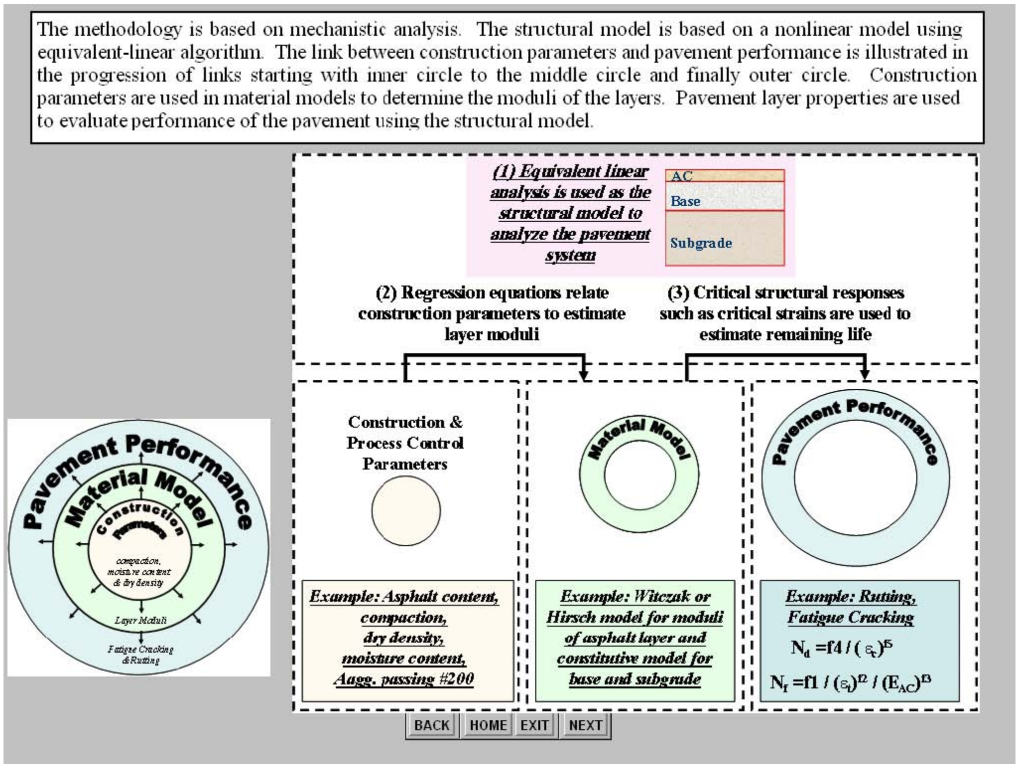

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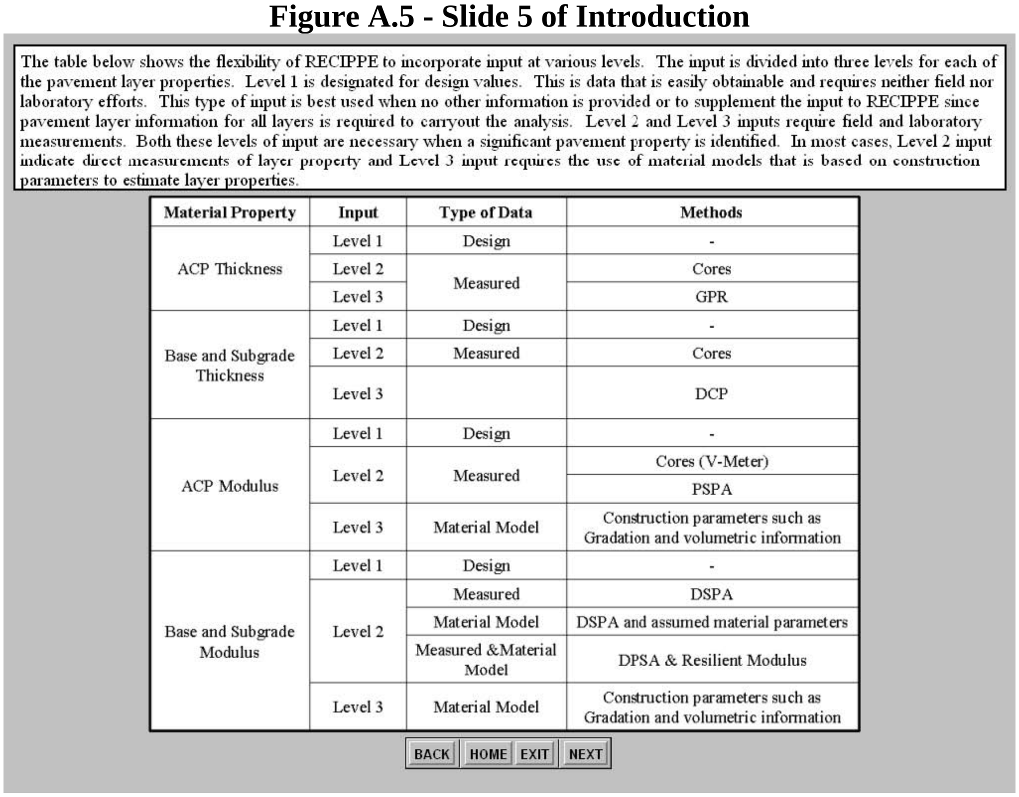

The table below shows the flexibility of RECIPPE to incorporate input at various levels. The input is divided into three levels for each of the pavement layer properties. Level 1 is designated for design values. This is data that is easily obtainable and requires neither field nor laboratory efforts. This type of input is best used when no other information is provided or to supplement the input to RECIPPE since pavement layer information for all layers is required to carryout the analysis. Level 2 and Level 3 inputs require field and laboratory measurements. Both these levels of input are necessary when a significant pavement property is identified. In most cases, Level 2 input indicate direct measurements of layer property and Level 3 input requires the use of material models that is based on construction parameters to estimate layer properties.

Material Property	Input	Type of Data	Methods
ACP Thickness	Level 1	Design	-
	Level 2	Measured	Cores
	Level 3		GPR
Base and Subgrade Thickness	Level 1	Design	-
	Level 2	Measured	Cores
	Level 3		DCP
ACP Modulus	Level 1	Design	-
	Level 2	Measured	Cores (V-Meter)
			PSPA
	Level 3	Material Model	Construction parameters such as Gradation and volumetric information
Base and Subgrade Modulus	Level 1	Design	-
	Level 2	Measured	DSPA
		Material Model	DSPA and assumed material parameters
		Measured &Material Model	DPSA & Resilient Modulus
	Level 3	Material Model	Construction parameters such as Gradation and volumetric information

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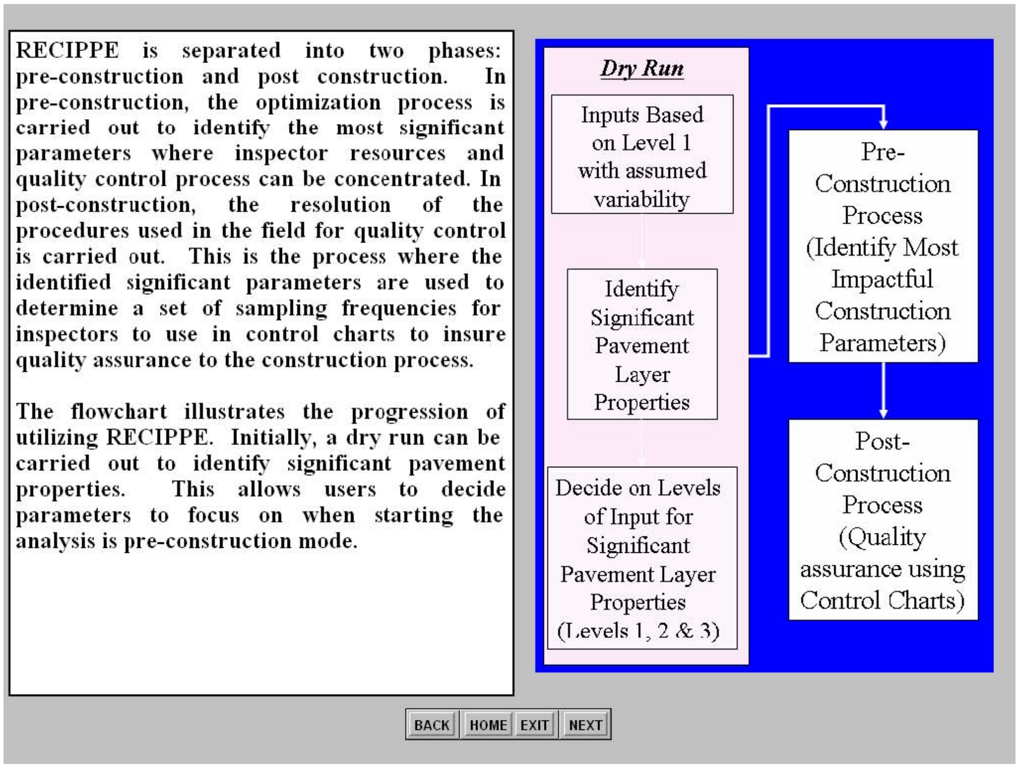
Figure A.6 - Slide 6 of Introduction



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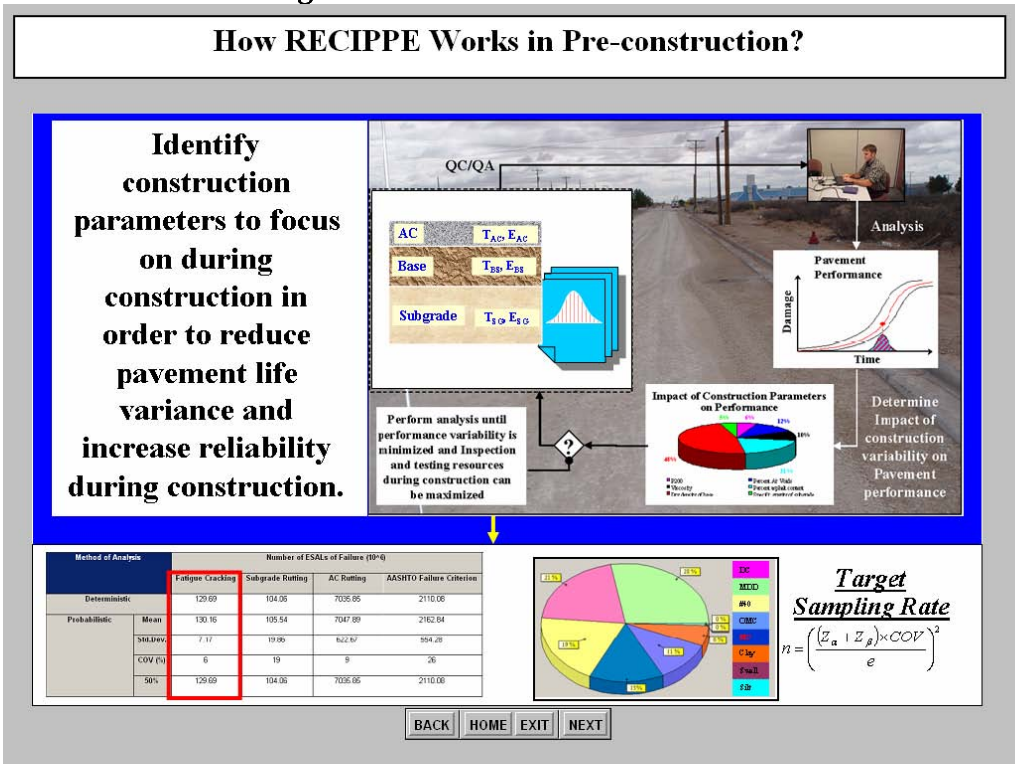

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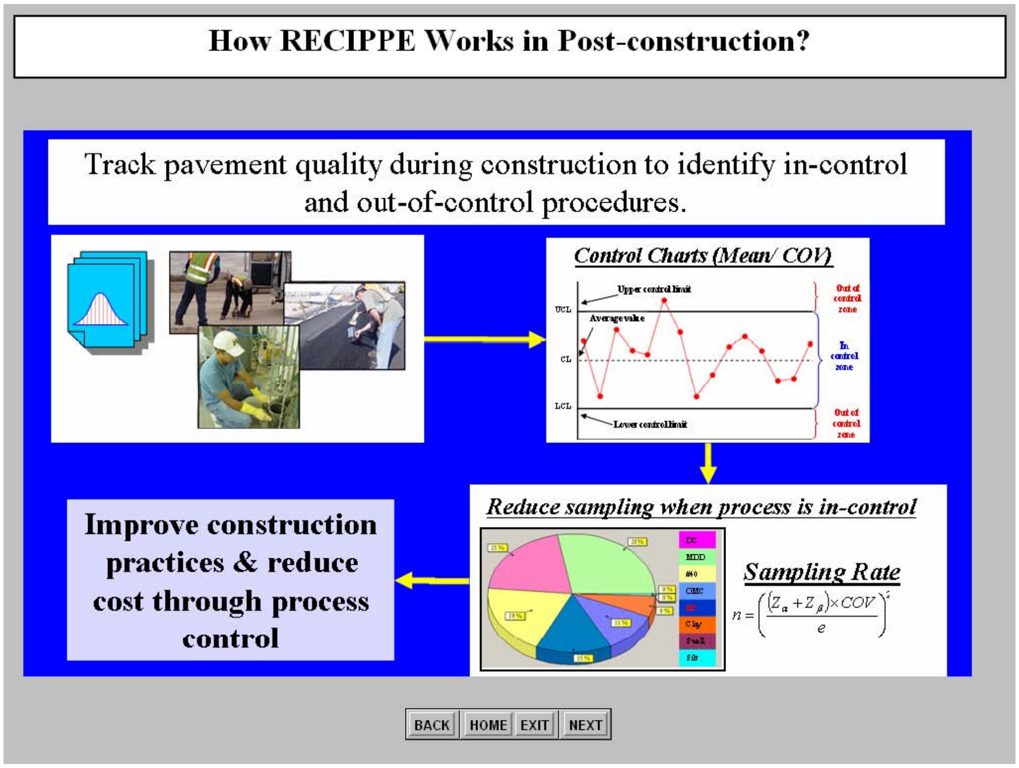

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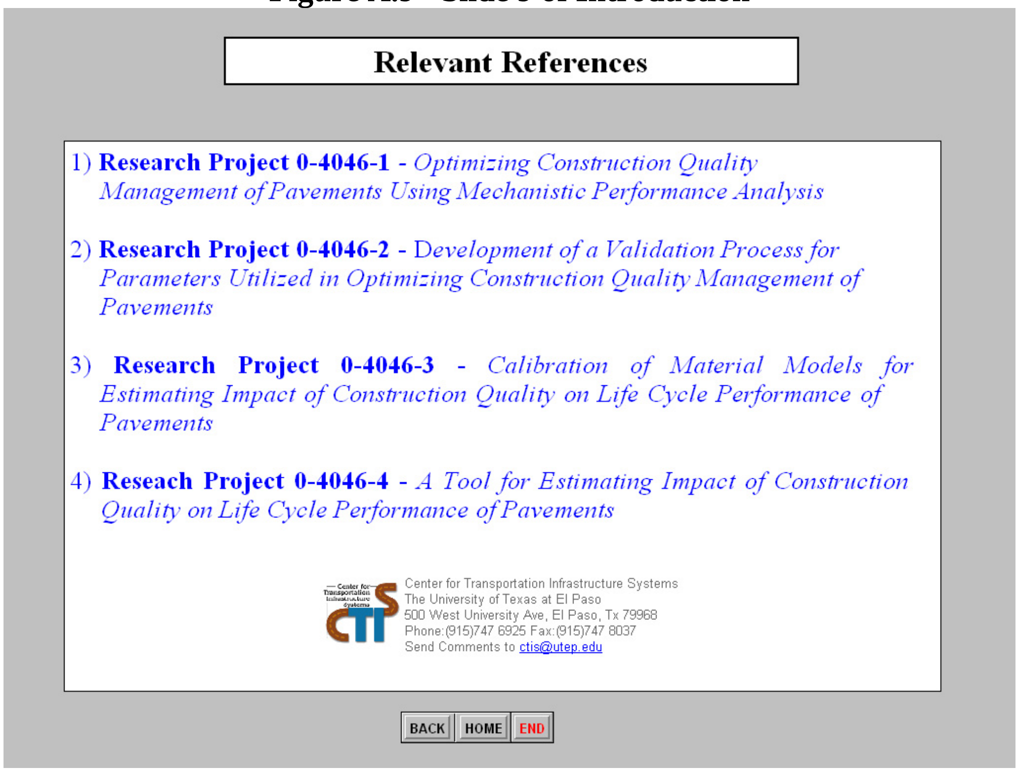

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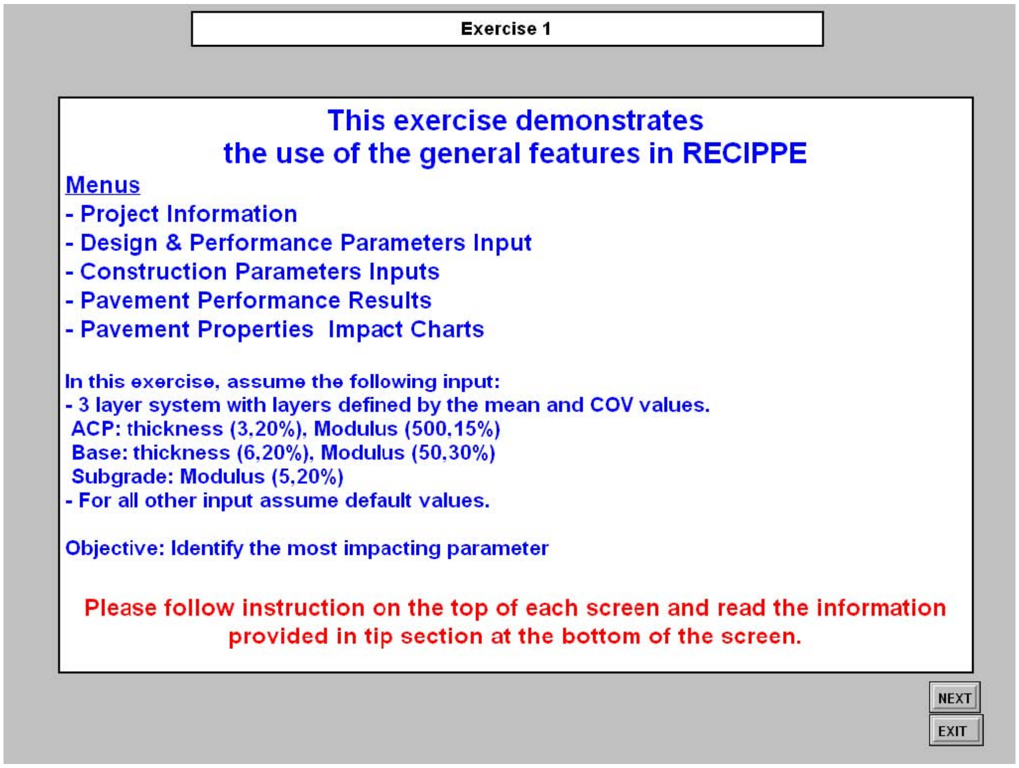
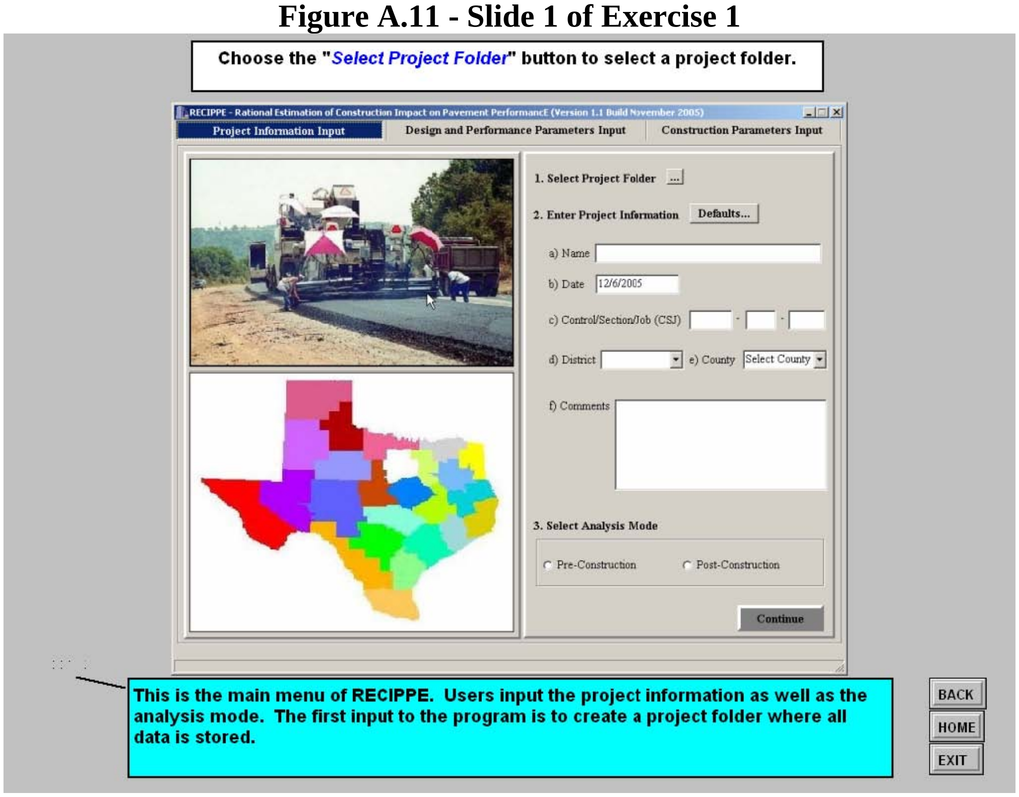


Figure A.11 - Slide 1 of Exercise 1



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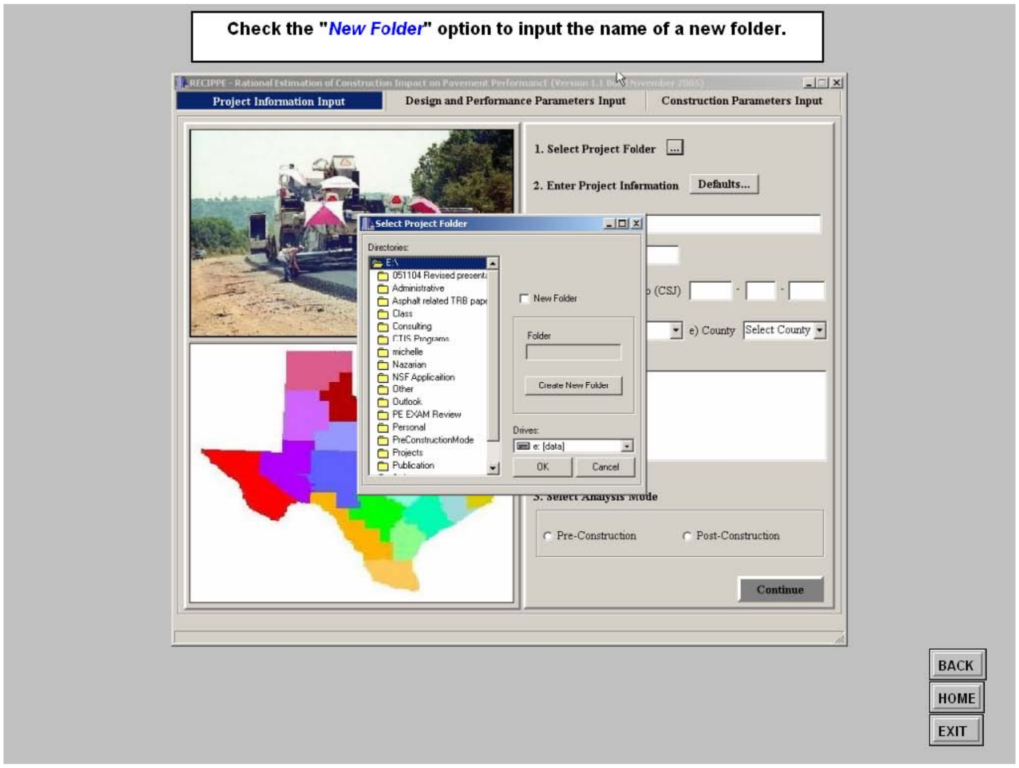

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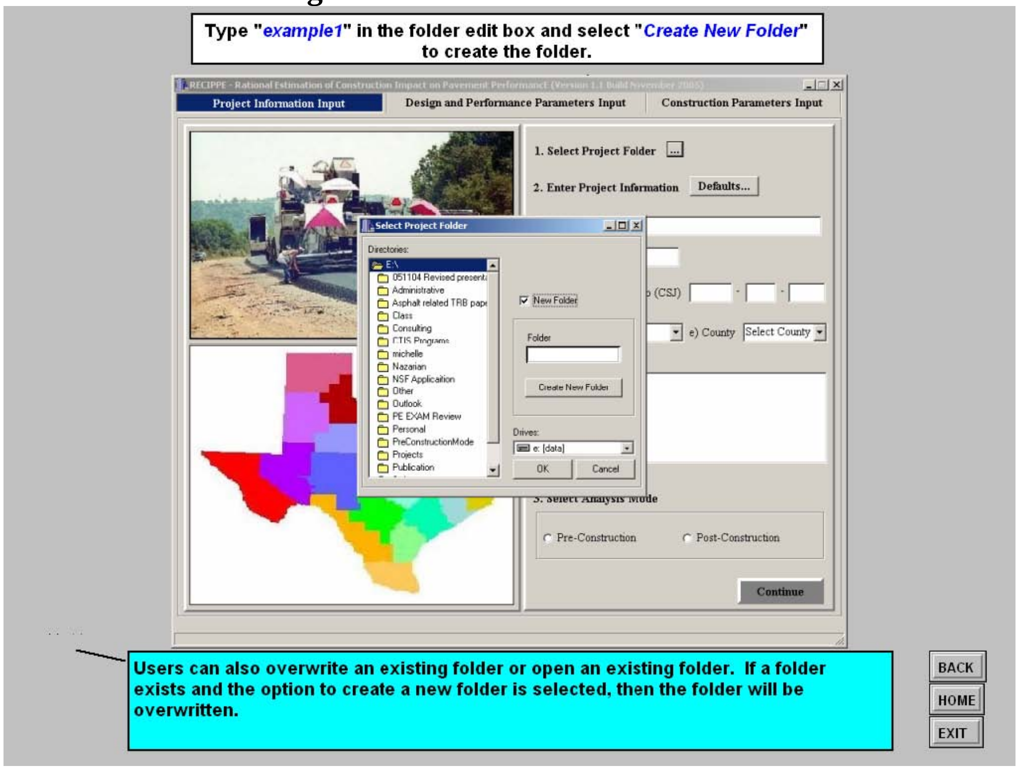

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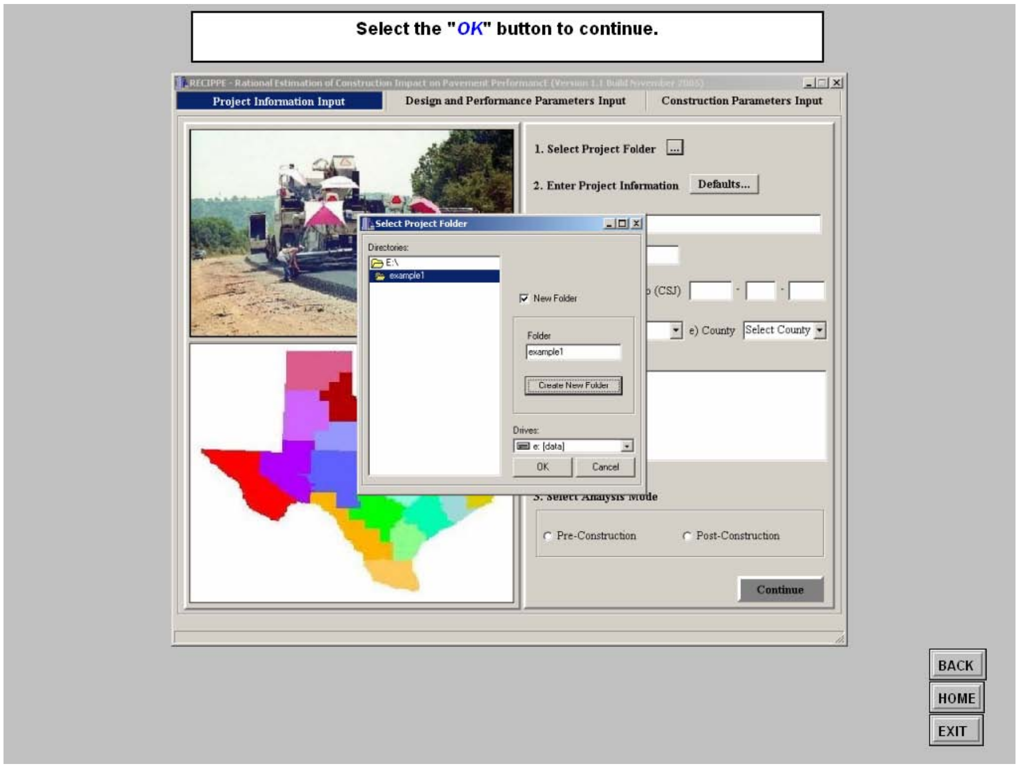

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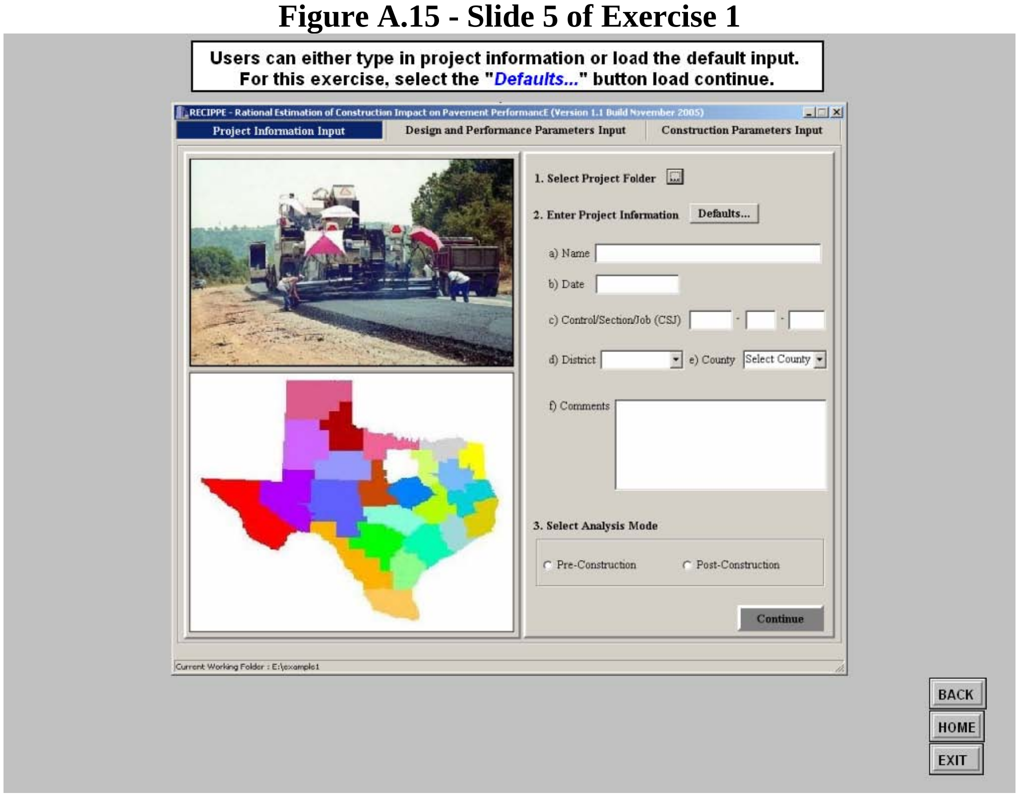

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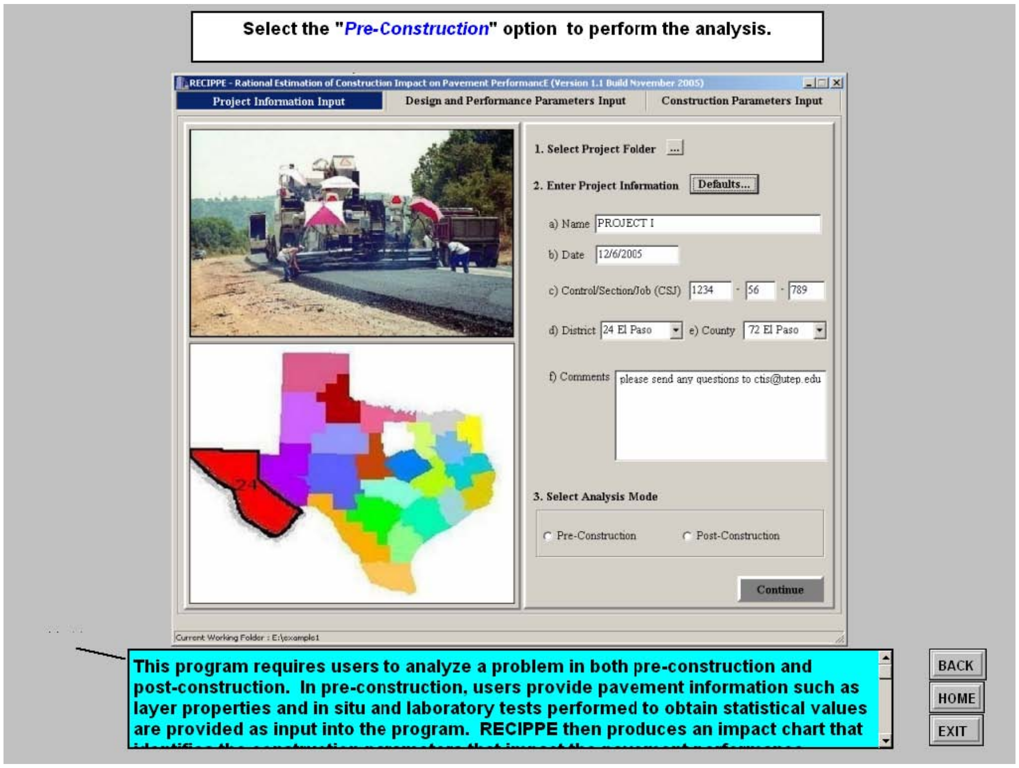

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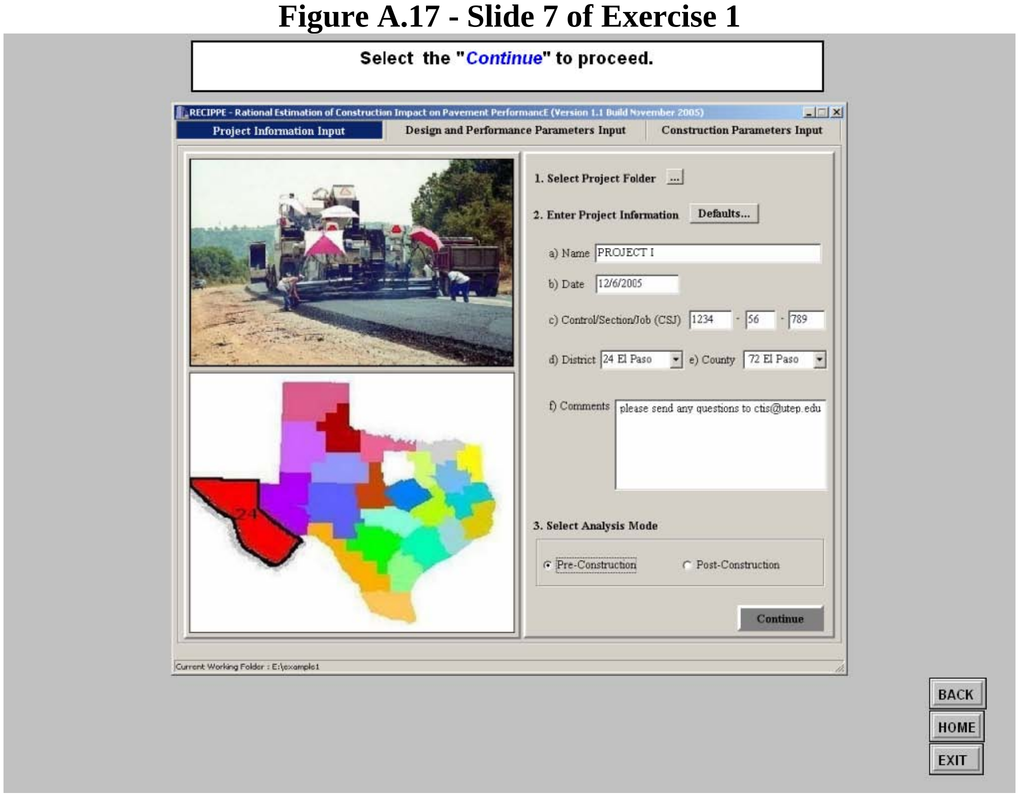

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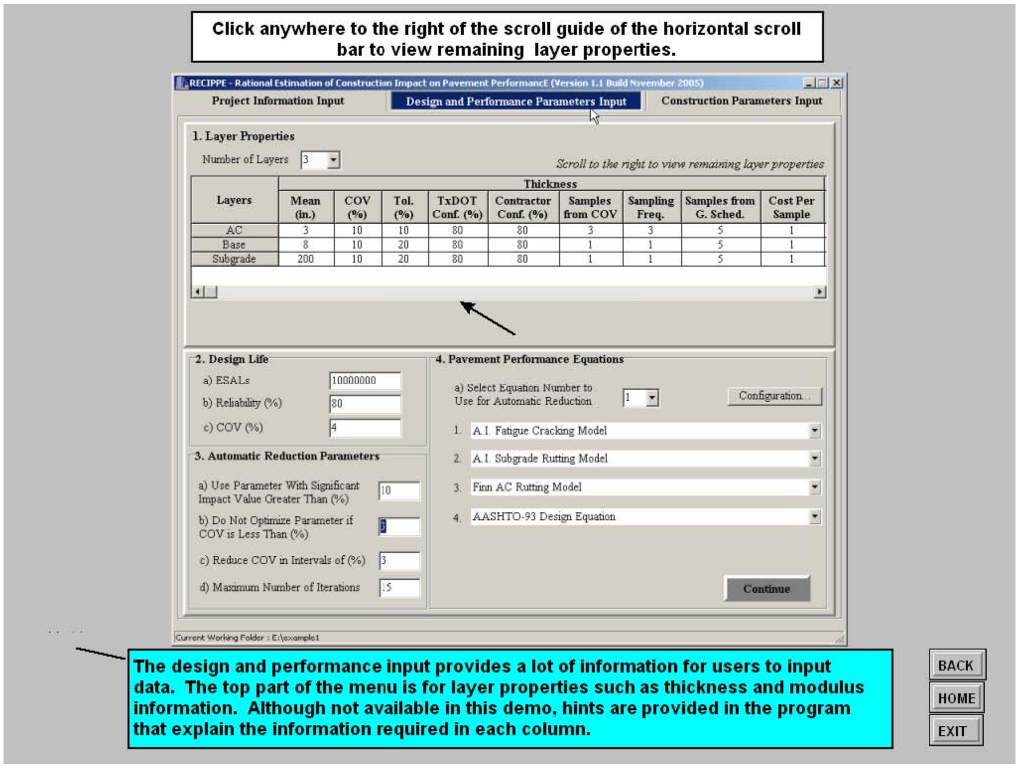

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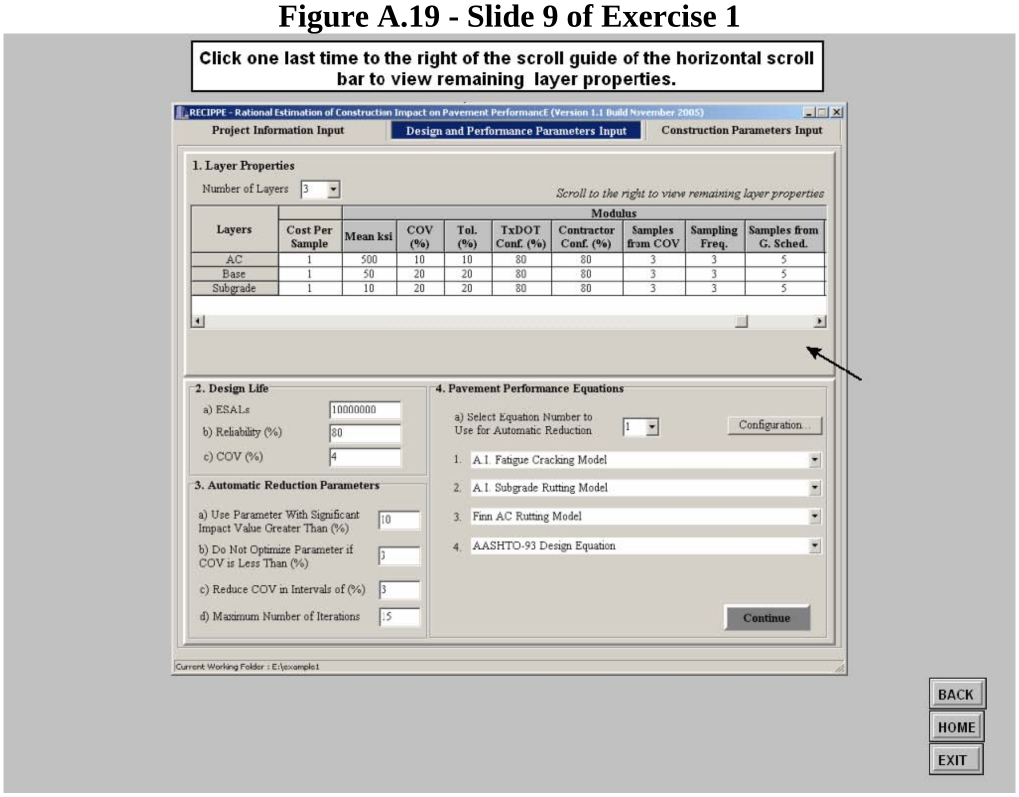

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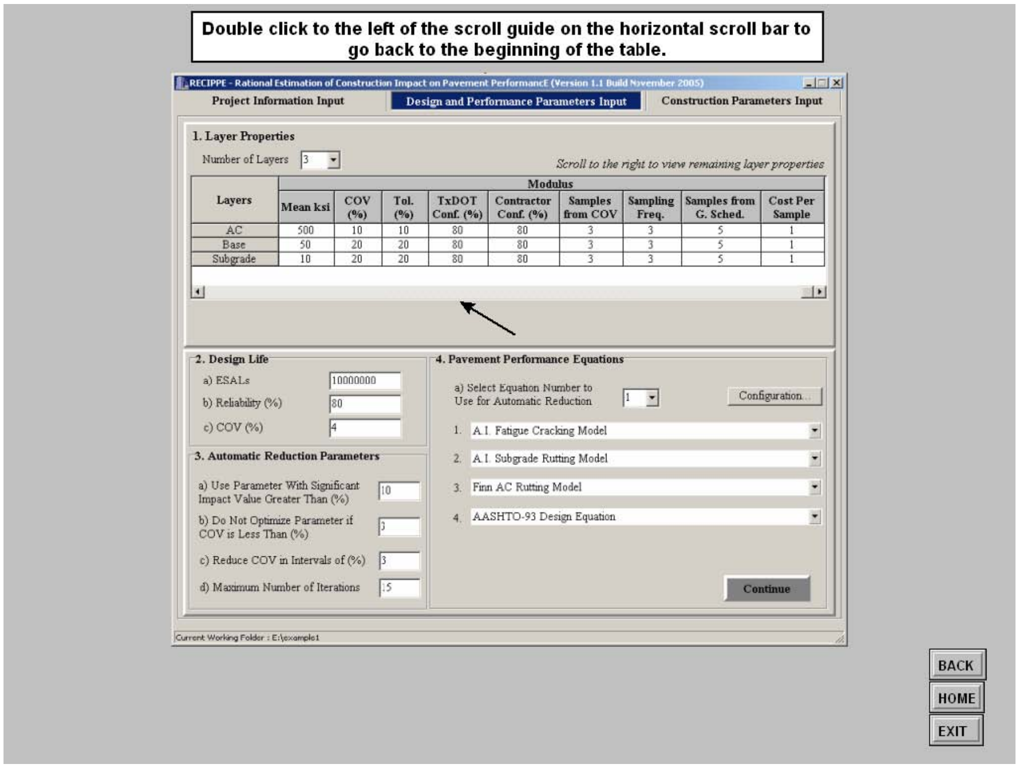

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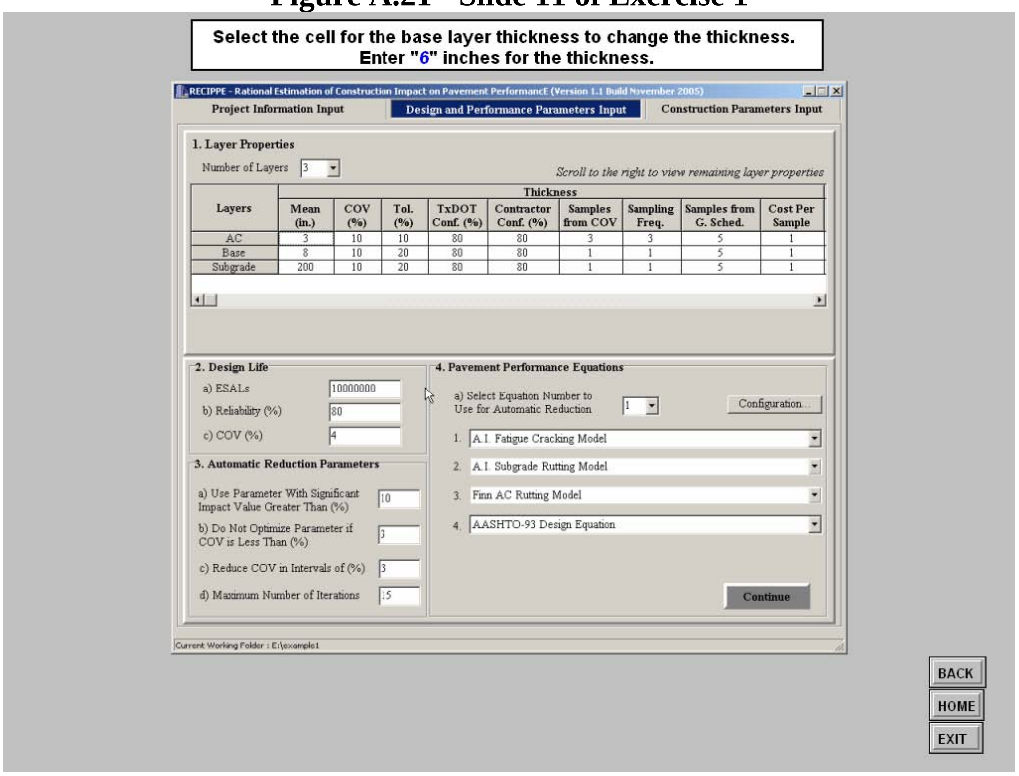

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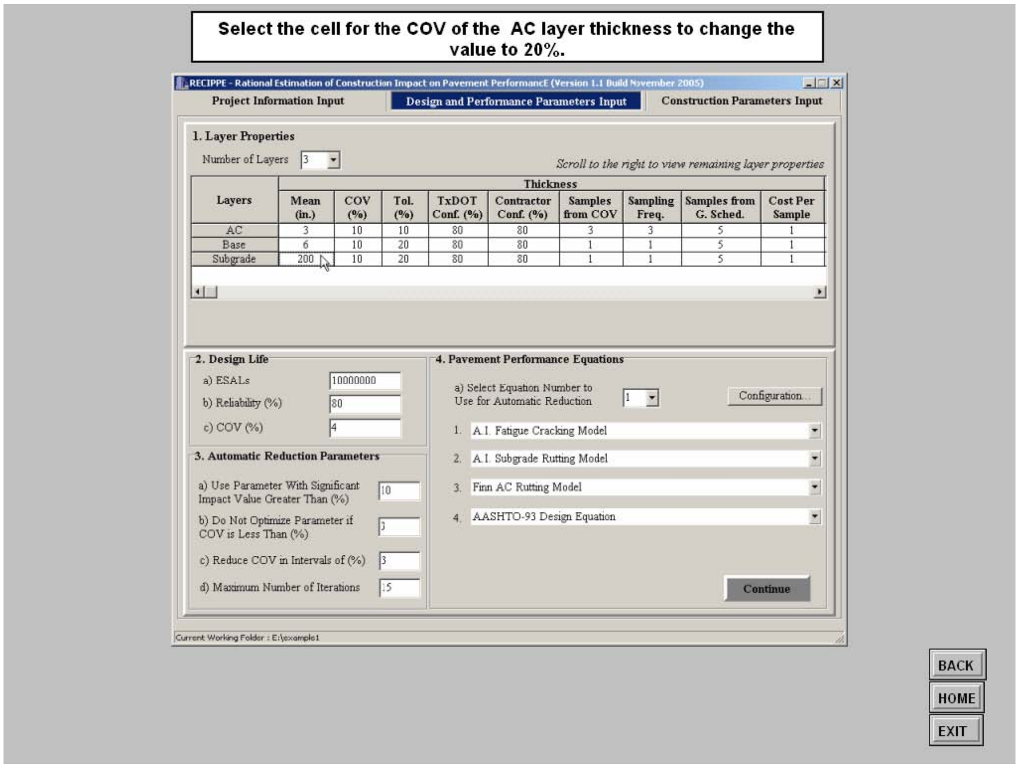

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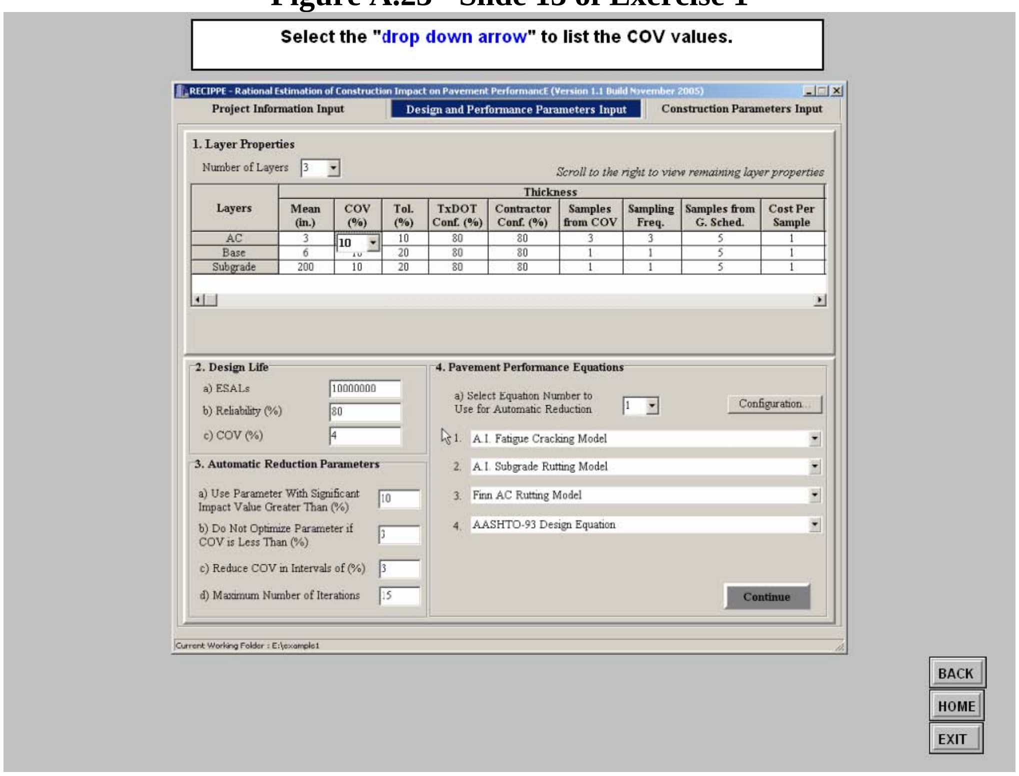

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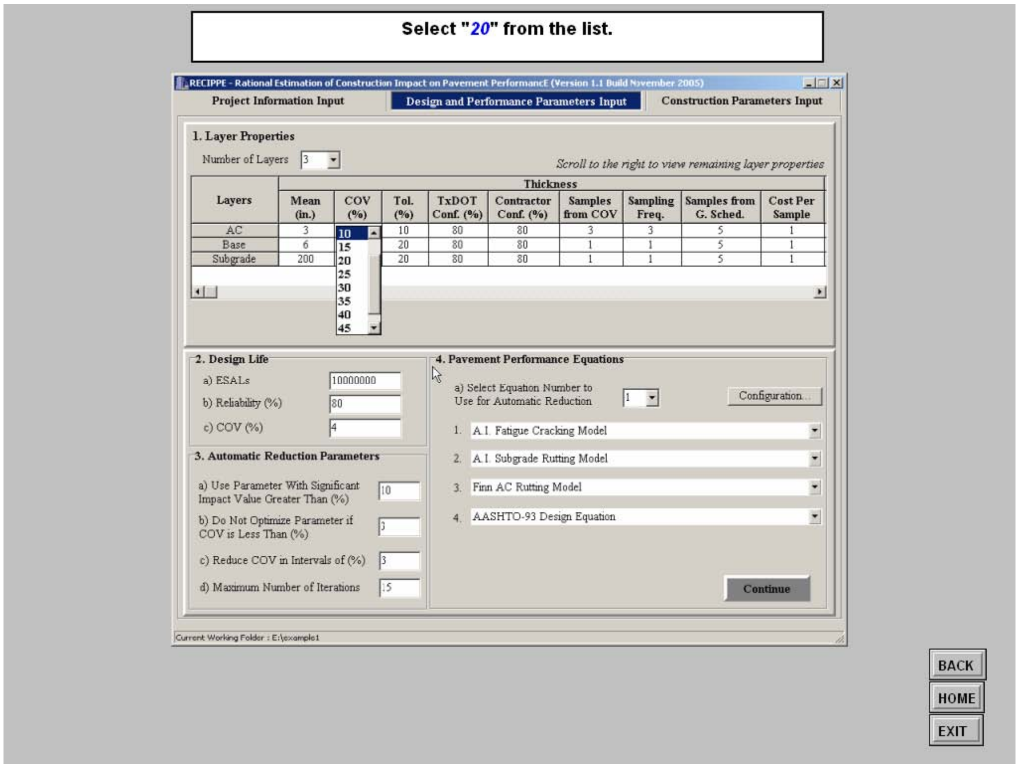


Figure A.25 - Slide 15 of Exercise 1

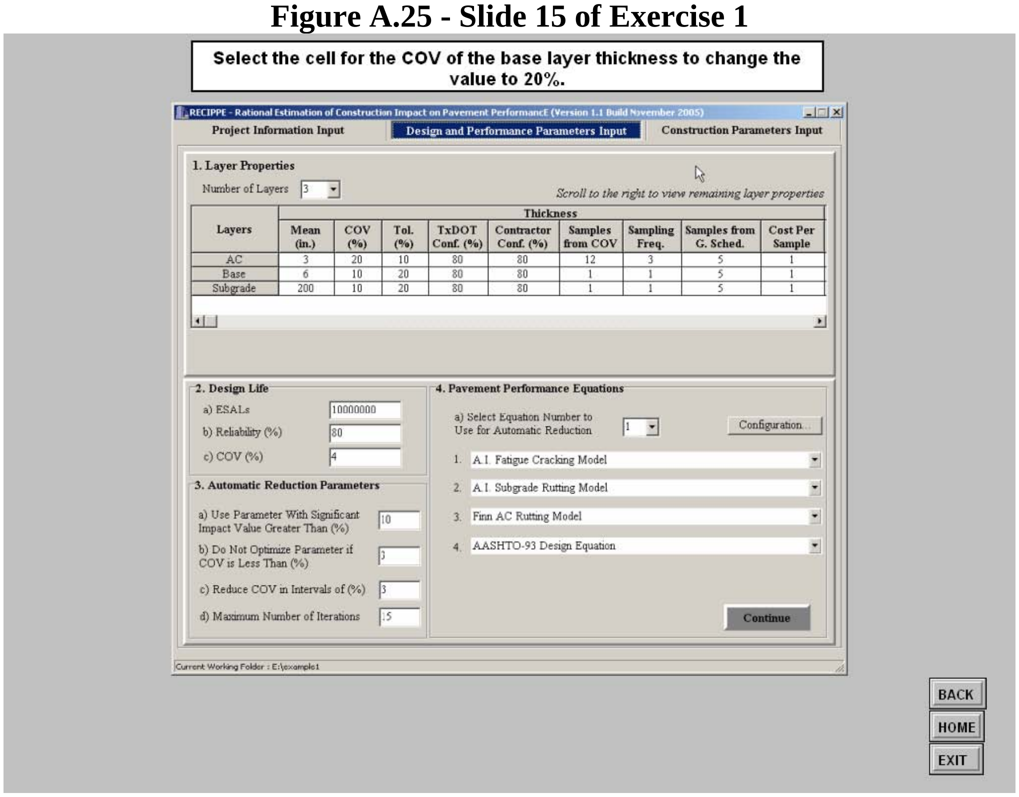


Figure A.26 - Slide 16 of Exercise 1

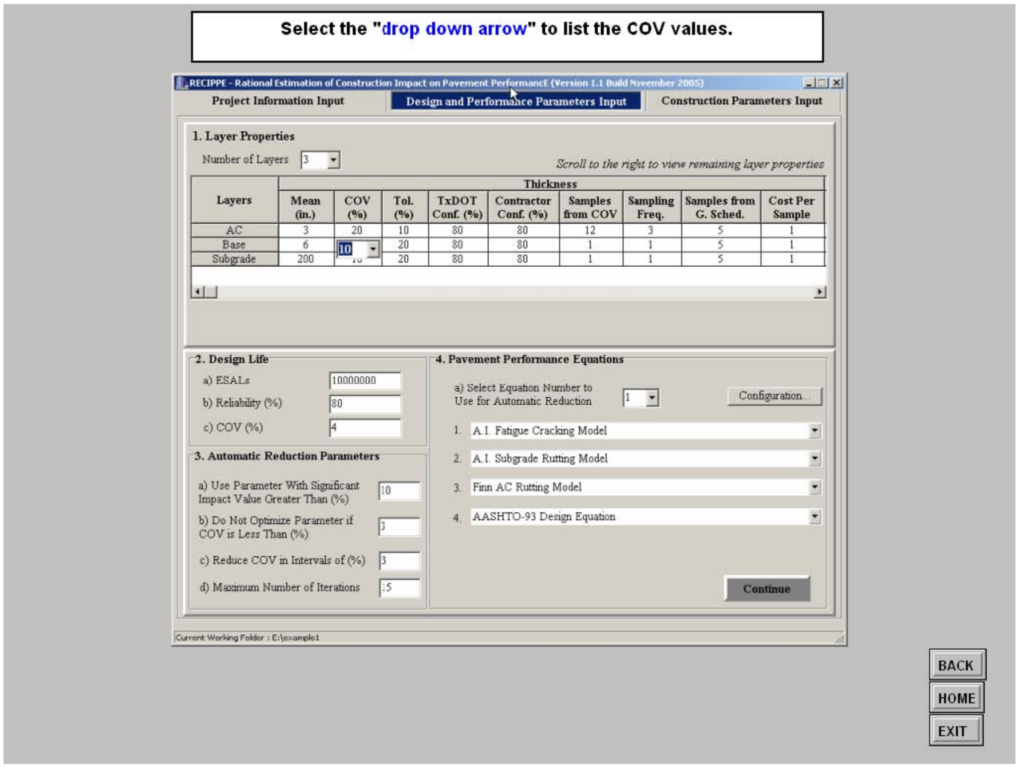


Figure A.27 - Slide 17 of Exercise 1

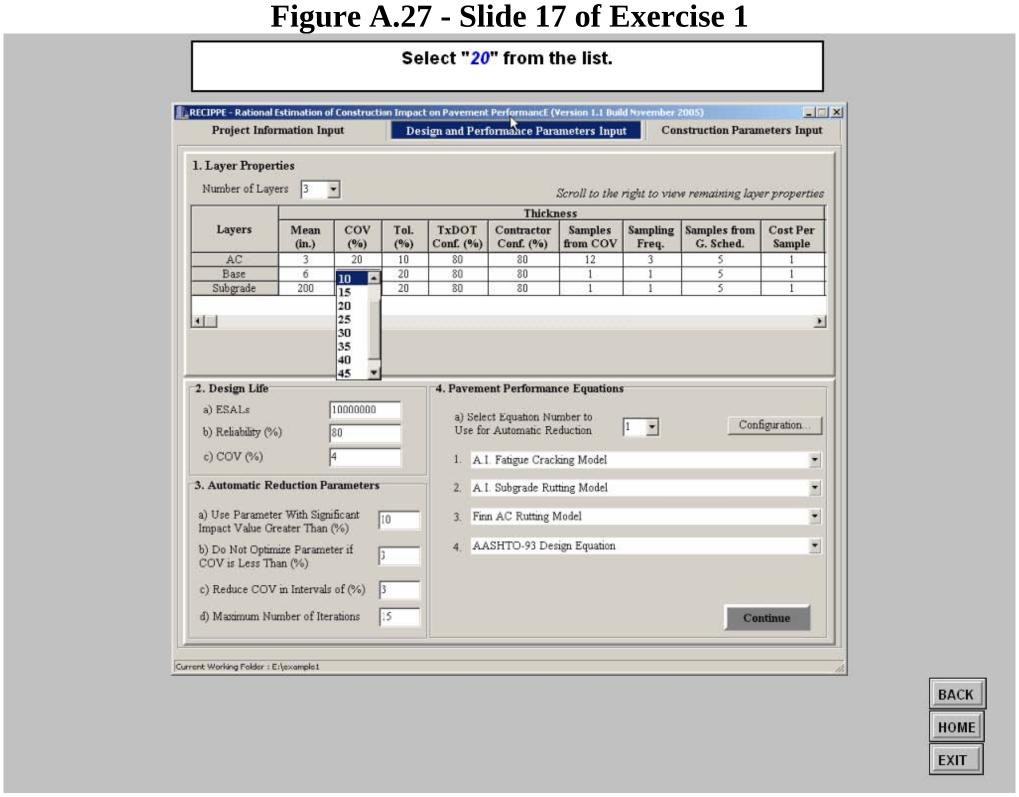


Figure A.28 - Slide 18 of Exercise 1

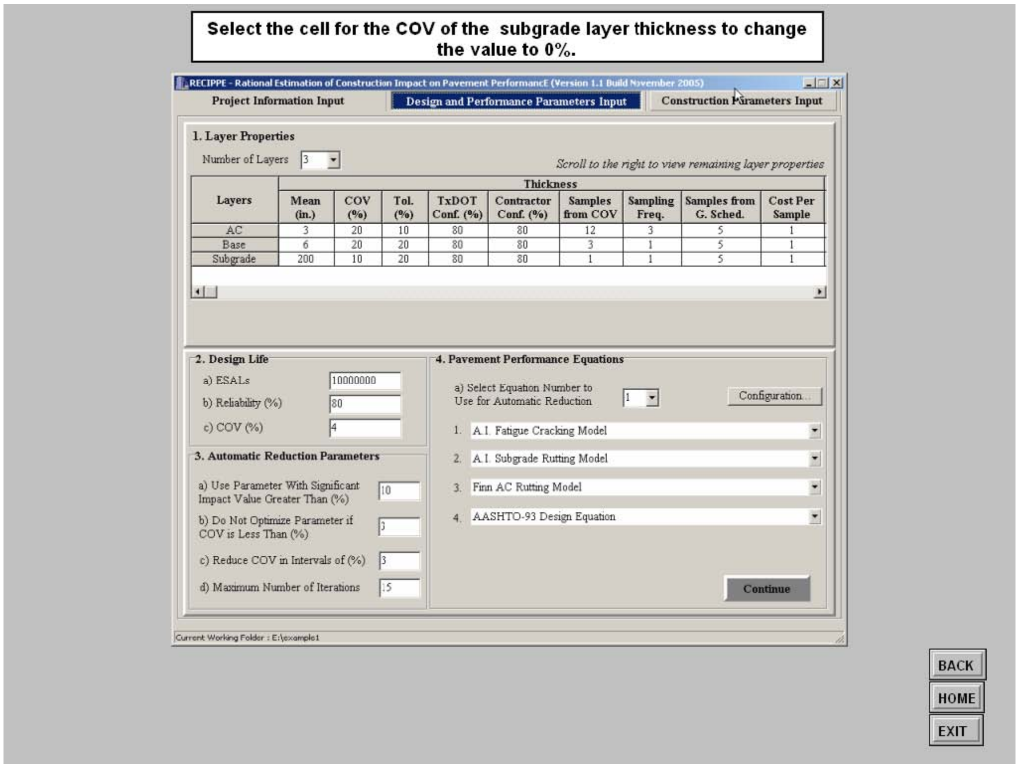


Figure A.29 - Slide 19 of Exercise 1

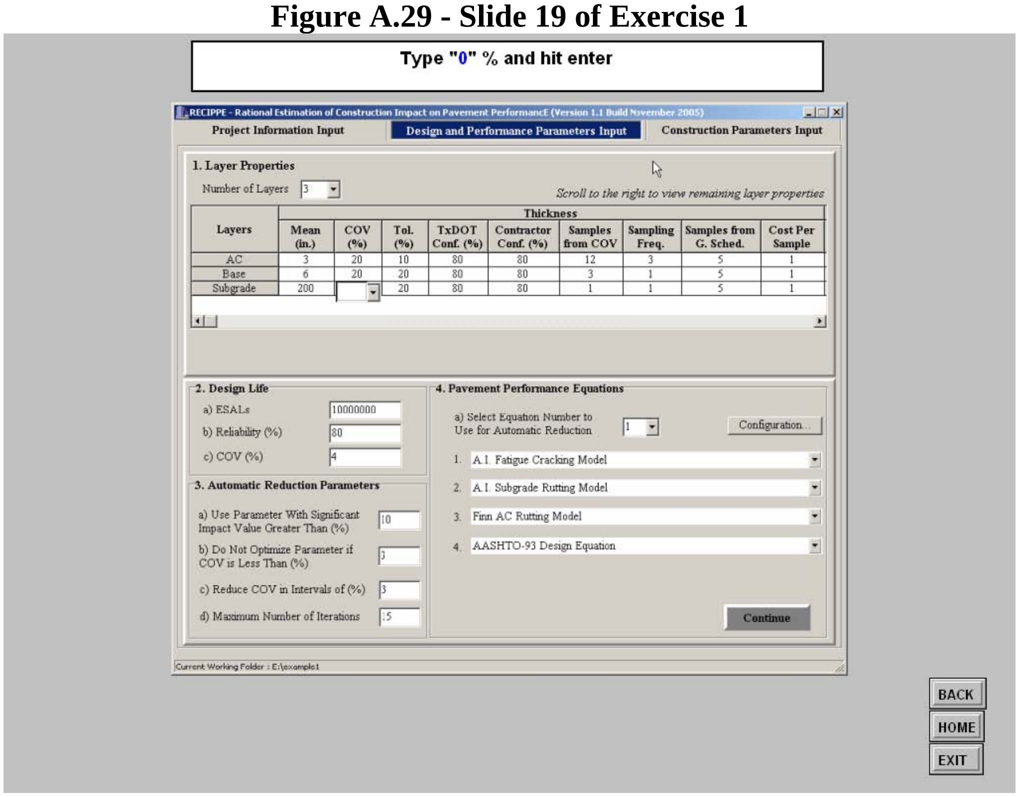


Figure A.30 - Slide 20 of Exercise 1

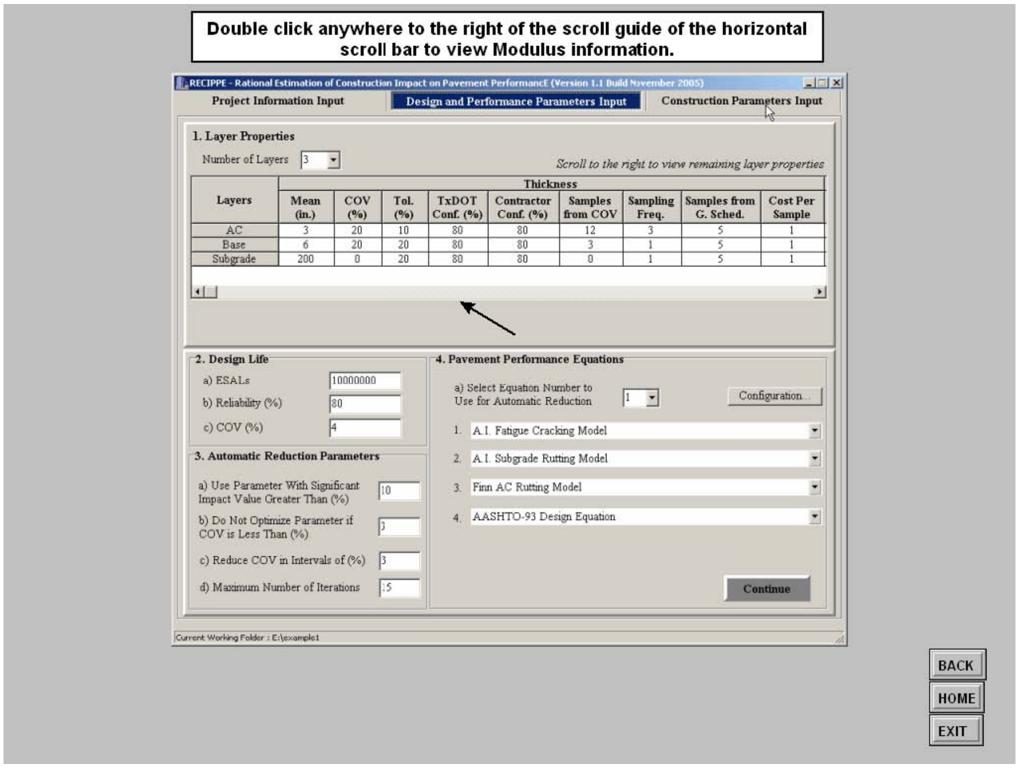


Figure A.31 - Slide 21 of Exercise 1

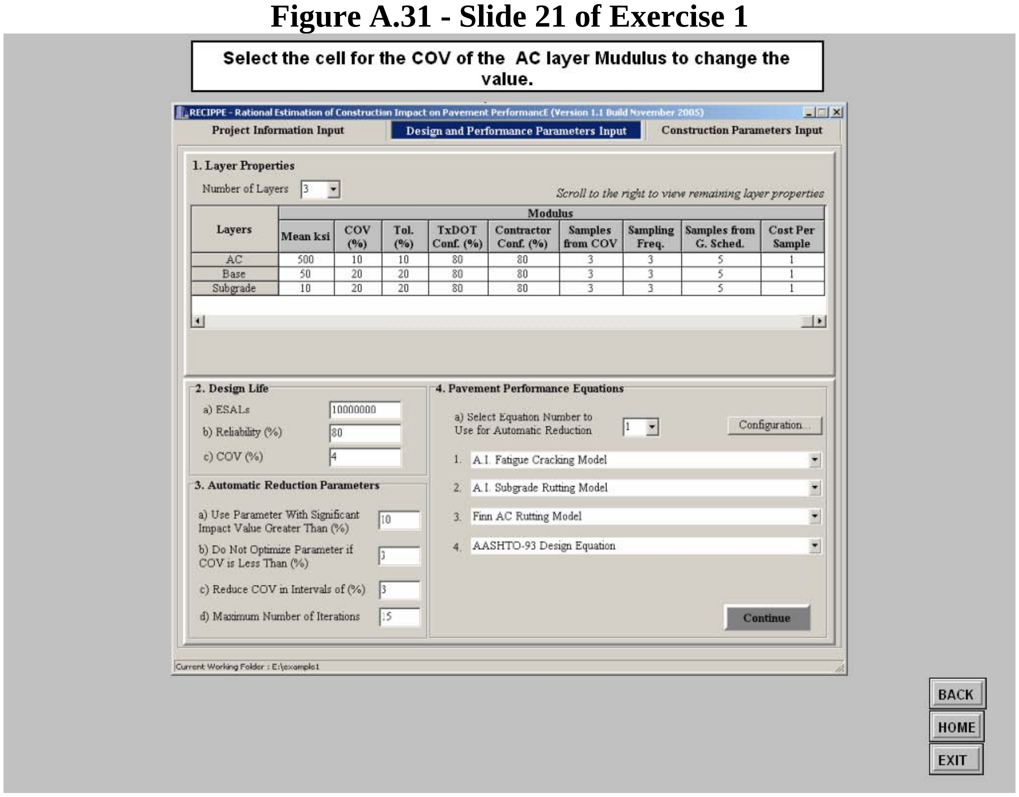


Figure A.32 - Slide 22 of Exercise 1

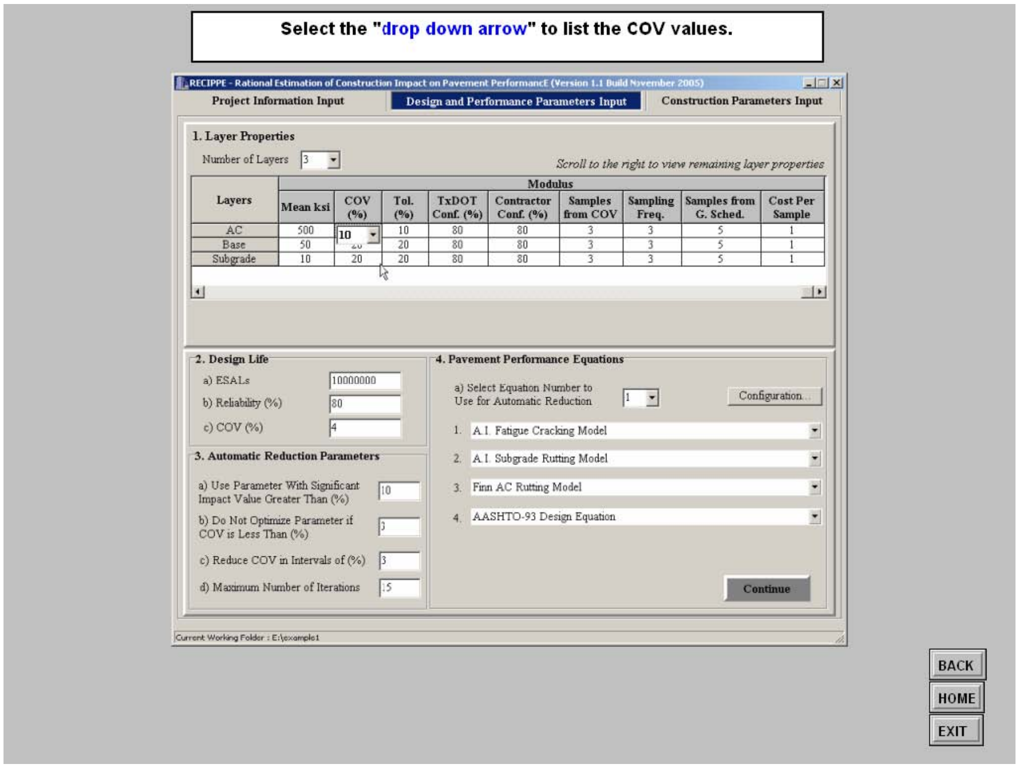


Figure A.33 - Slide 23 of Exercise 1

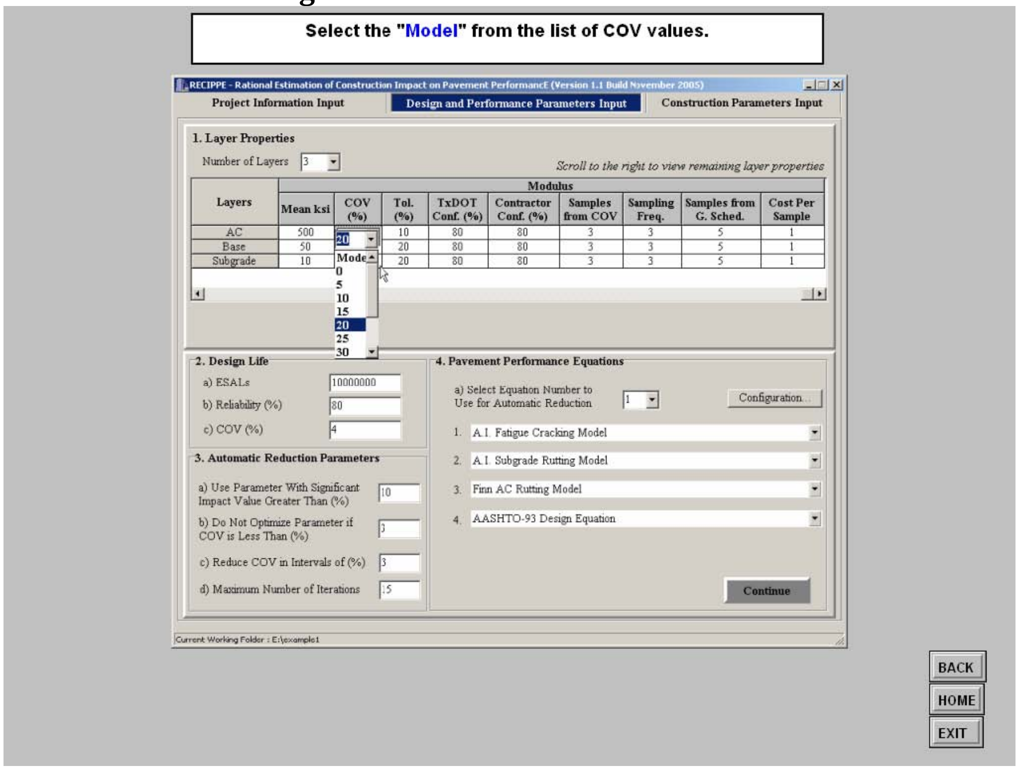


Figure A.34 - Slide 24 of Exercise 1

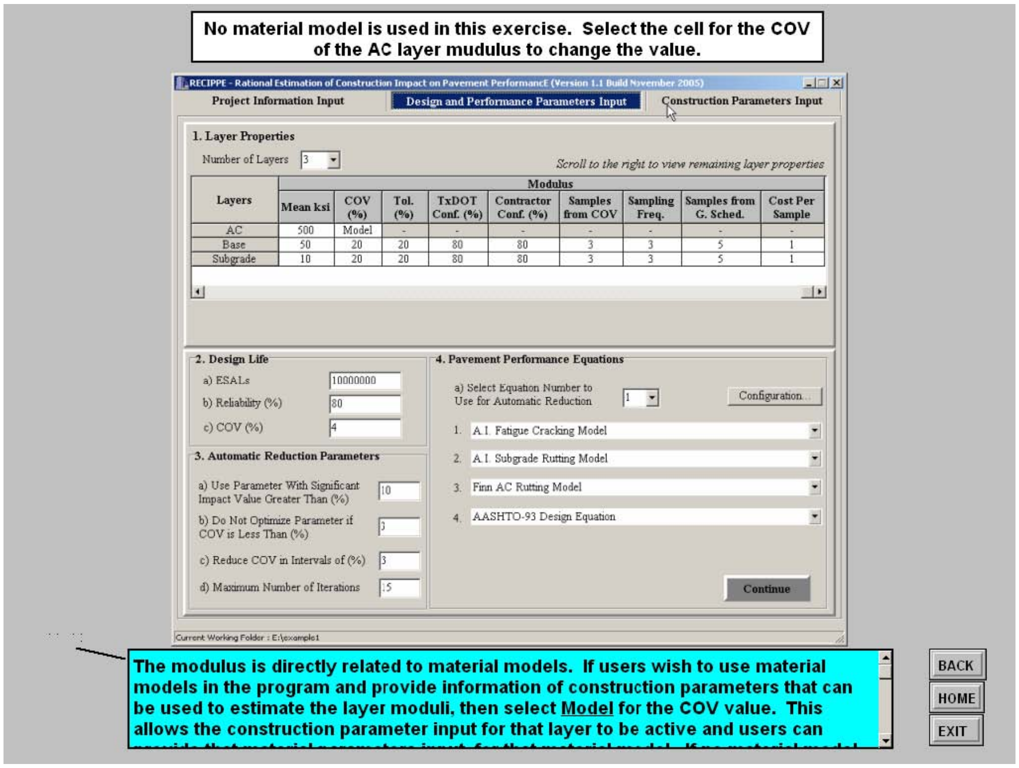


Figure A.35 - Slide 25 of Exercise 1

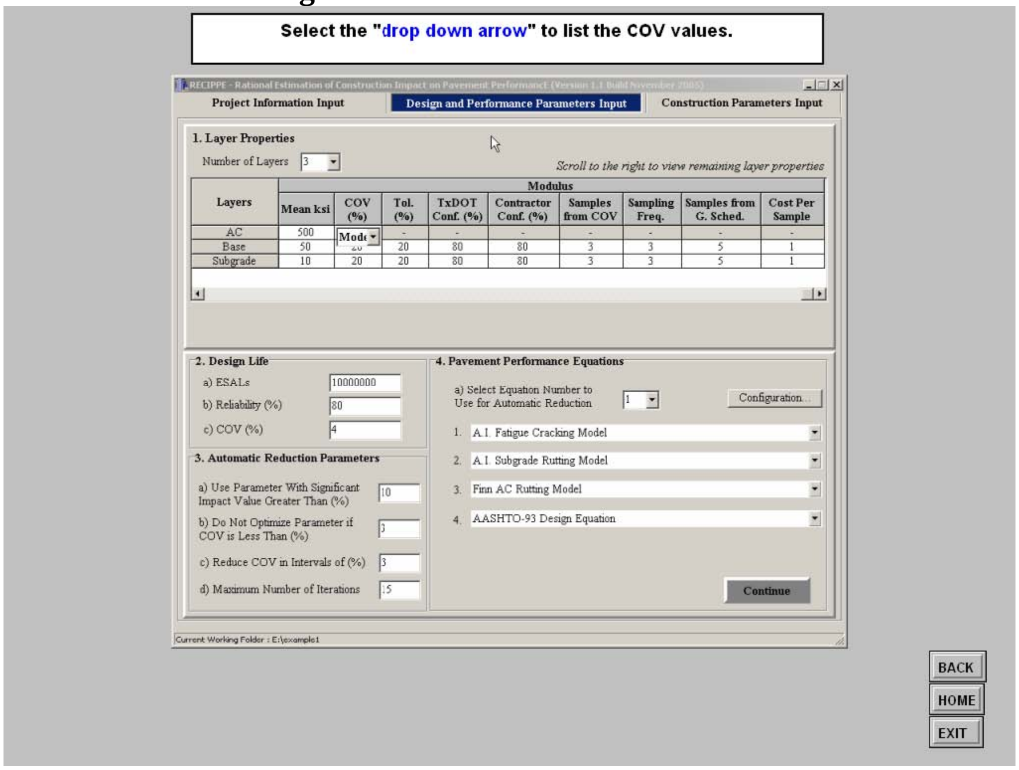


Figure A.36 - Slide 26 of Exercise 1

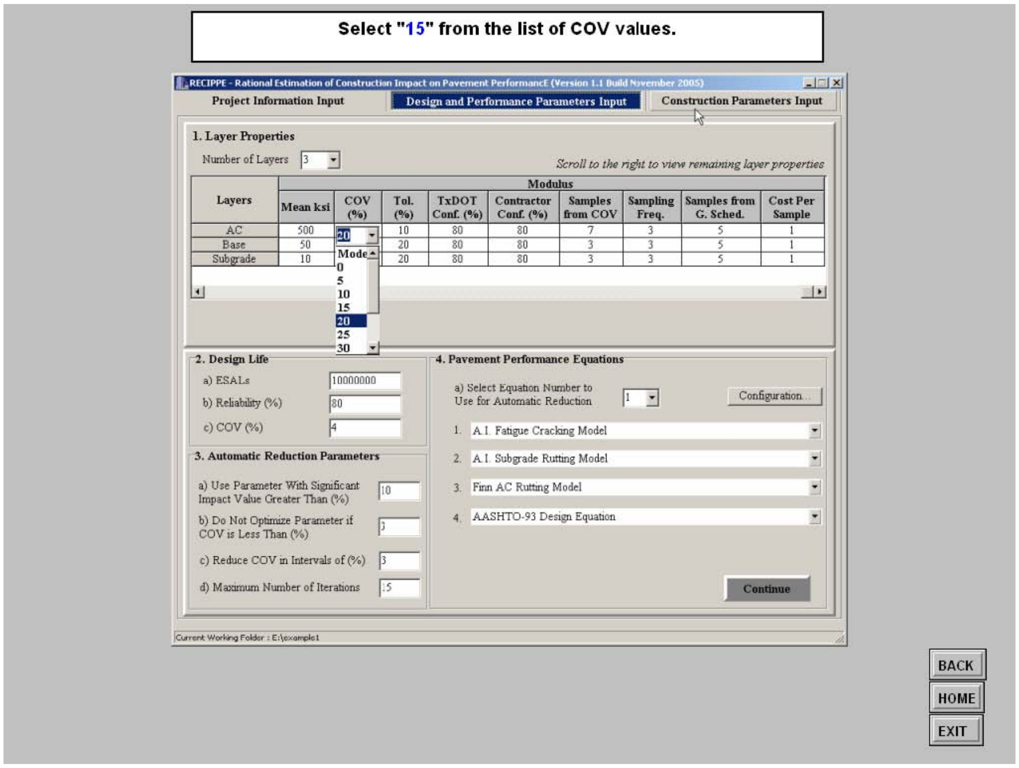


Figure A.37 - Slide 27 of Exercise 1

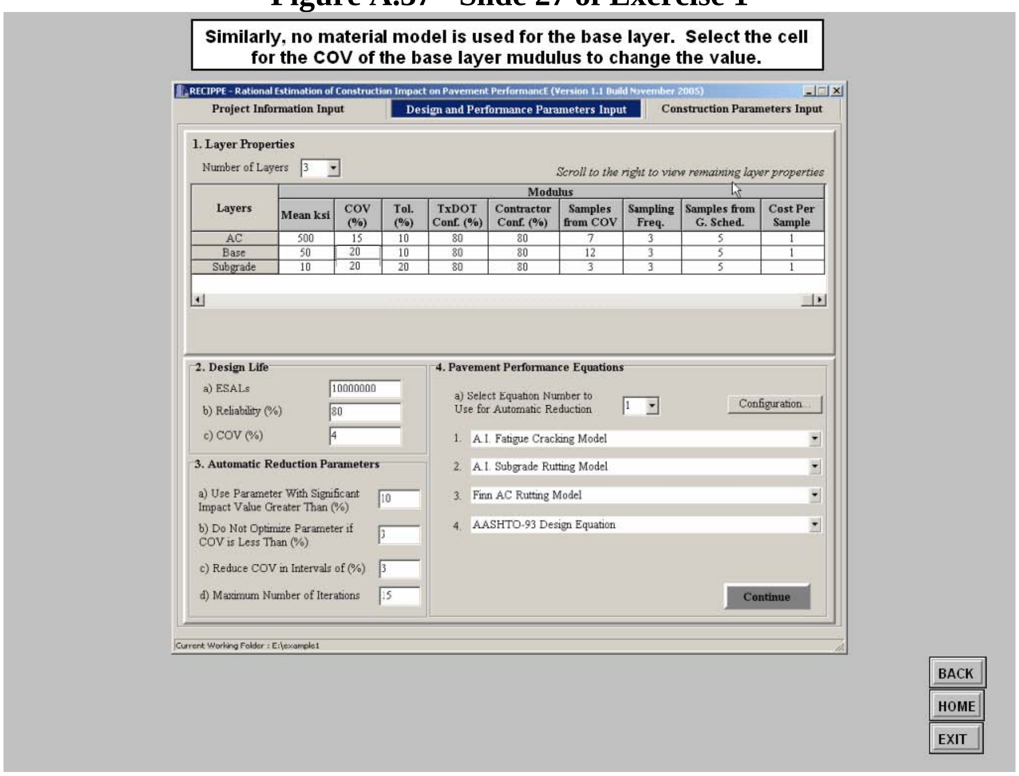


Figure A.38 - Slide 28 of Exercise 1

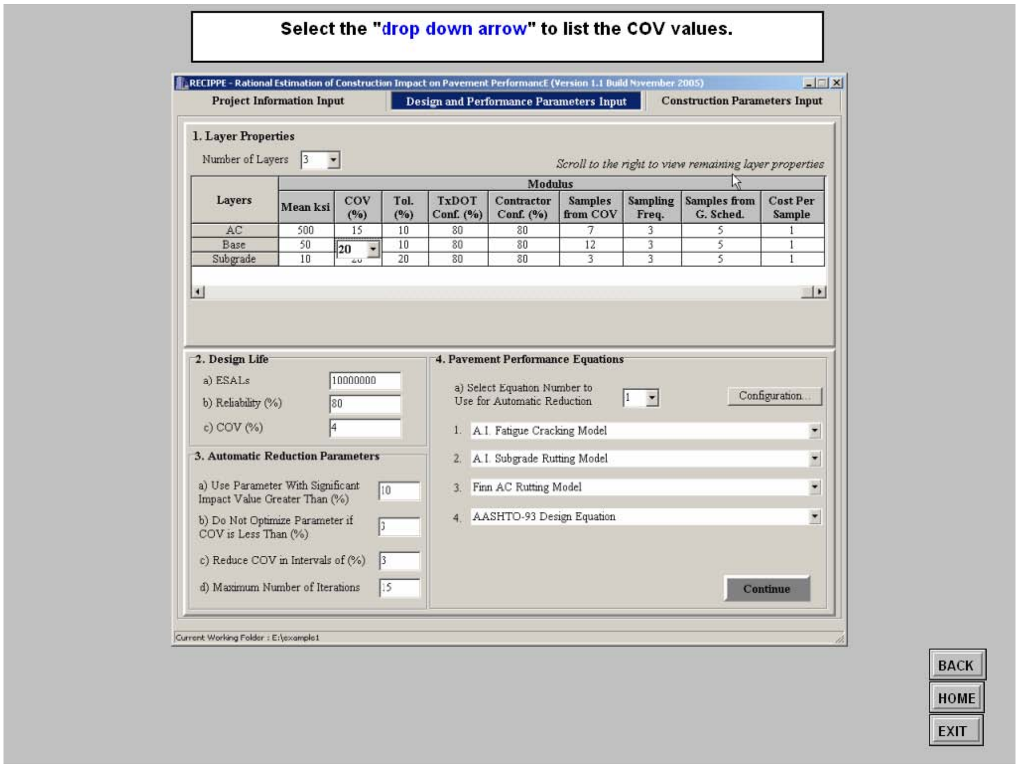


Figure A.39 - Slide 29 of Exercise 1

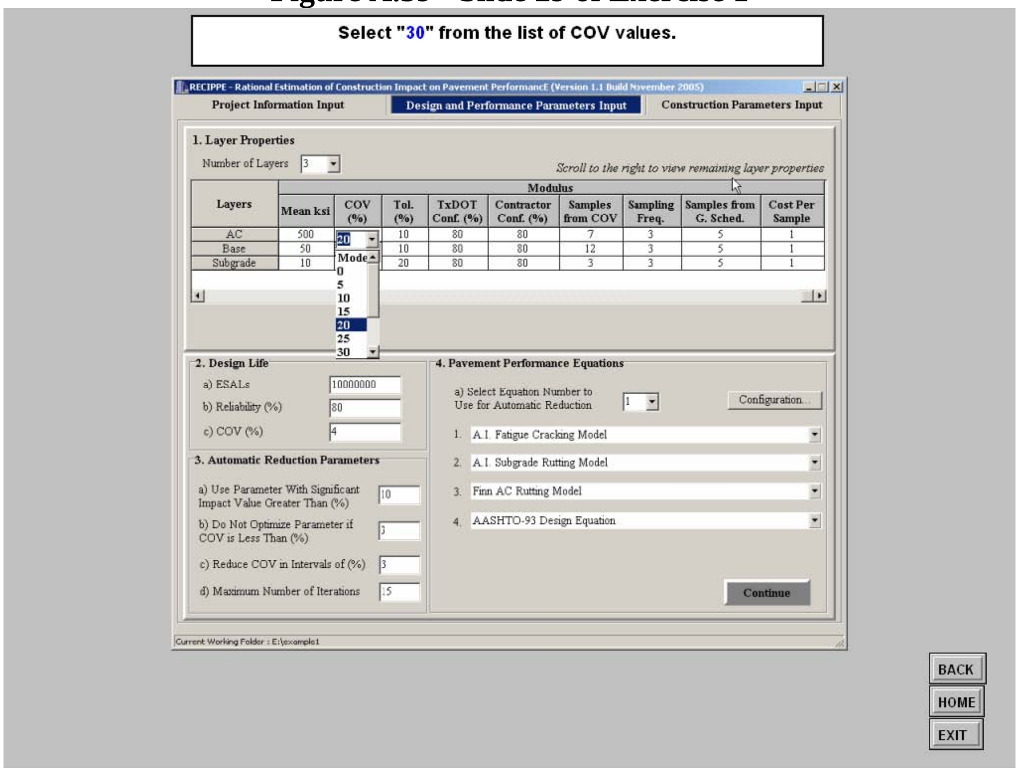


Figure A.40 - Slide 30 of Exercise 1

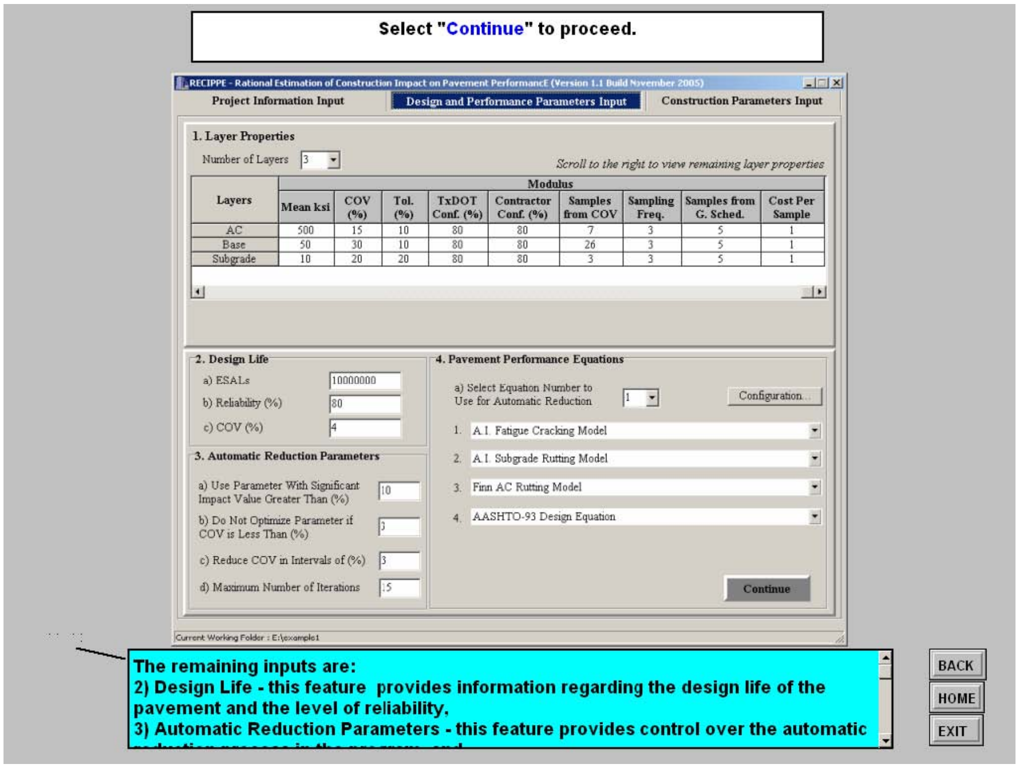


Figure A.41 - Slide 31 of Exercise 1

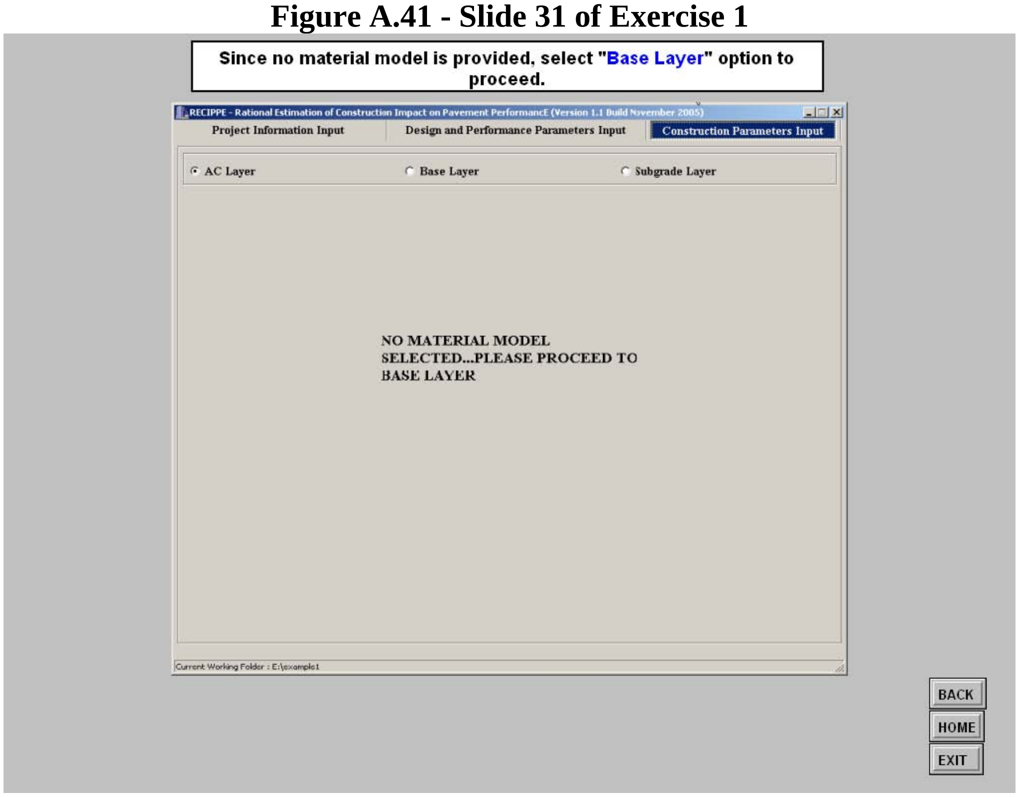


Figure A.42 - Slide 32 of Exercise 1

Figure A.43 - Slide 33 of Exercise 1

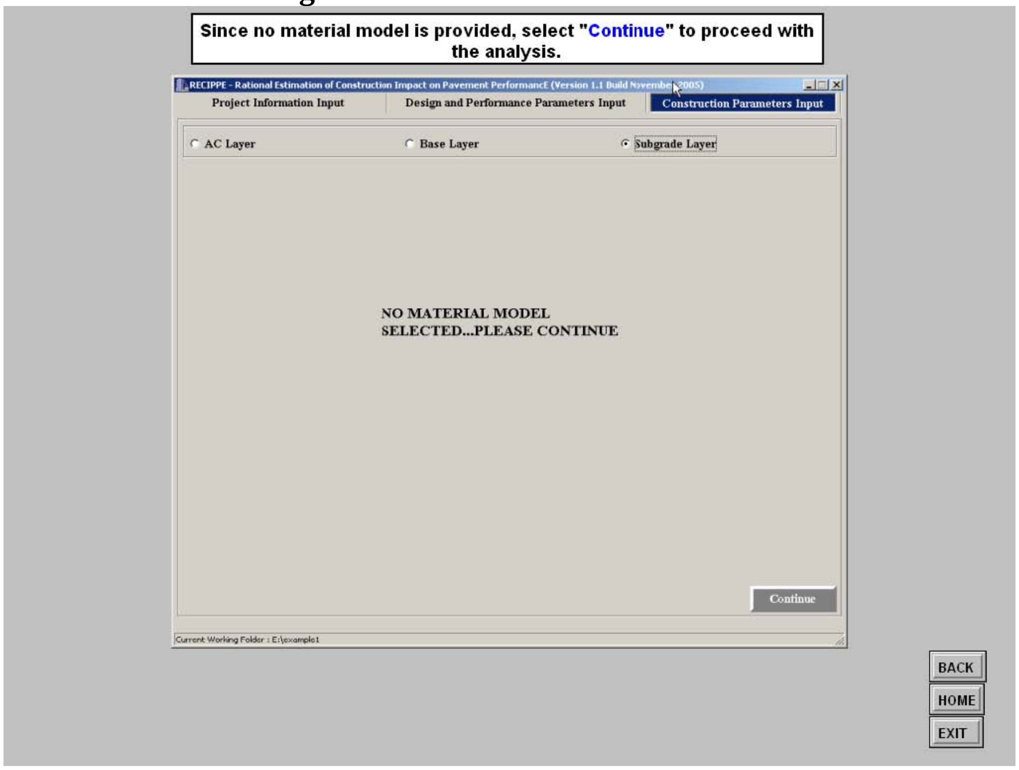


Figure A.44 - Slide 34 of Exercise 1

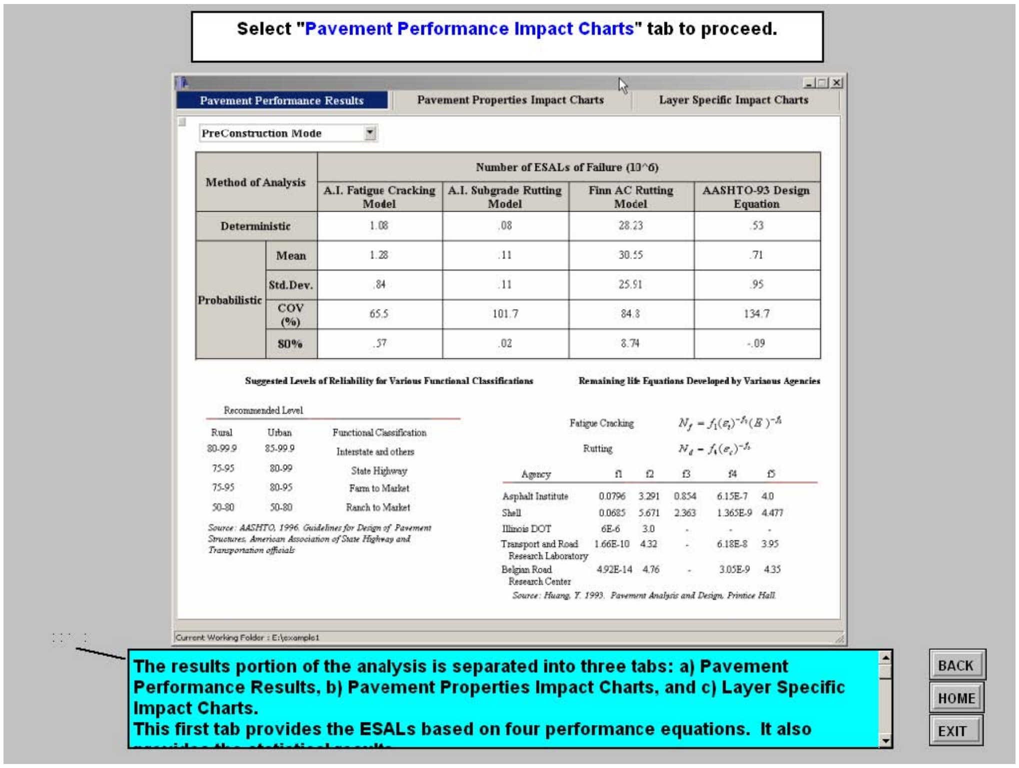


Figure A.45 - Slide 35 of Exercise 1

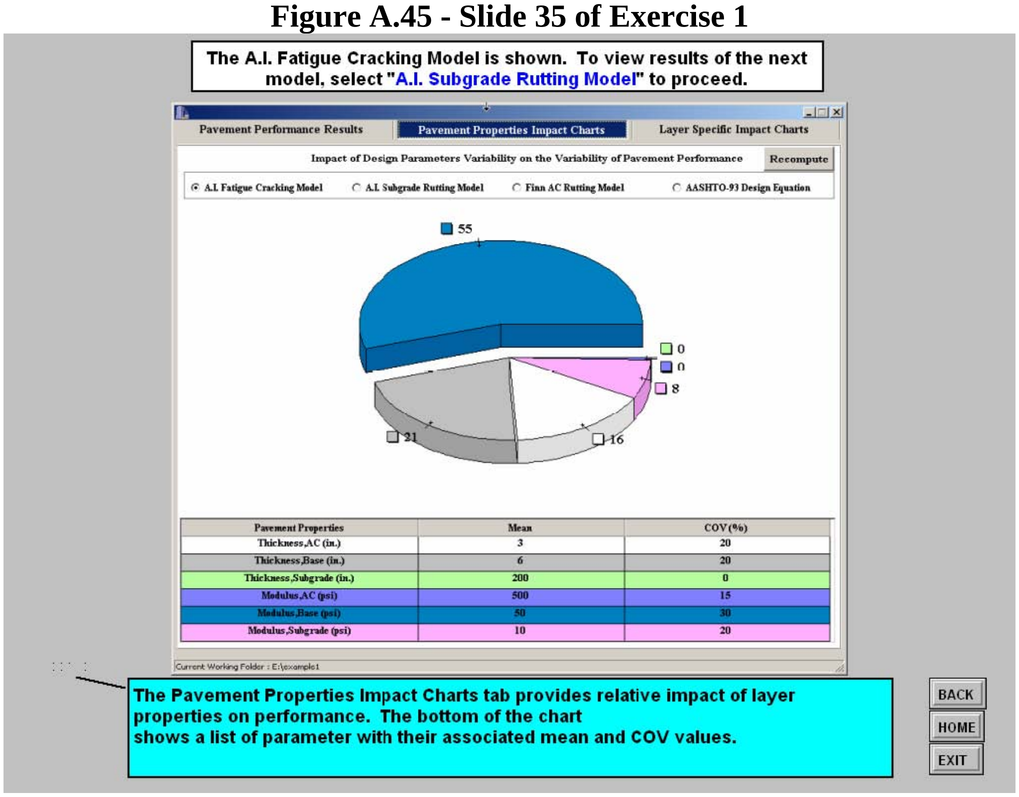


Figure A.46 - Slide 36 of Exercise 1

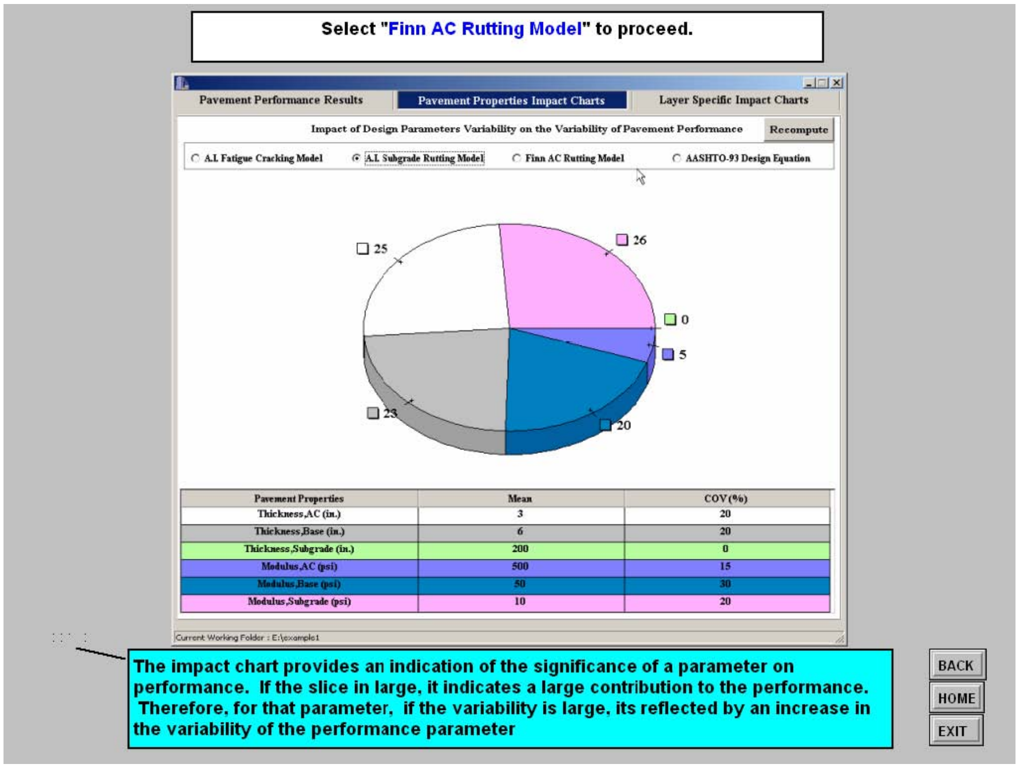


Figure A.47 - Slide 37 of Exercise 1

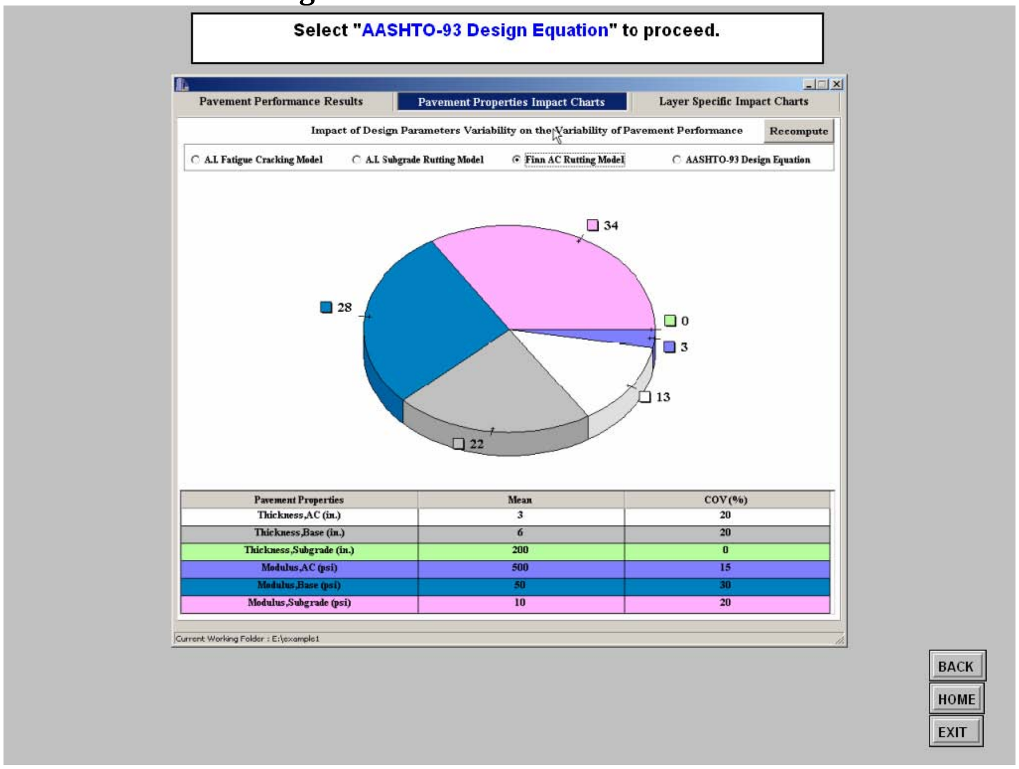


Figure A.48 - Slide 38 of Exercise 1

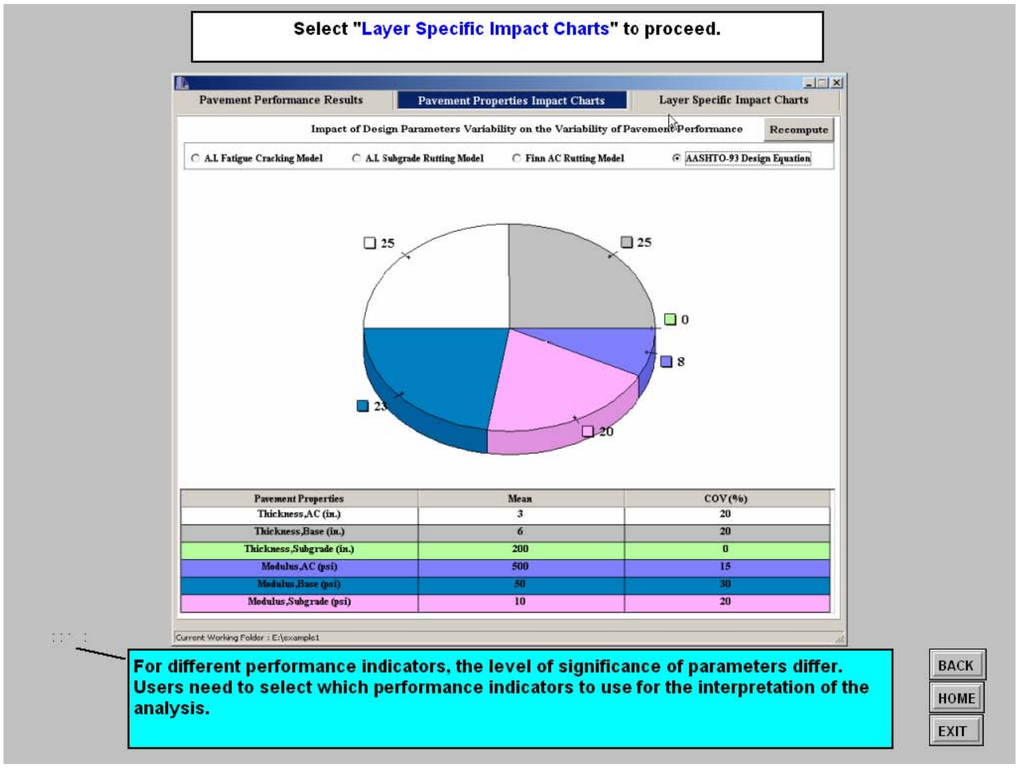


Figure A.49 - Slide 39 of Exercise 1

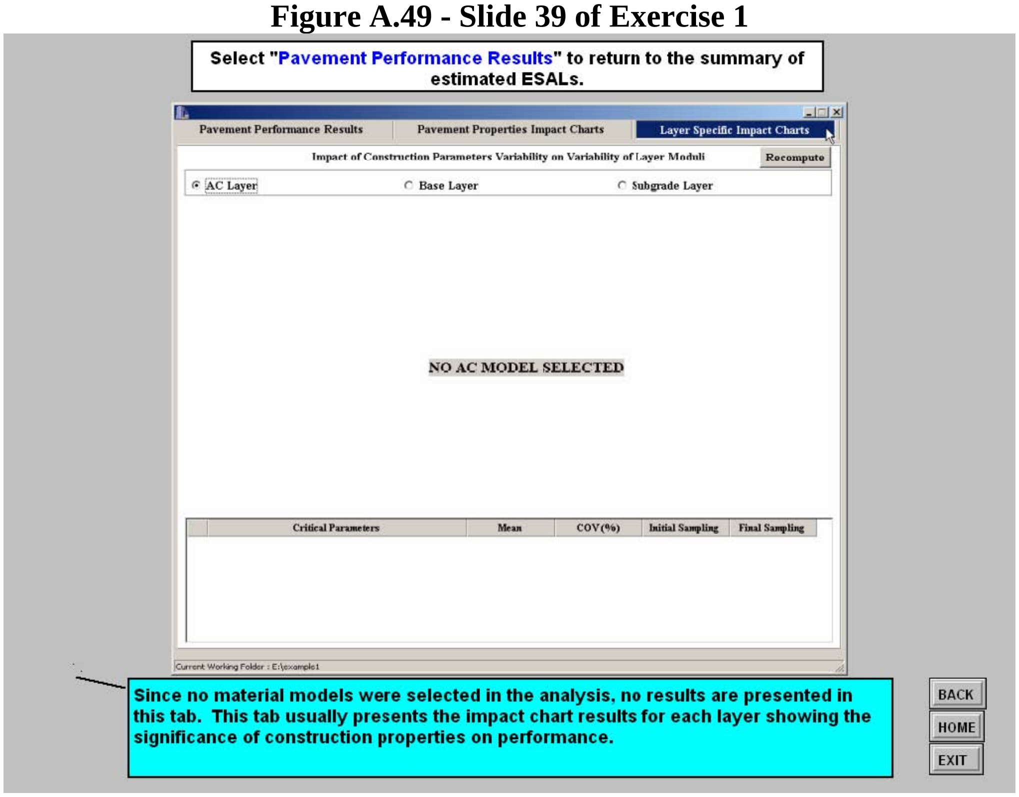


Figure A.50 - Slide 40 of Exercise 1

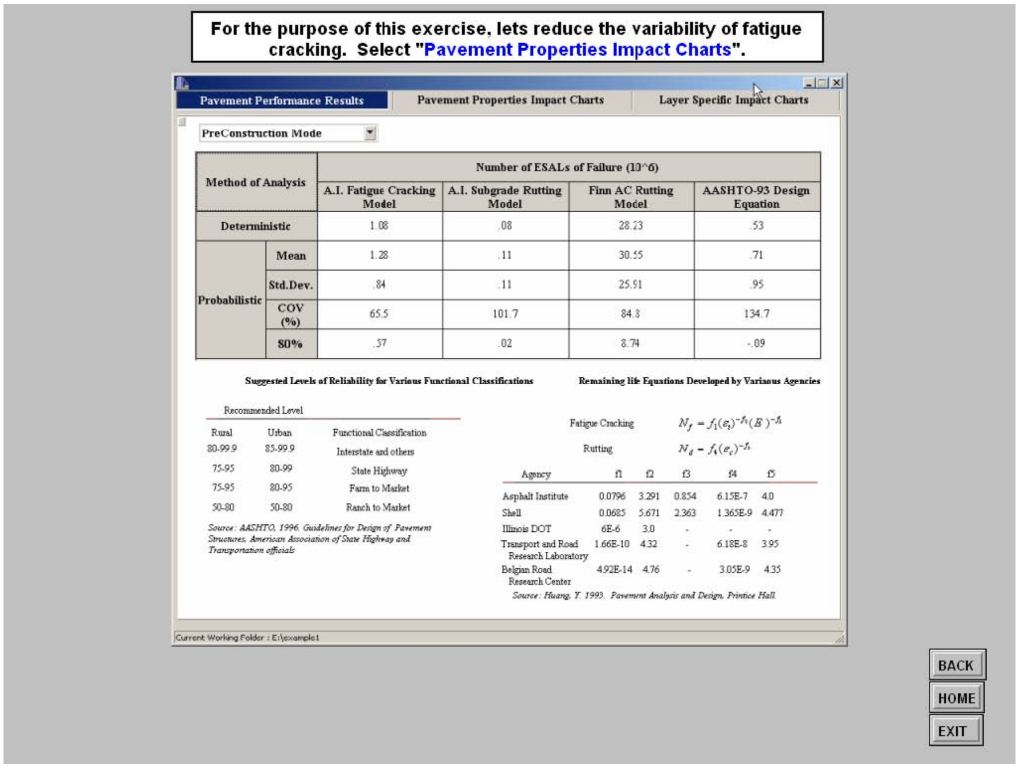


Figure A.51 - Slide 41 of Exercise 1

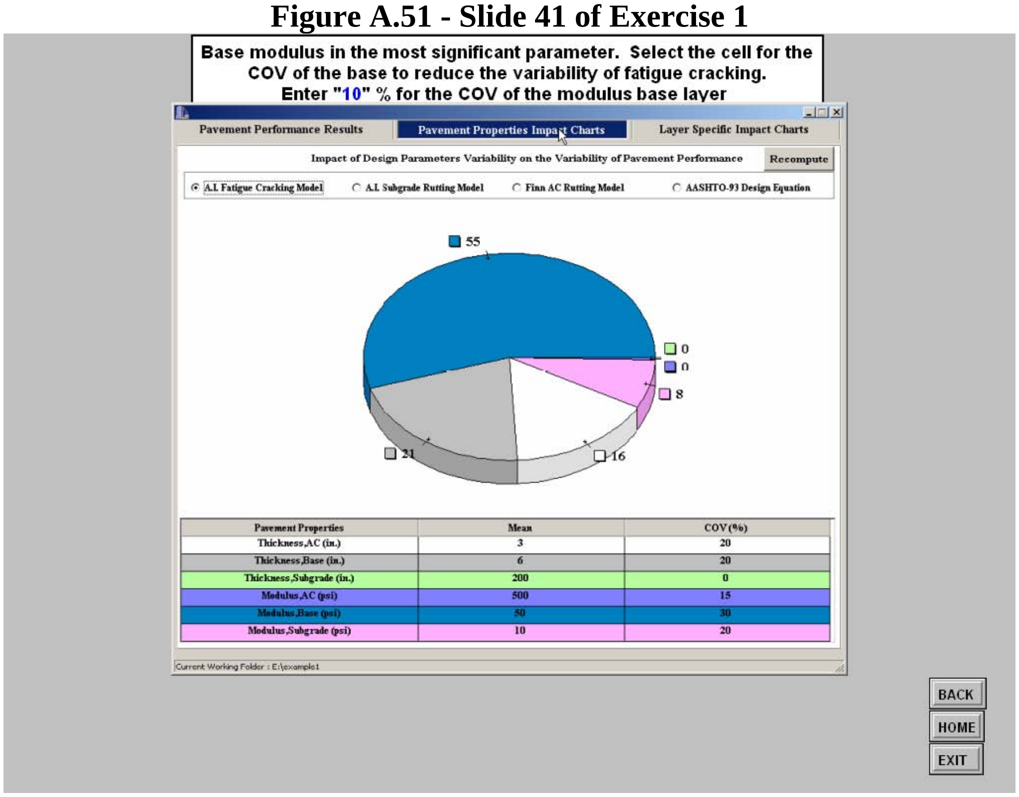


Figure A.52 - Slide 42 of Exercise 1

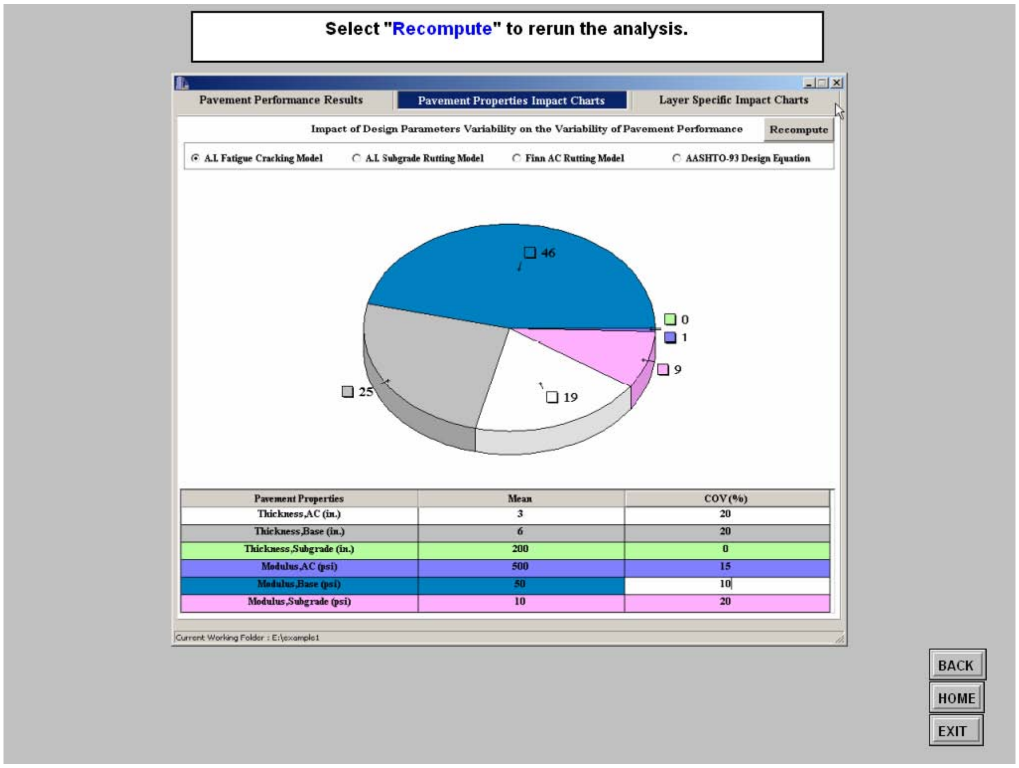


Figure A.53 - Slide 43 of Exercise 1

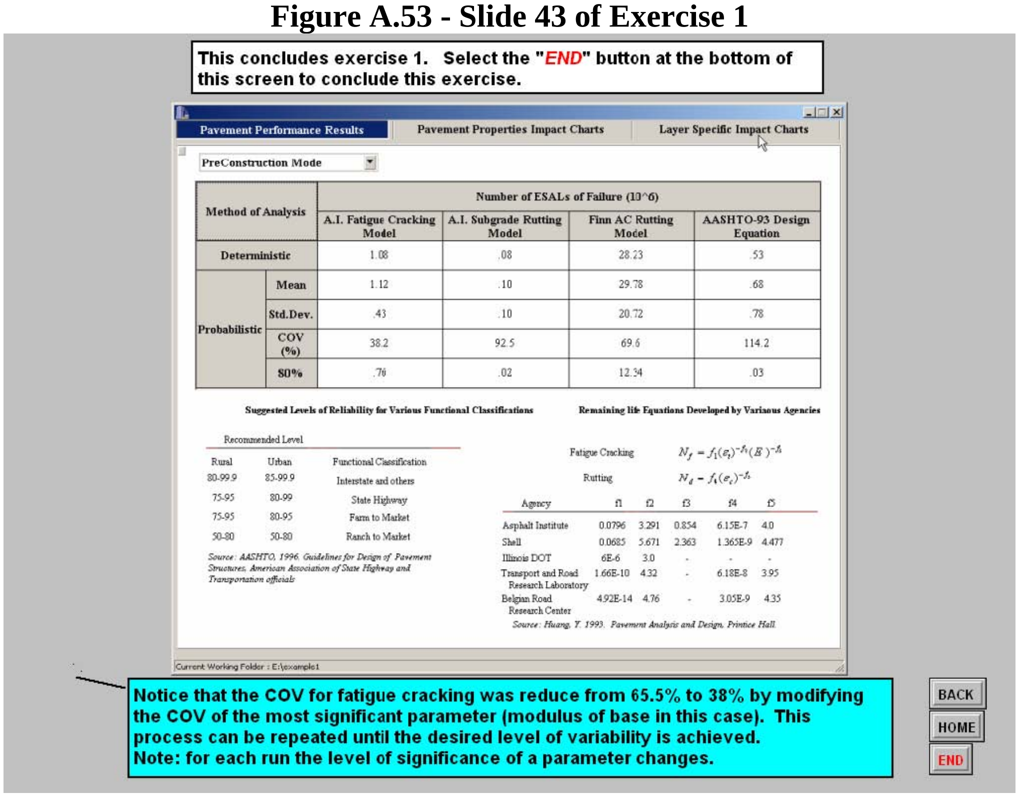


Figure A.54 - Slide 44 of Exercise 1

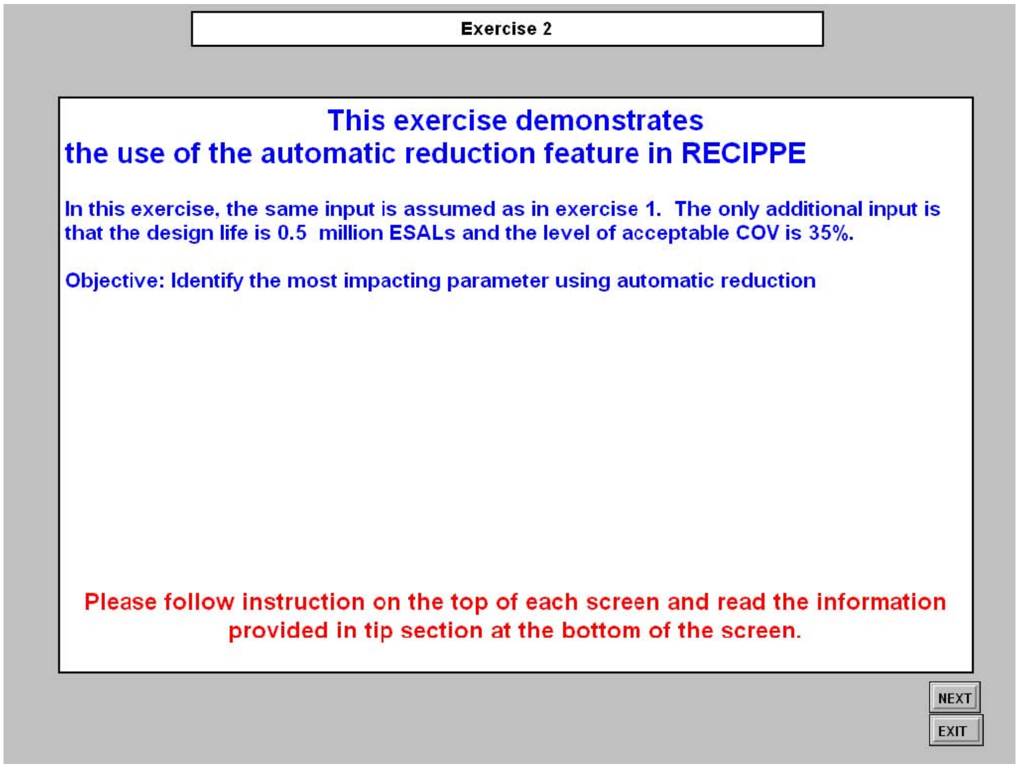


Figure A.55 - Slide 1 of Exercise 2

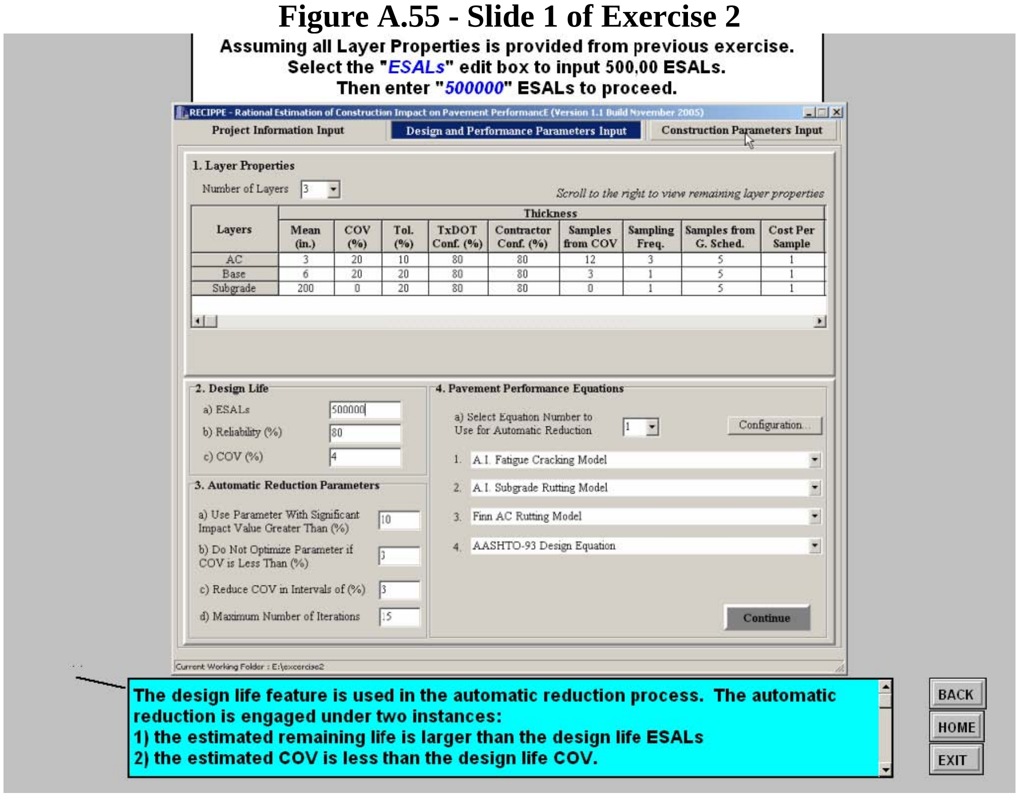


Figure A.56 - Slide 2 of Exercise 2

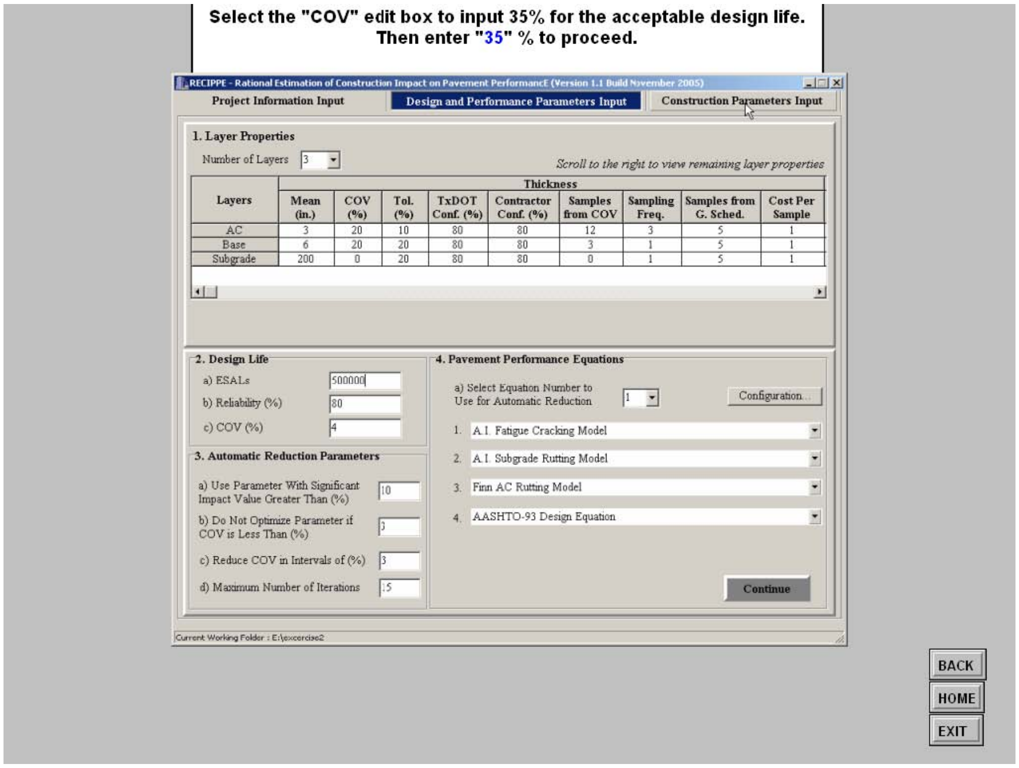


Figure A.57 - Slide 3 of Exercise 2

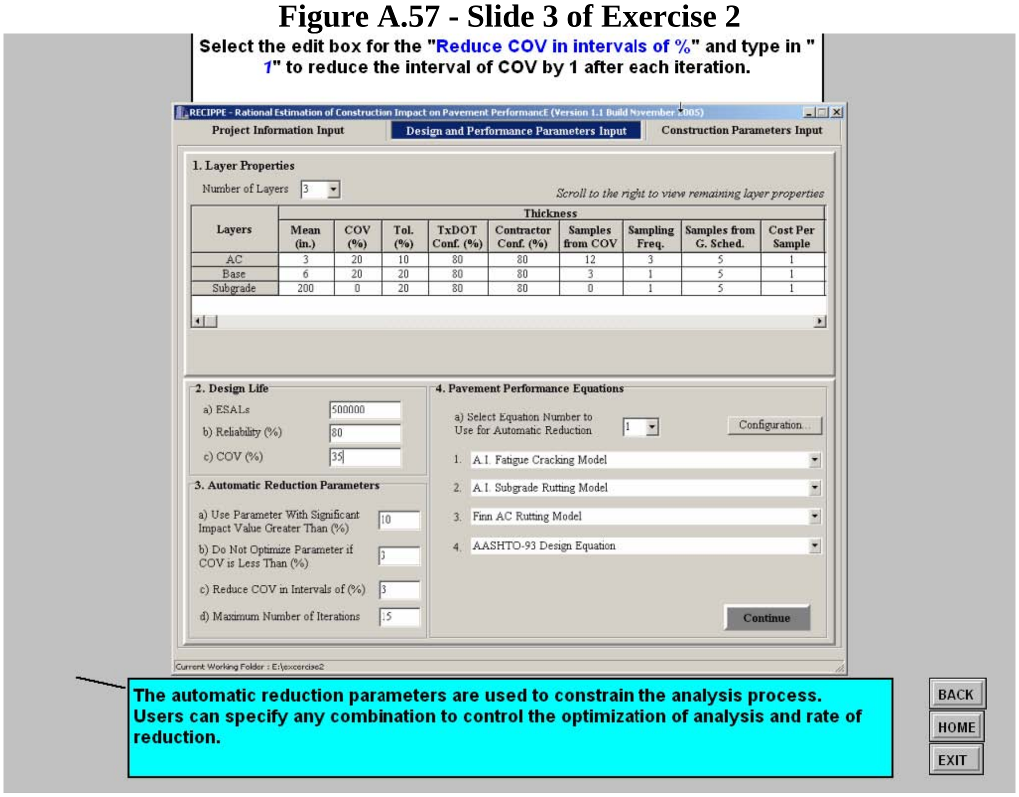


Figure A.58 - Slide 4 of Exercise 2

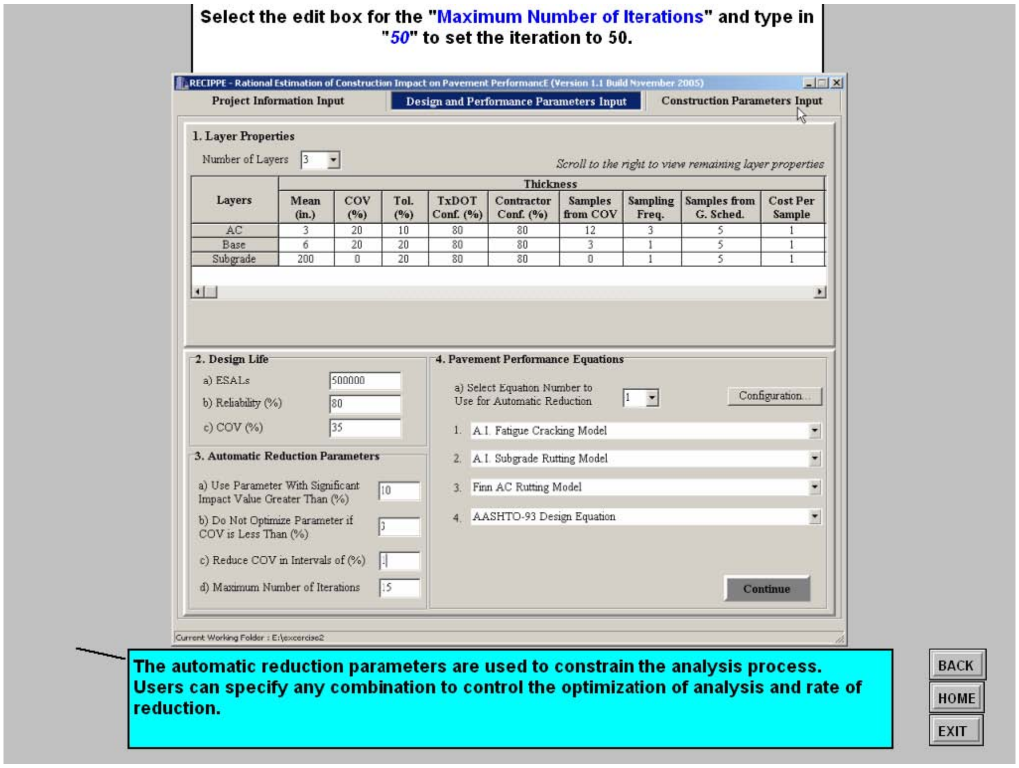


Figure A.59 - Slide 5 of Exercise 2

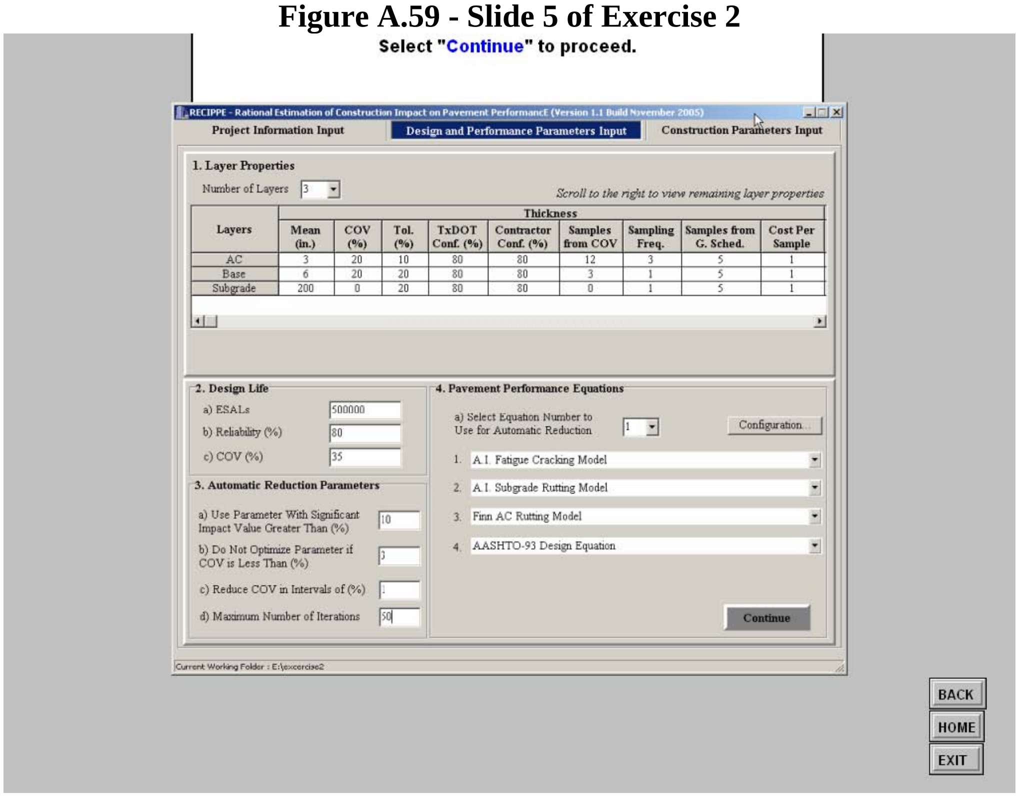


Figure A.60 - Slide 6 of Exercise 2

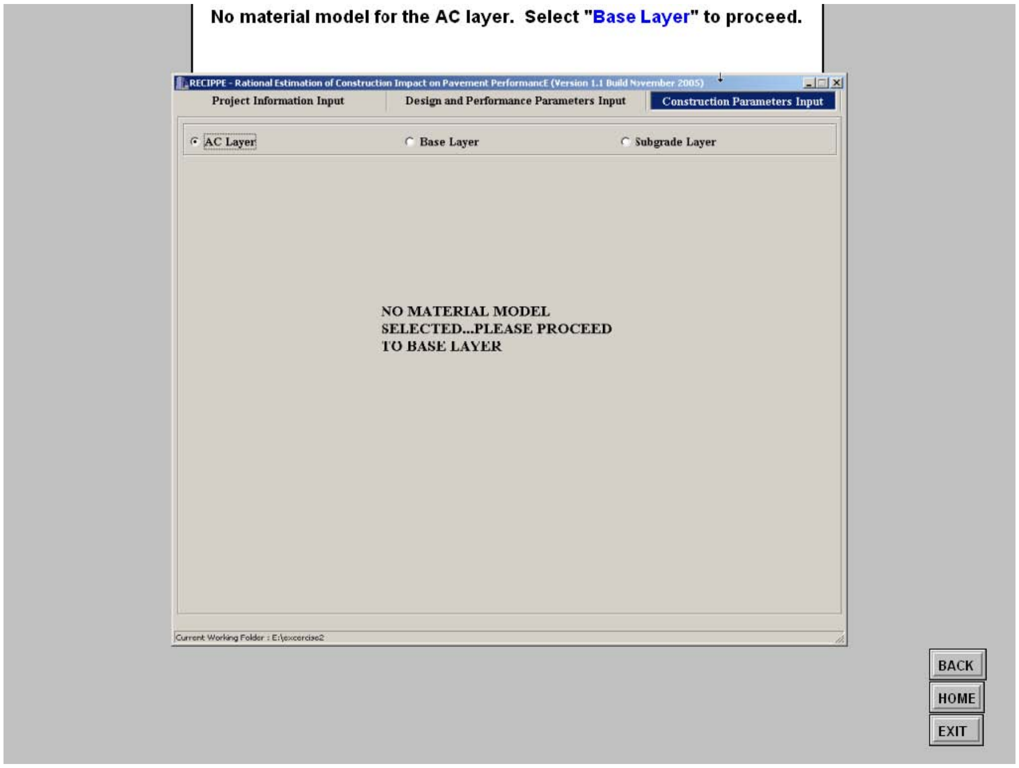


Figure A.61 - Slide 7 of Exercise 2

Figure A.62 - Slide 8 of Exercise 2

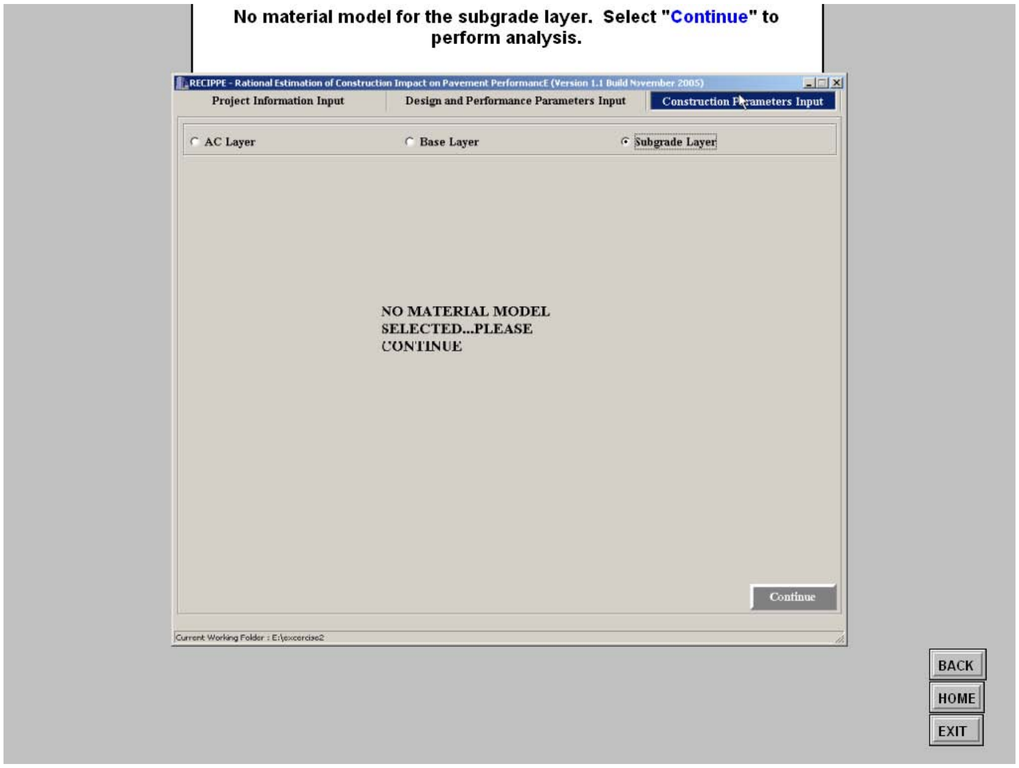


Figure A.63 - Slide 9 of Exercise 2

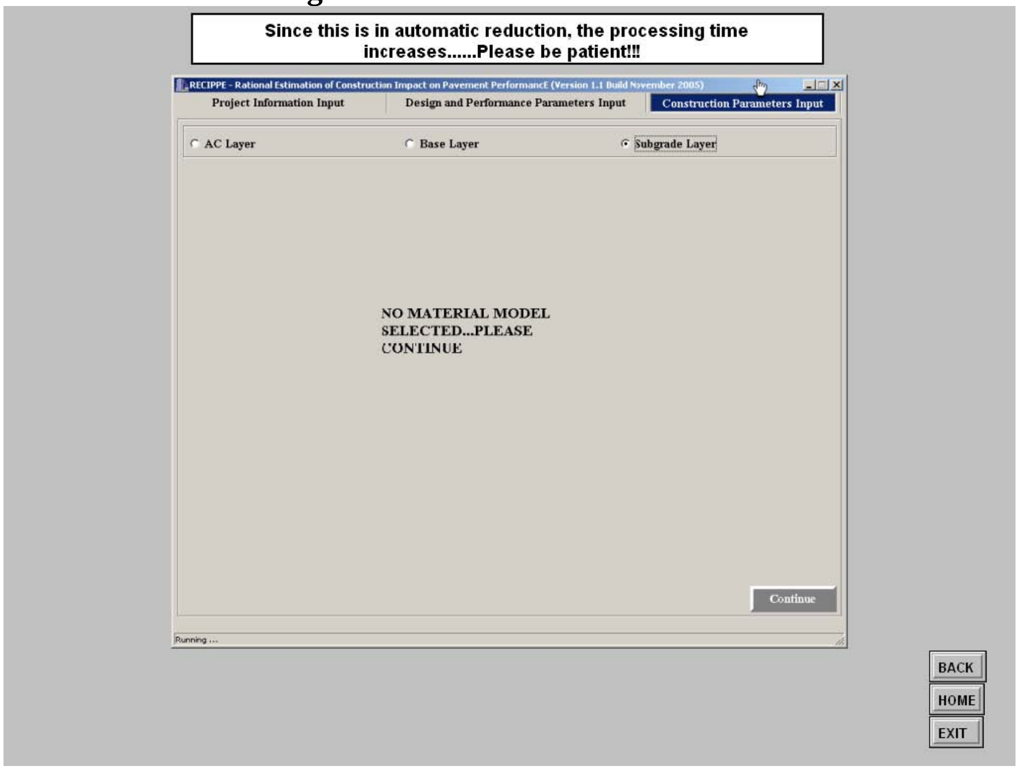


Figure A.64 - Slide 10 of Exercise 2

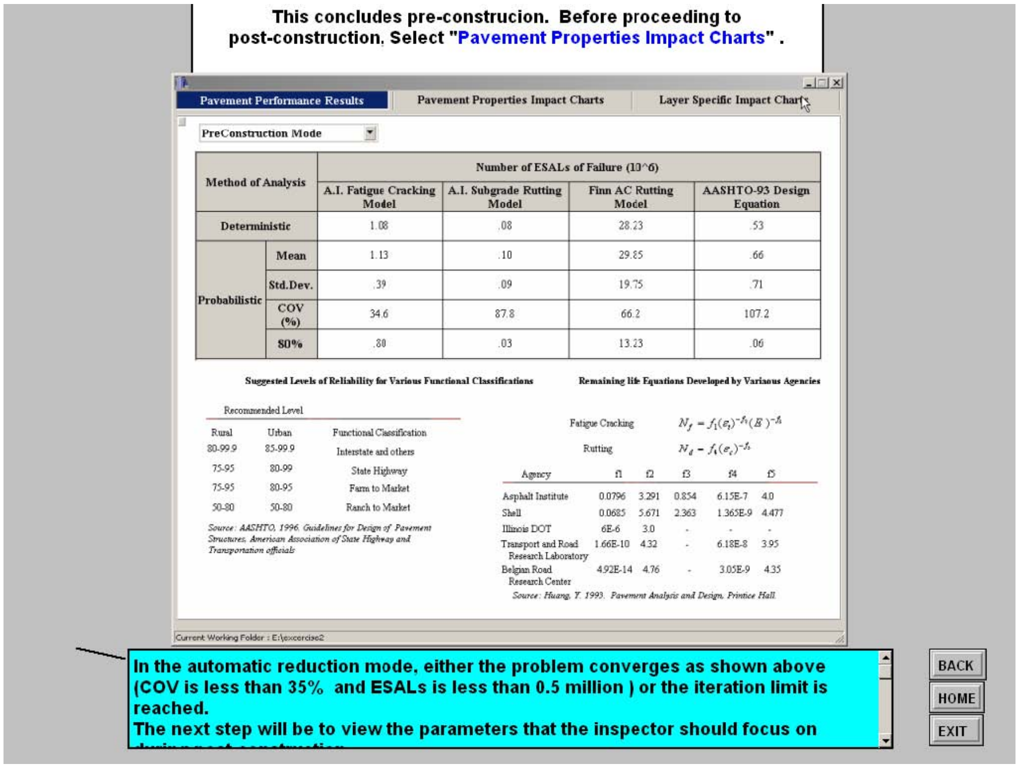


Figure A.65 - Slide 11 of Exercise 2

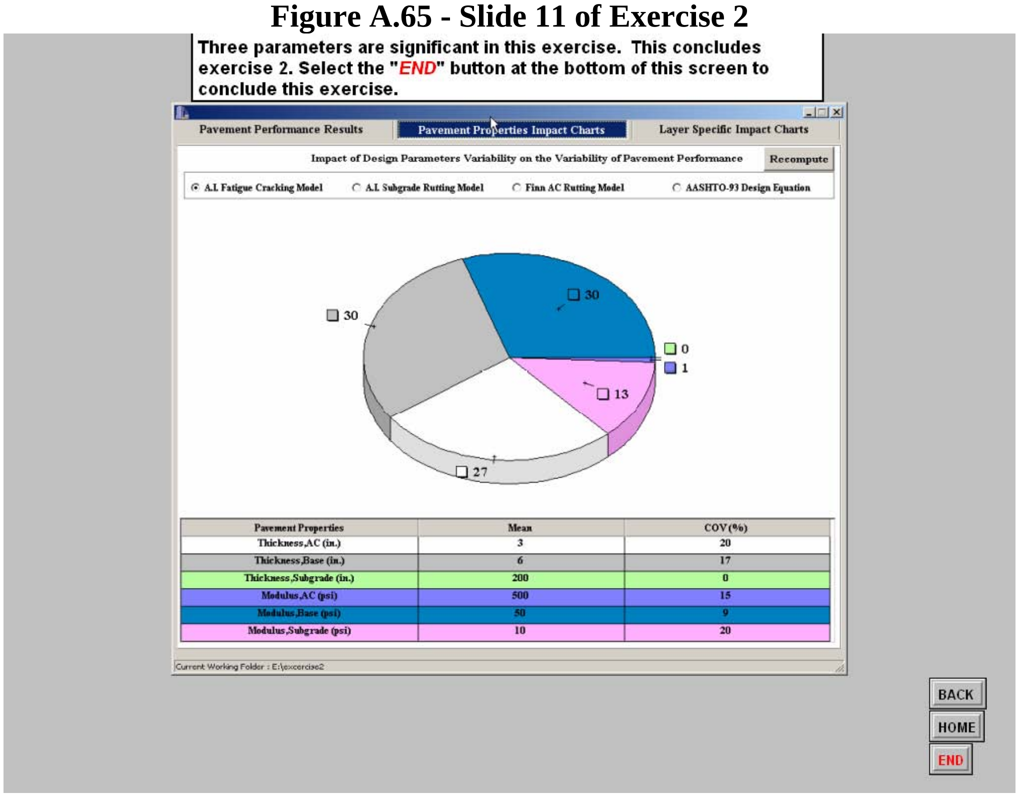


Figure A.66 - Slide 12 of Exercise 2

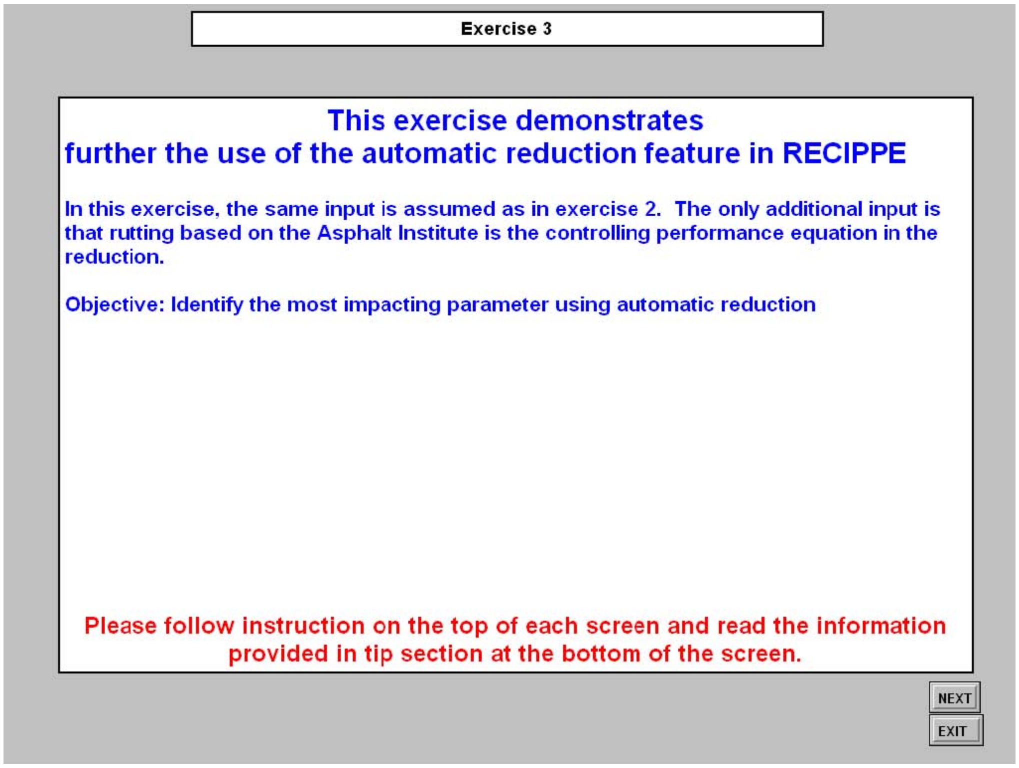


Figure A.67 - Slide 1 of Exercise 3

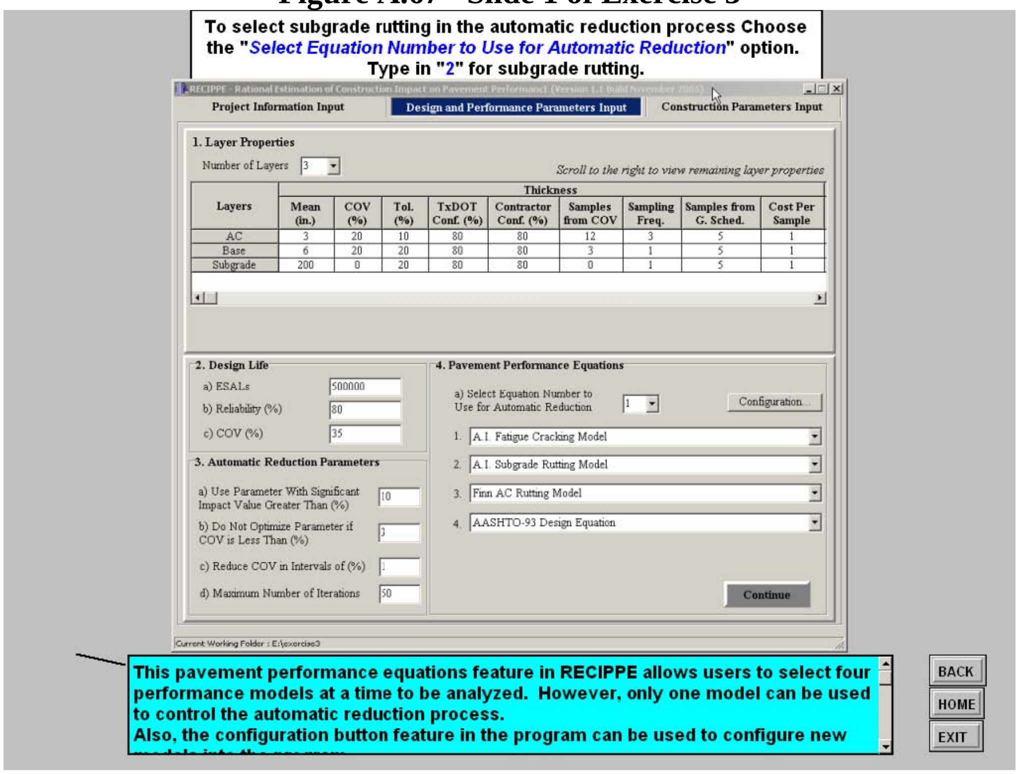


Figure A.68 - Slide 2 of Exercise 3

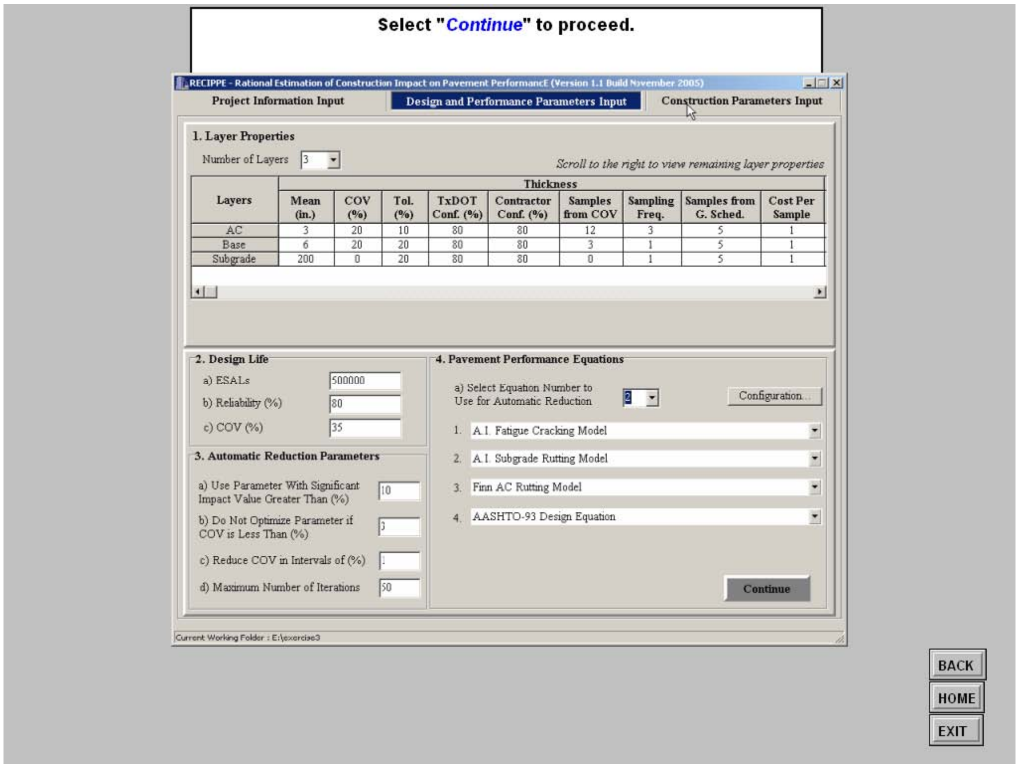


Figure A.69 - Slide 3 of Exercise 3

Figure A.70 - Slide 4 of Exercise 3

Figure A.71 - Slide 5 of Exercise 3

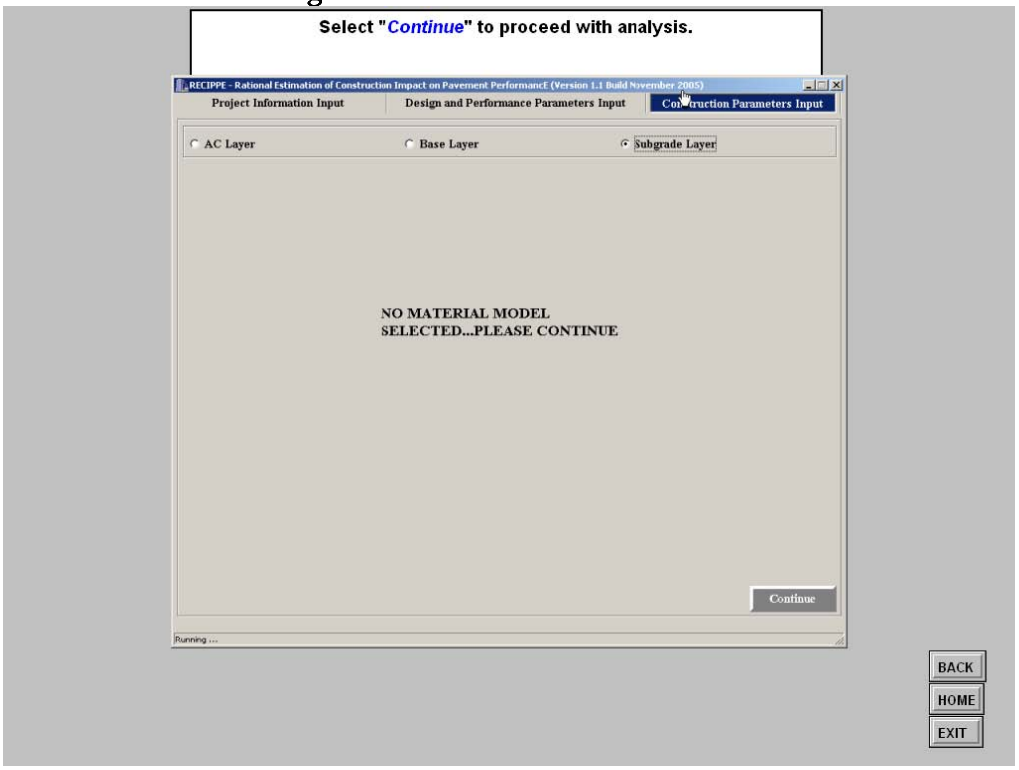


Figure A.72 - Slide 6 of Exercise 3

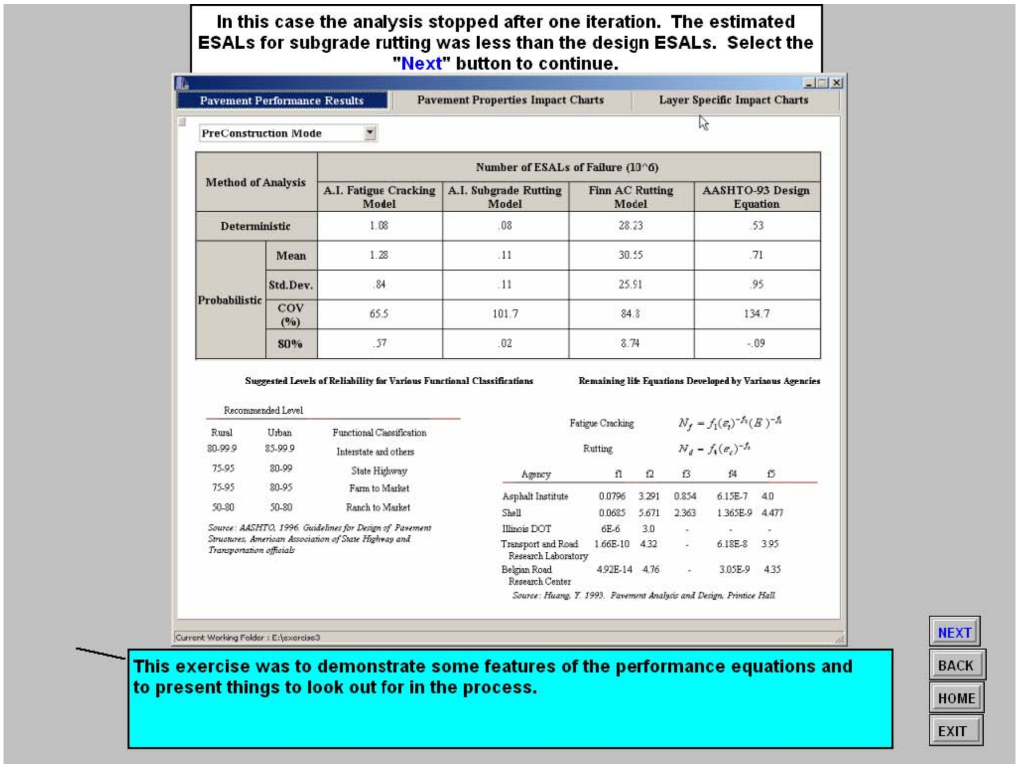


Figure A.73 - Slide 7 of Exercise 3

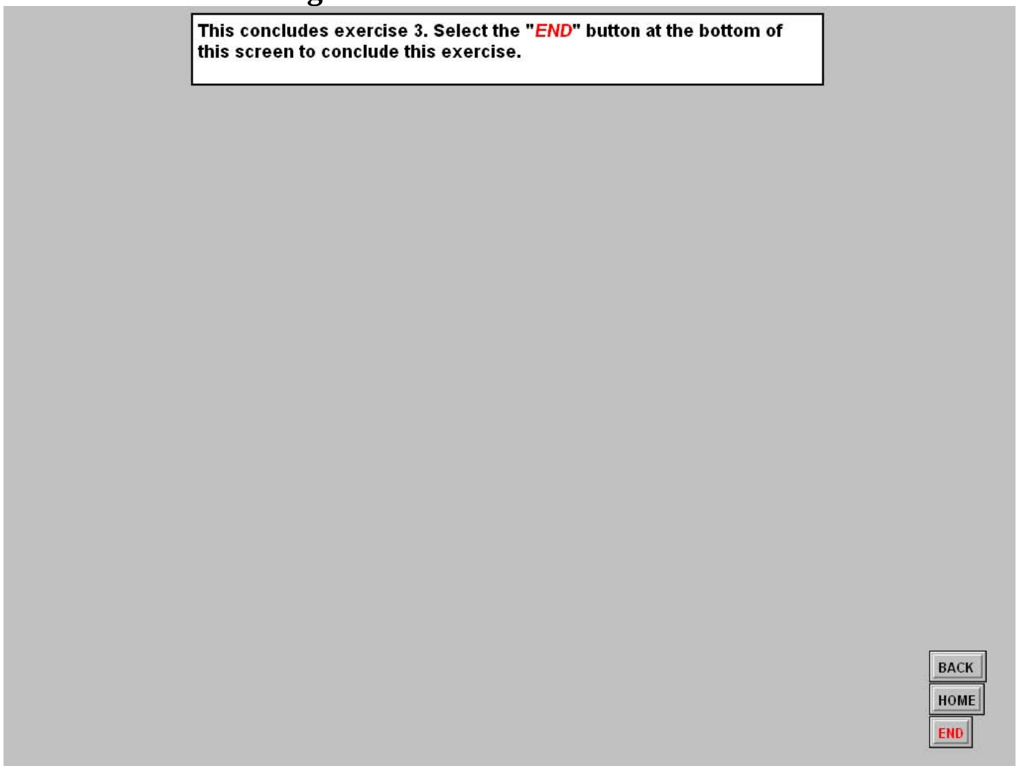


Figure A.74 - Slide 8 of Exercise 3

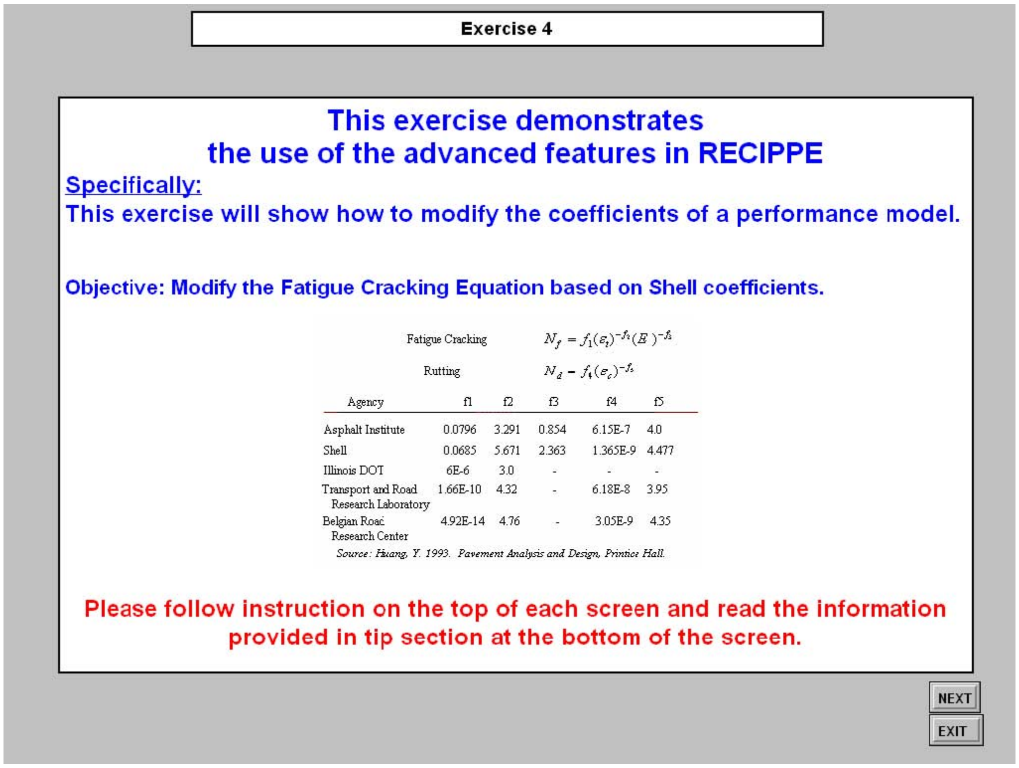


Figure A.75 - Slide 1 of Exercise 4

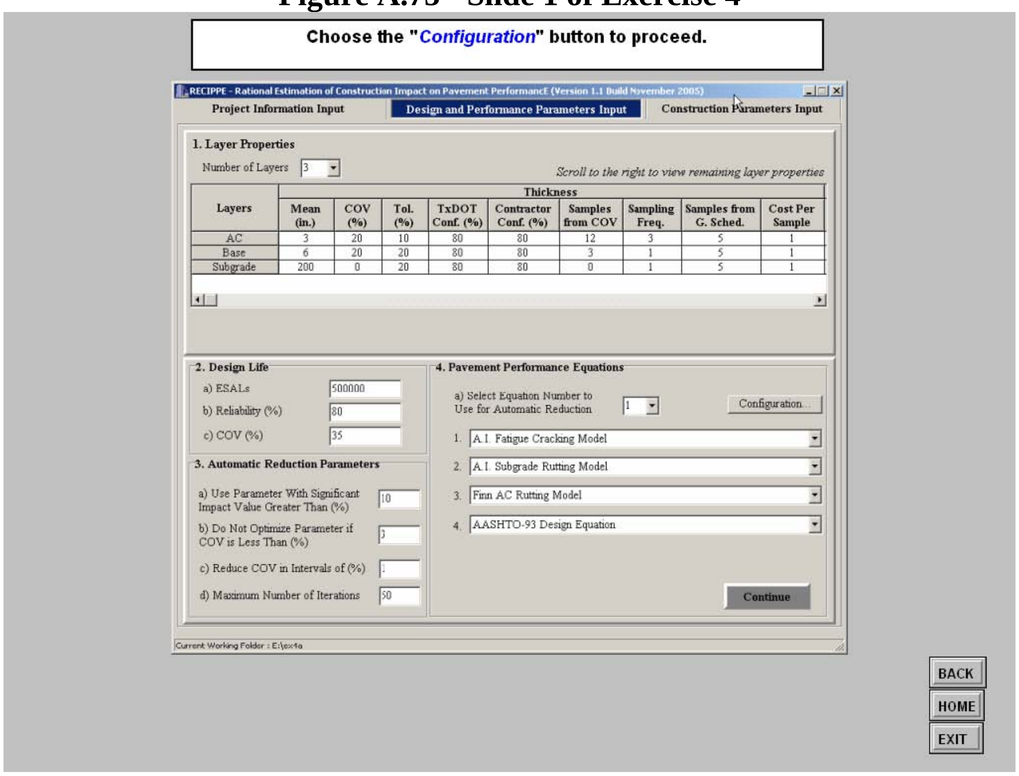


Figure A.76 - Slide 2 of Exercise 4

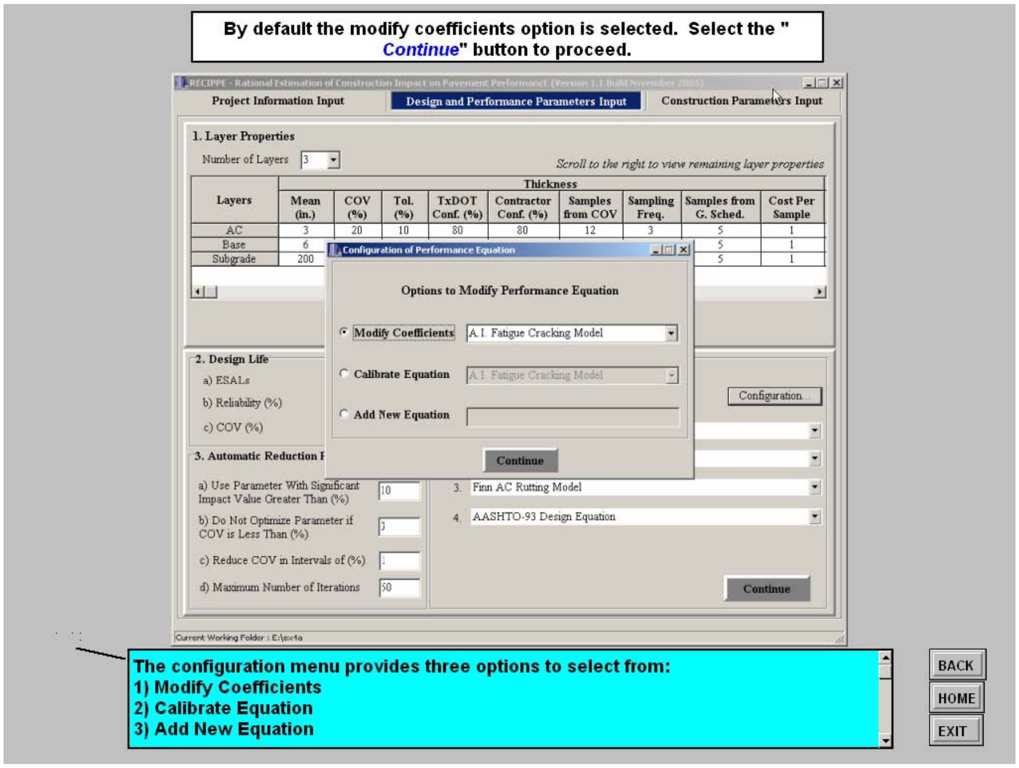


Figure A.77 - Slide 3 of Exercise 4

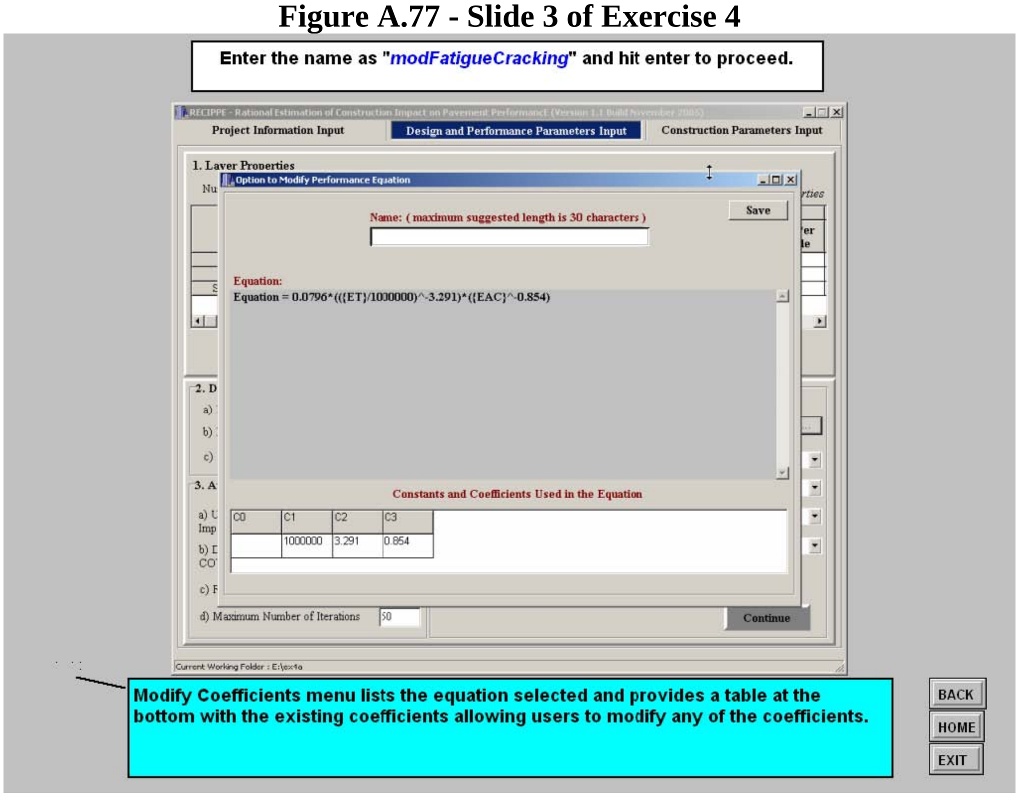


Figure A.78 - Slide 4 of Exercise 4

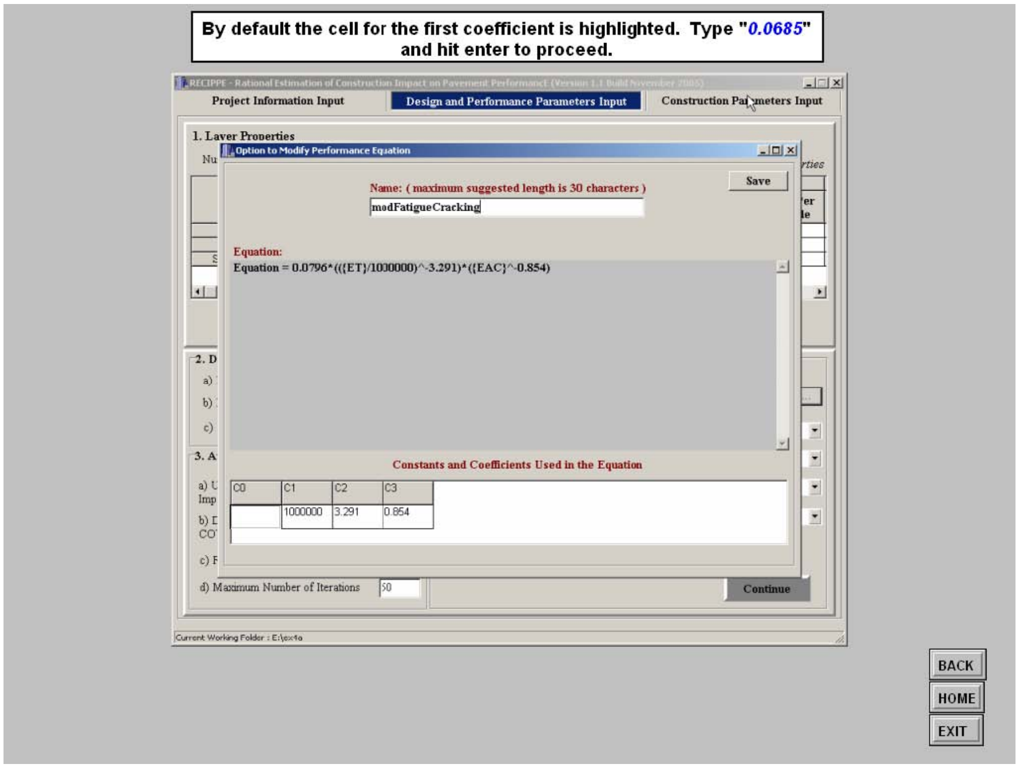


Figure A.79 - Slide 5 of Exercise 4

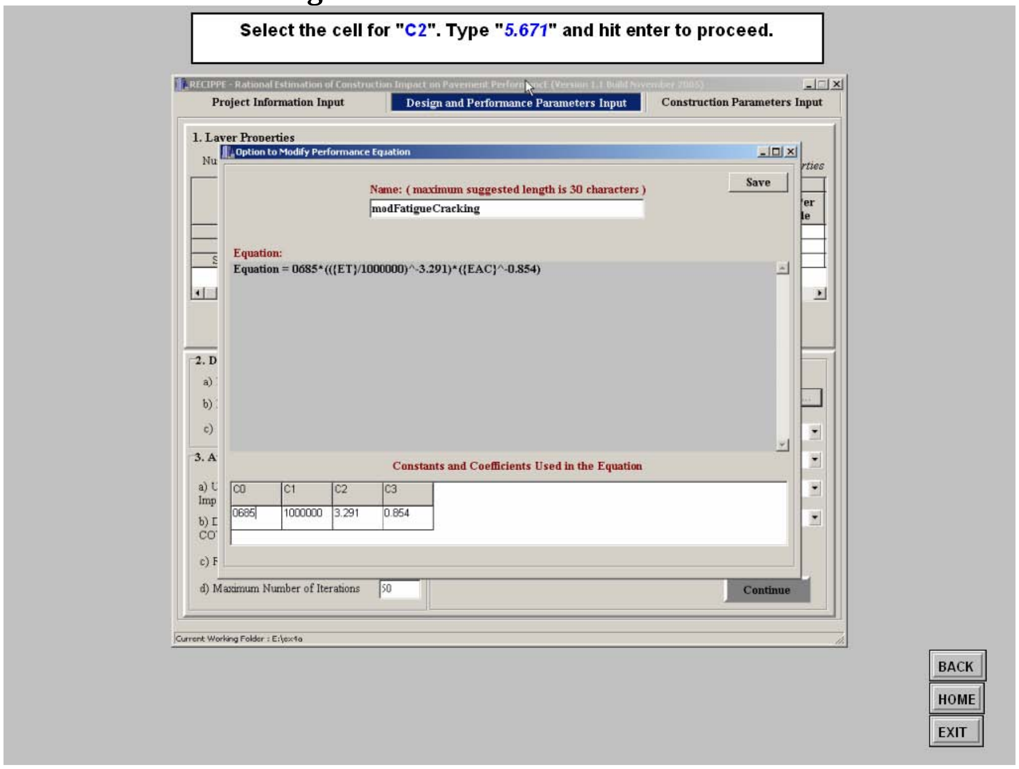


Figure A.80 - Slide 6 of Exercise 4

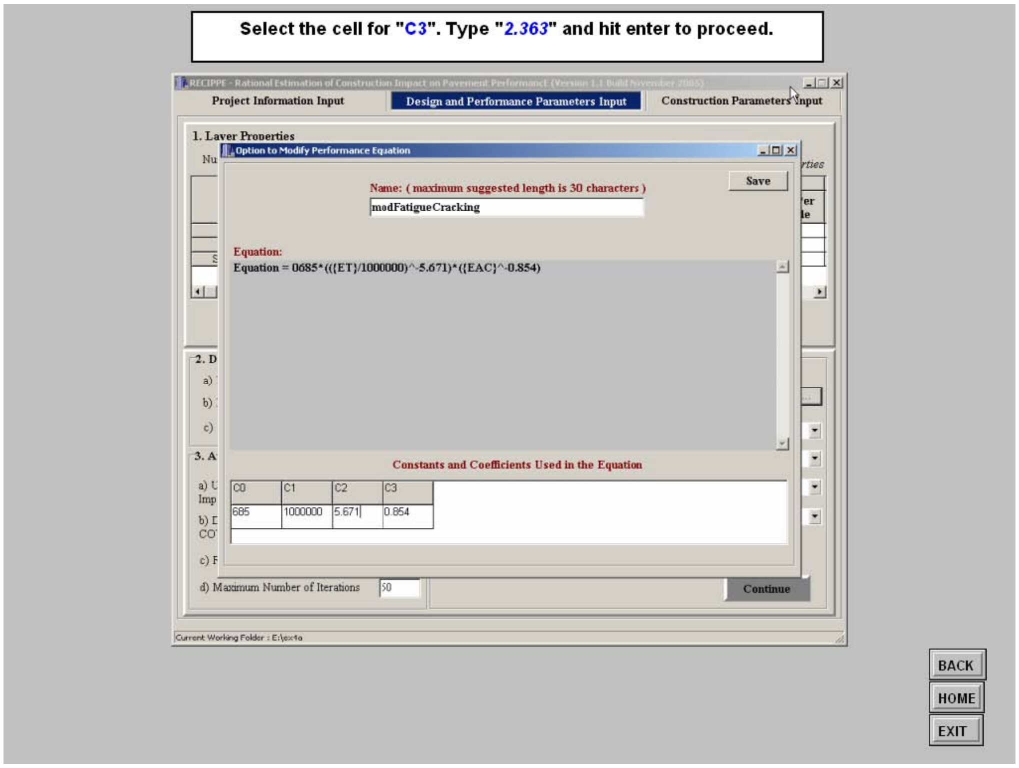


Figure A.81 - Slide 7 of Exercise 4

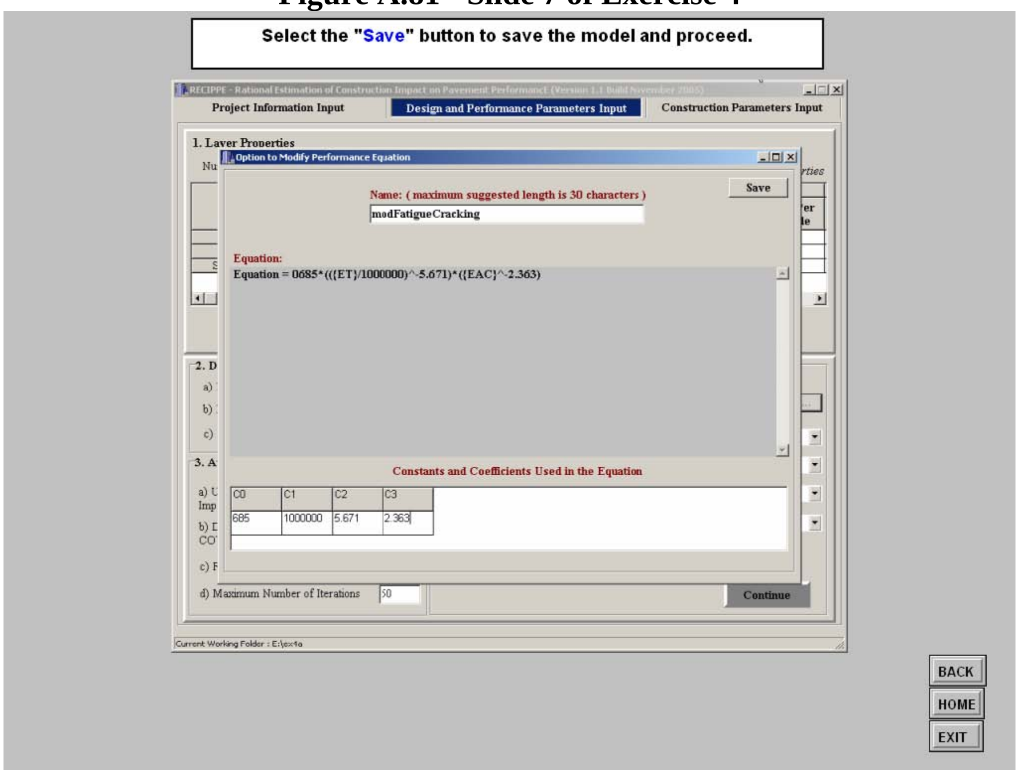


Figure A.82 - Slide 8 of Exercise 4

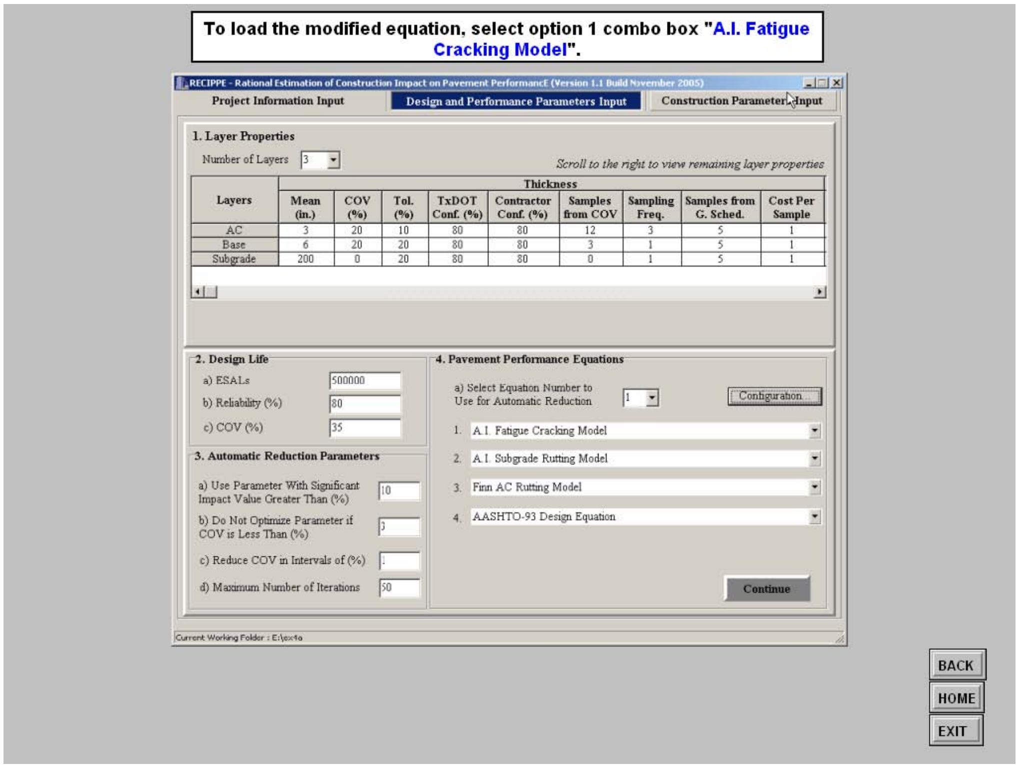


Figure A.83 - Slide 9 of Exercise 4

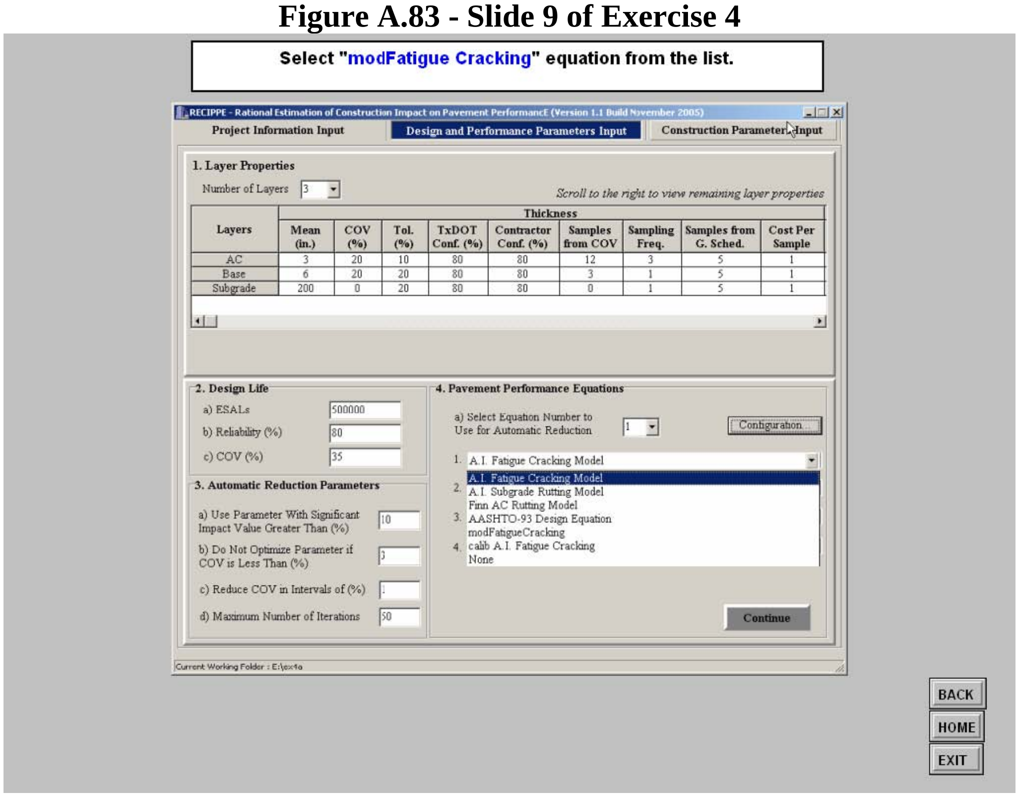


Figure A.84 - Slide 10 of Exercise 4

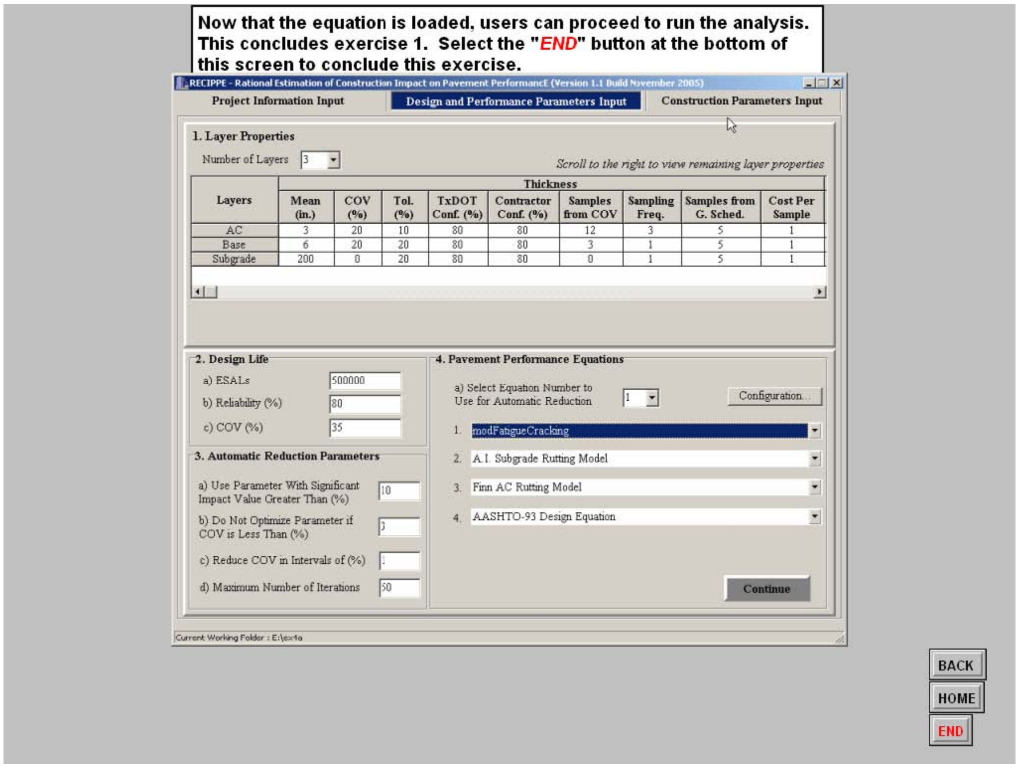


Figure A.85 - Slide 11 of Exercise 4

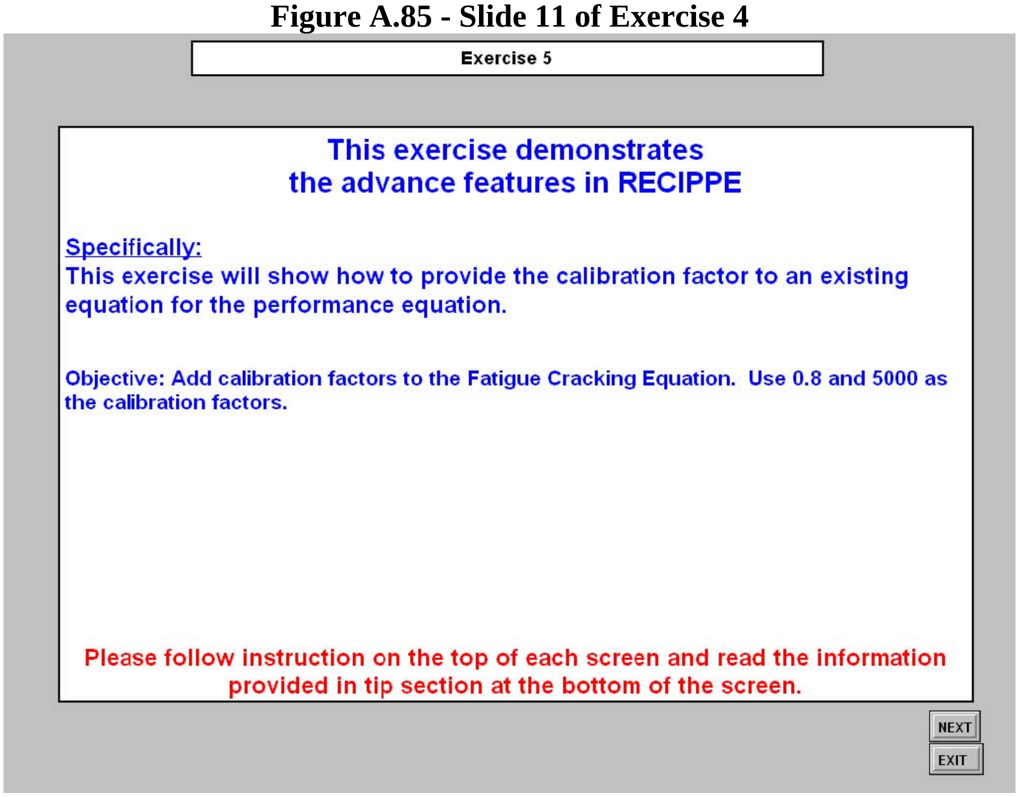
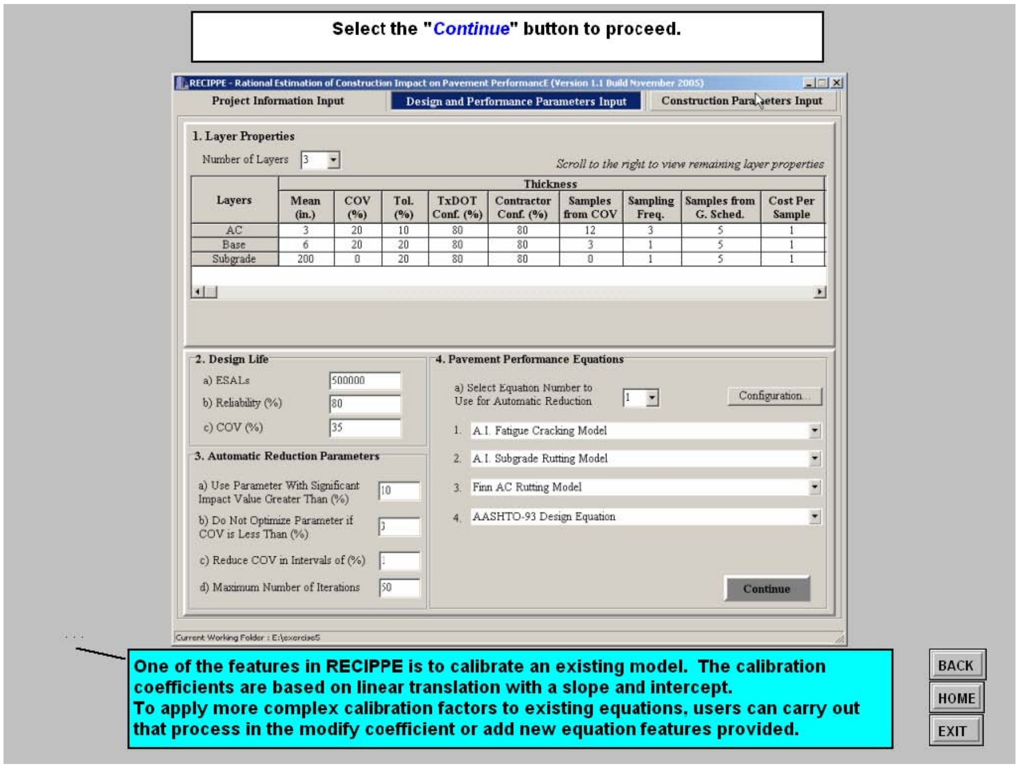


Figure A.86 - Slide 1 of Exercise 5



Layers	Thickness Mean (in.)	COV (%)	Tol. (%)	TxDOT Conf. (%)	Contractor Conf. (%)	Samples from COV	Sampling Freq.	Samples from G. Sched.	Cost Per Sample
AC	3	20	10	80	80	12	3	5	1
Base	6	20	20	80	80	3	1	5	1
Subgrade	200	0	20	80	80	0	1	5	1

Figure A.87 - Slide 2 of Exercise 5

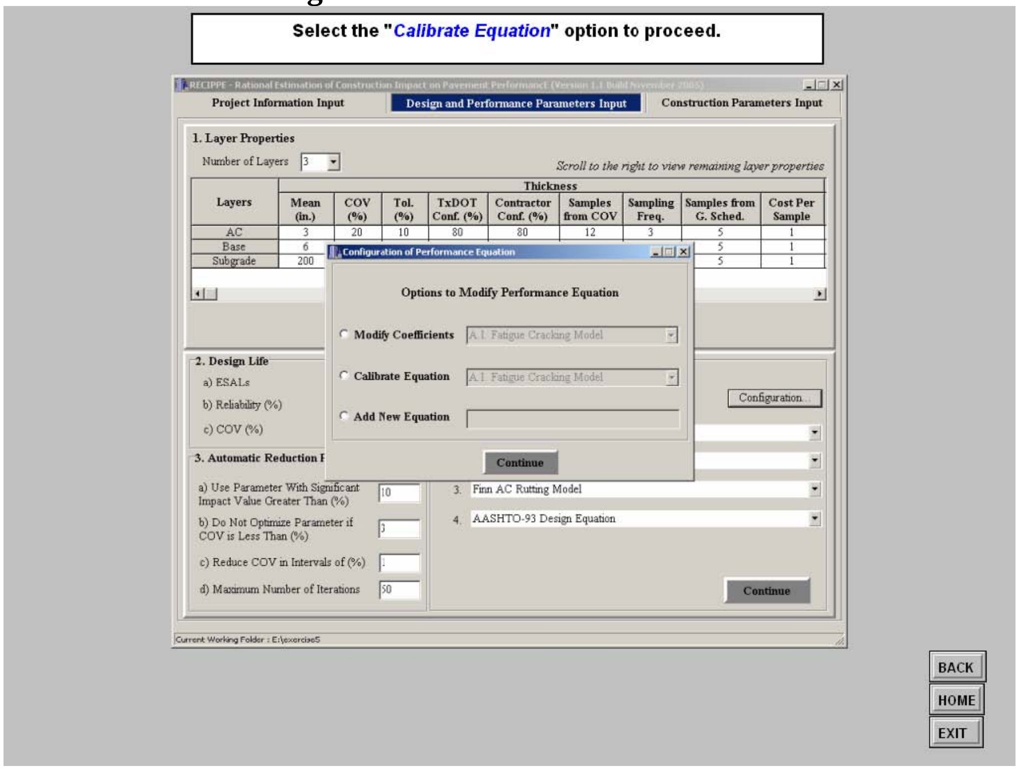


Figure A.88 - Slide 3 of Exercise 5

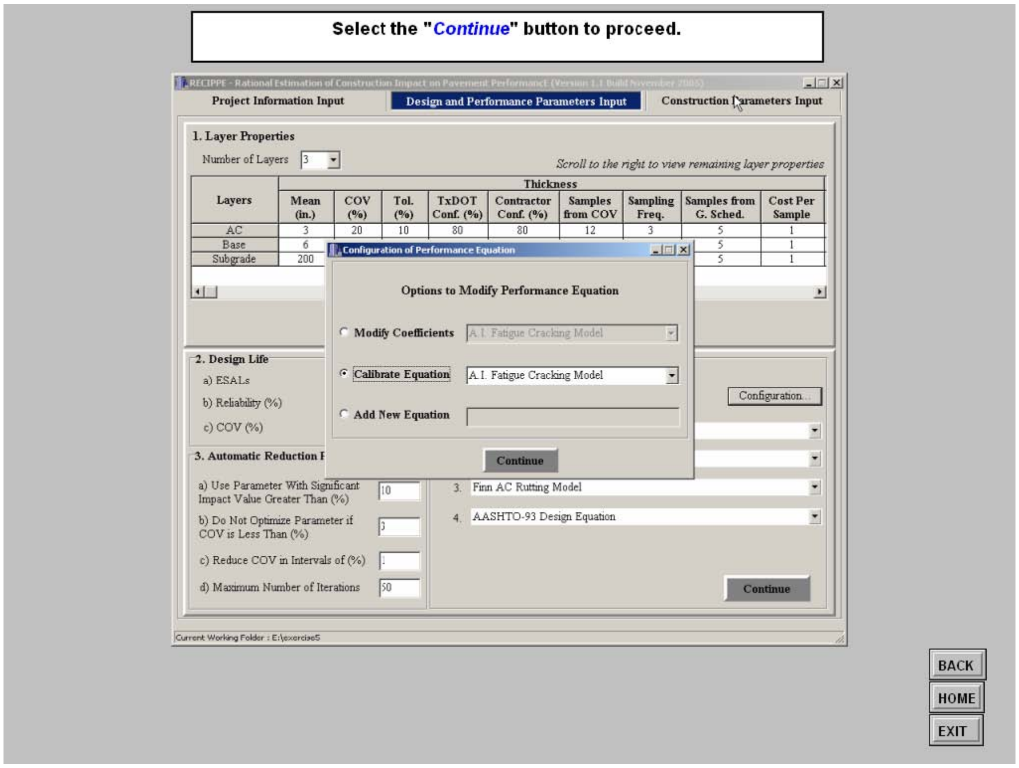


Figure A.89 - Slide 4 of Exercise 5

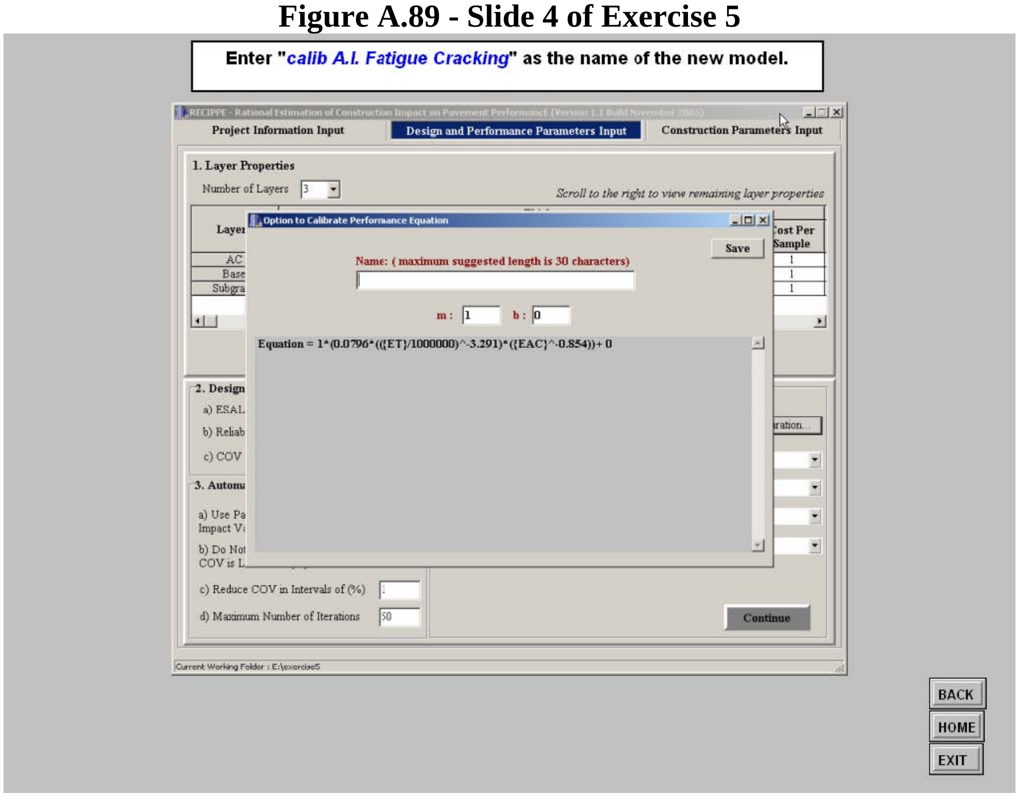


Figure A.90 - Slide 5 of Exercise 5

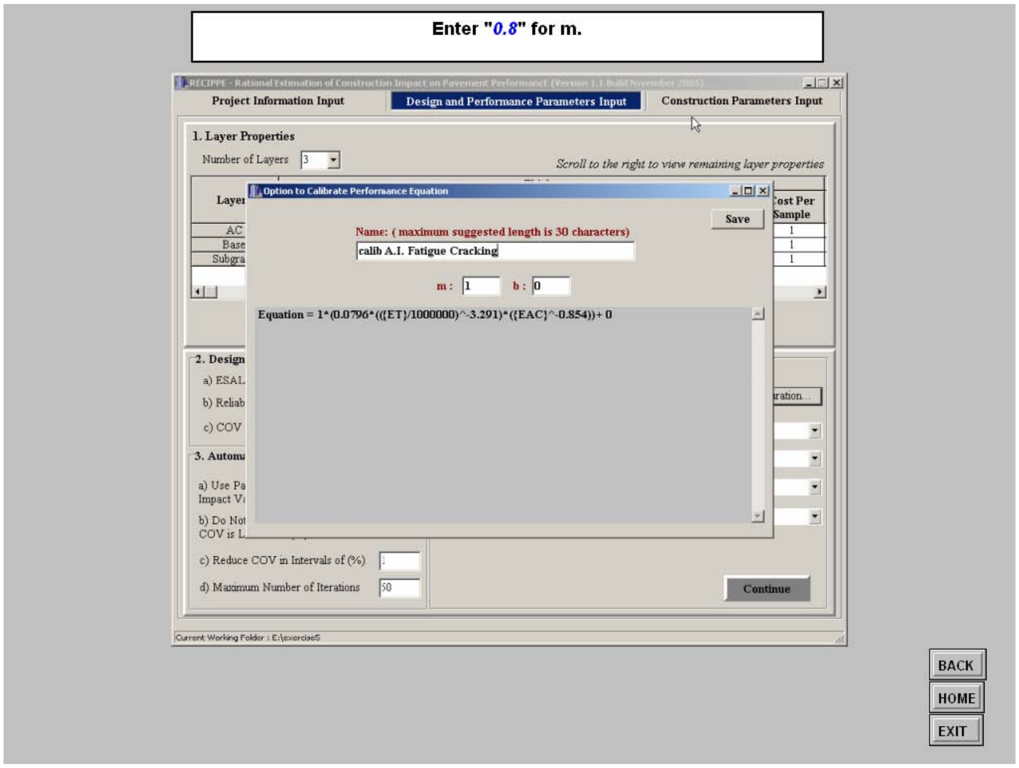


Figure A.91 - Slide 6 of Exercise 5

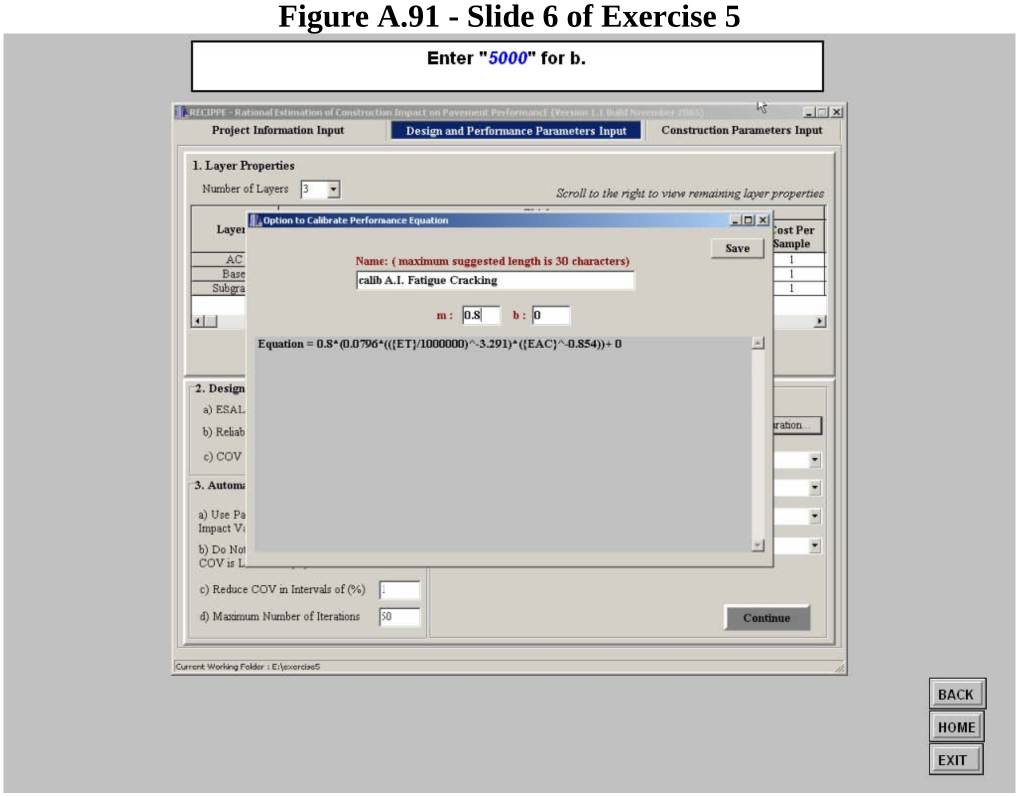


Figure A.92 - Slide 7 of Exercise 5

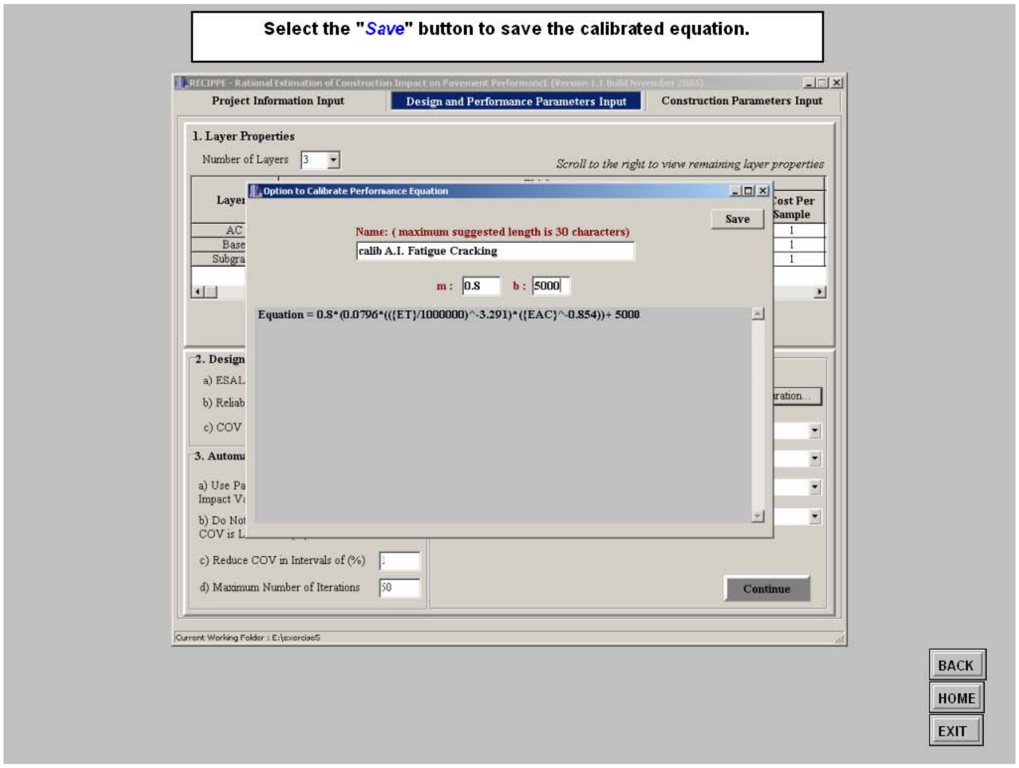


Figure A.93 - Slide 8 of Exercise 5

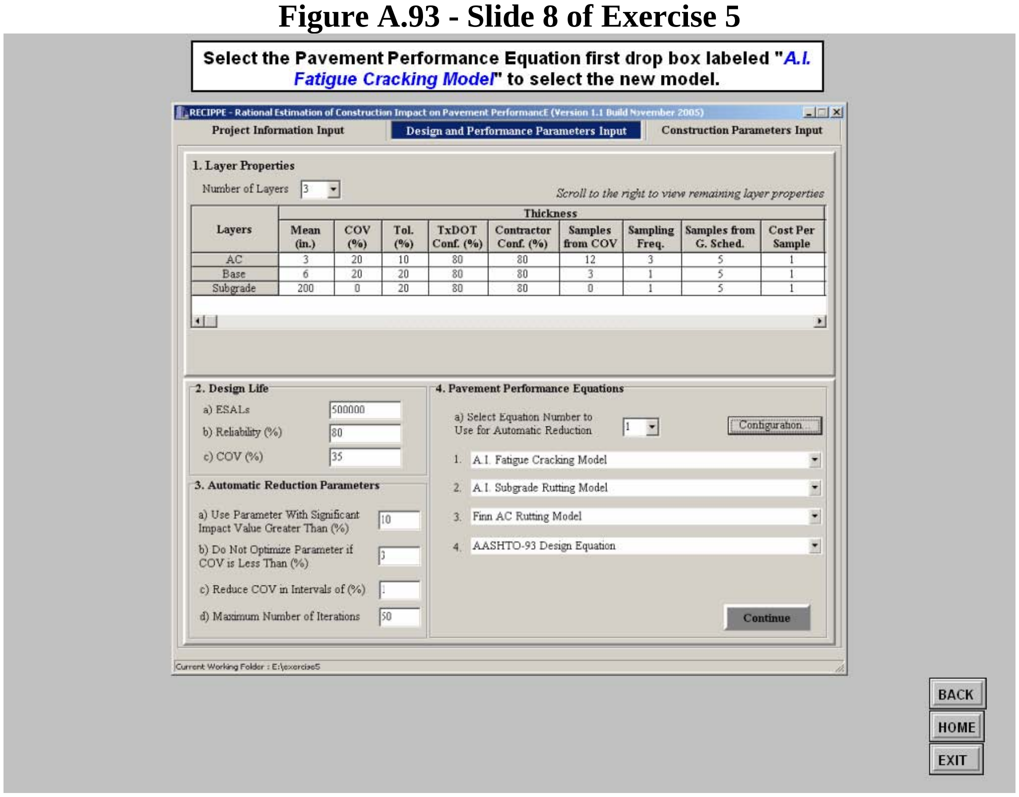


Figure A.94 - Slide 9 of Exercise 5

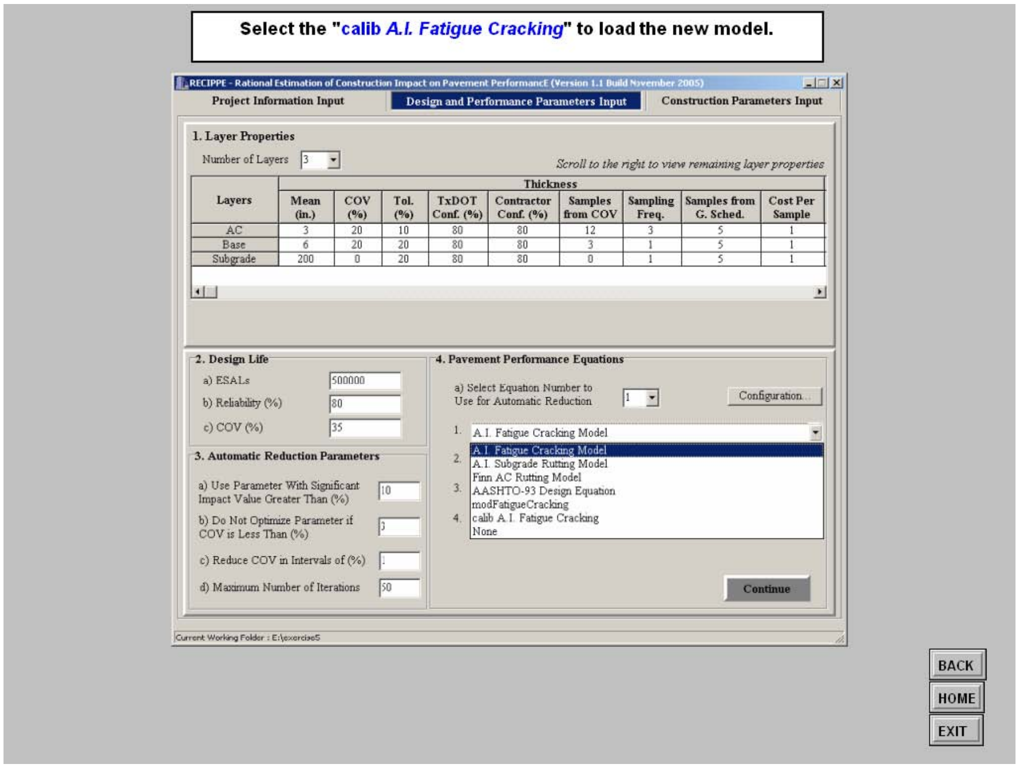


Figure A.95 - Slide 10 of Exercise 5

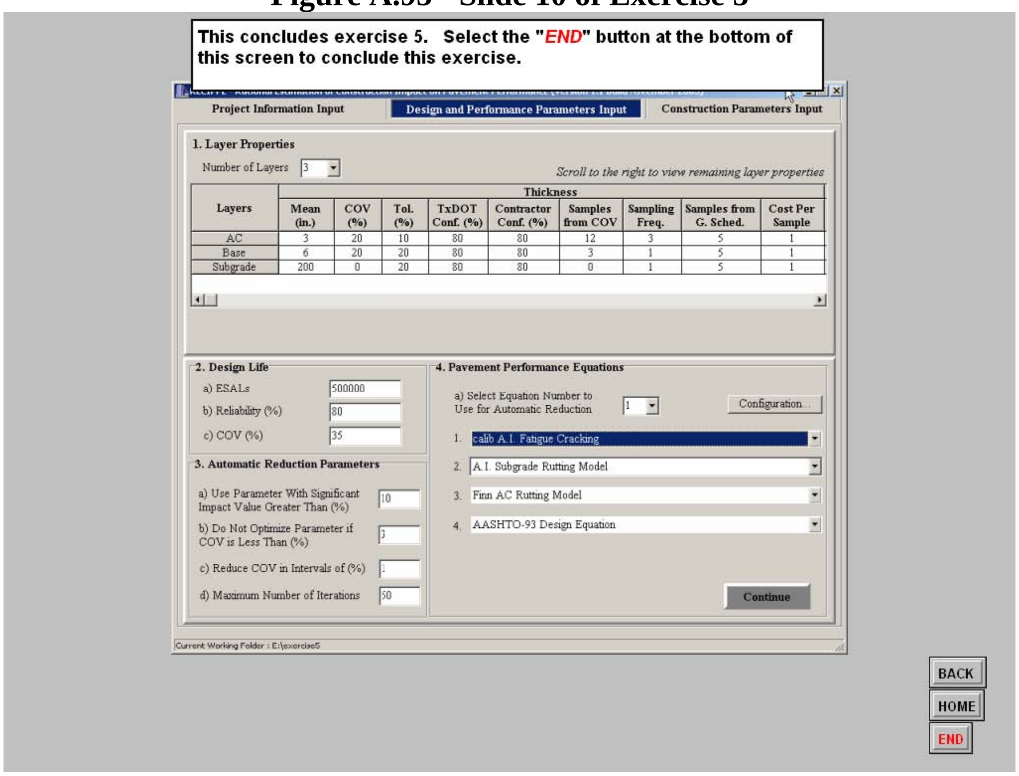


Figure A.96 - Slide 11 of Exercise 5

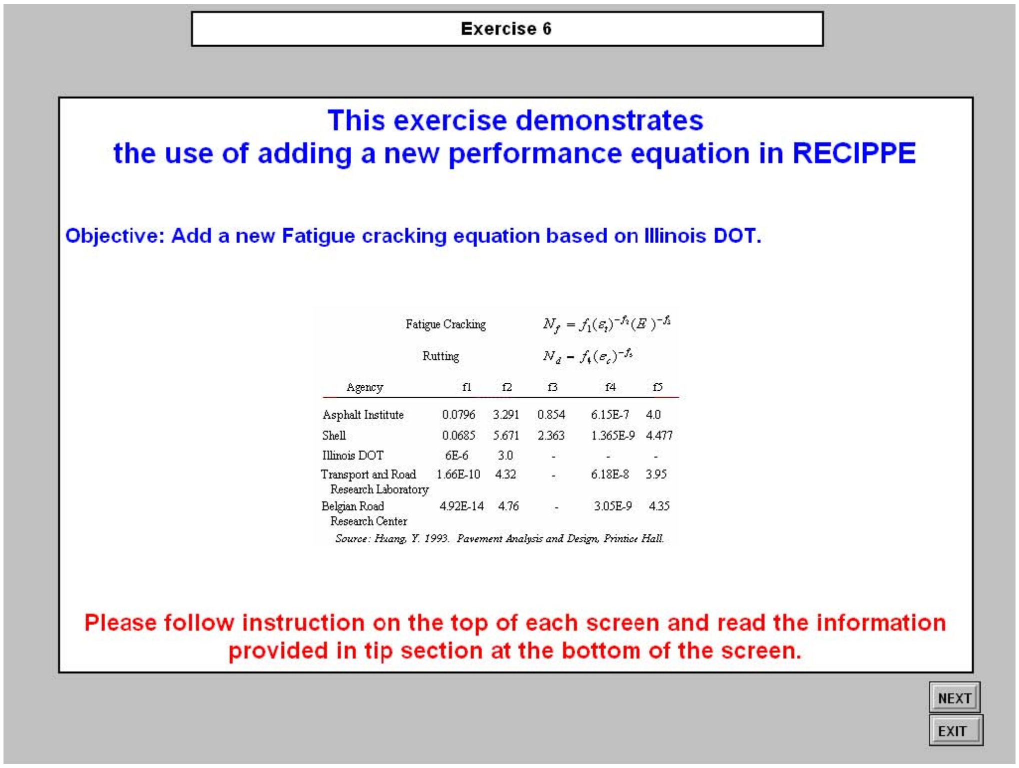


Figure A.97 - Slide 1 of Exercise 6

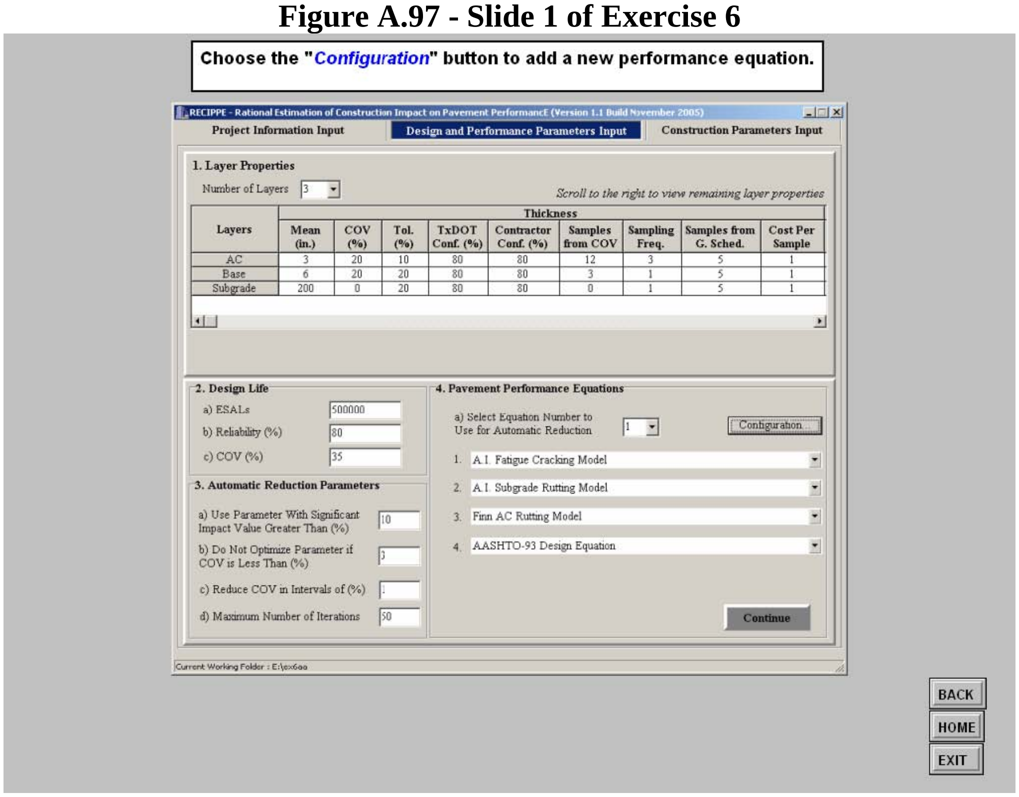


Figure A.98 - Slide 2 of Exercise 6

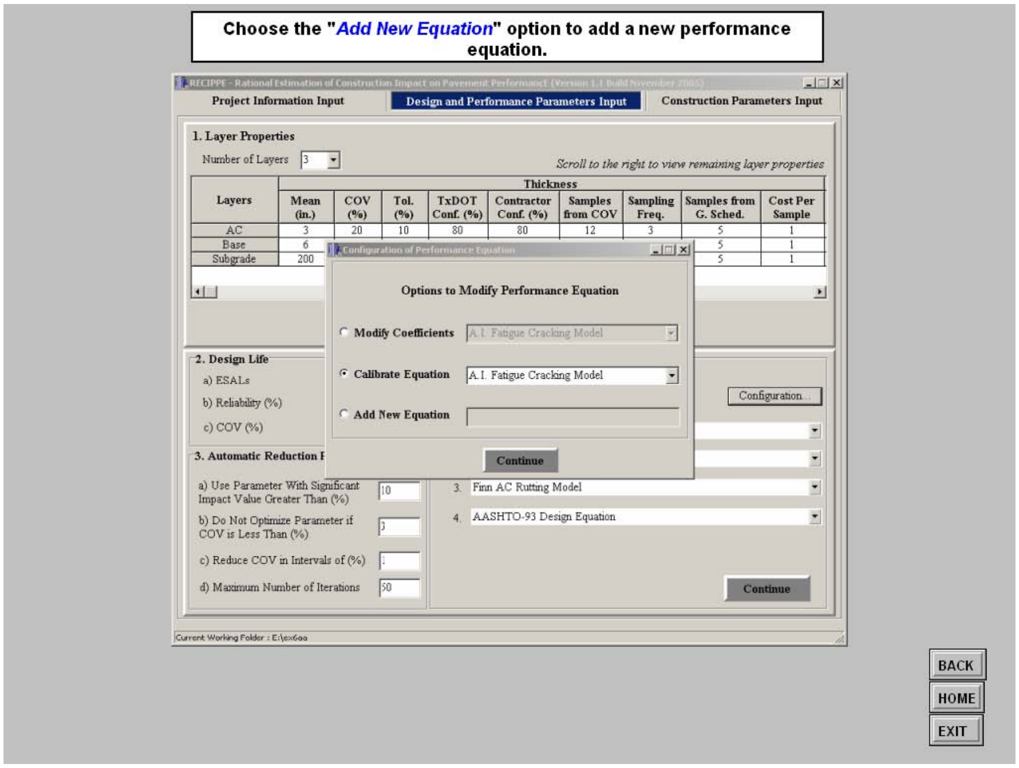


Figure A.99 - Slide 3 of Exercise 6

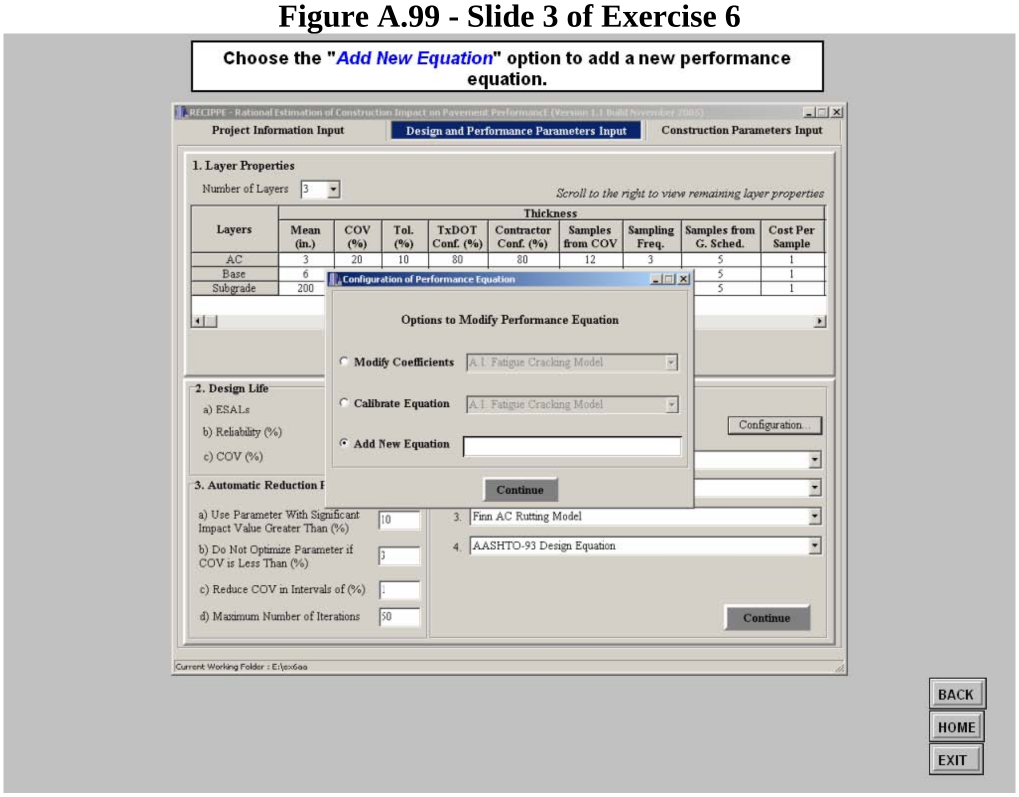


Figure A.100 - Slide 4 of Exercise 6

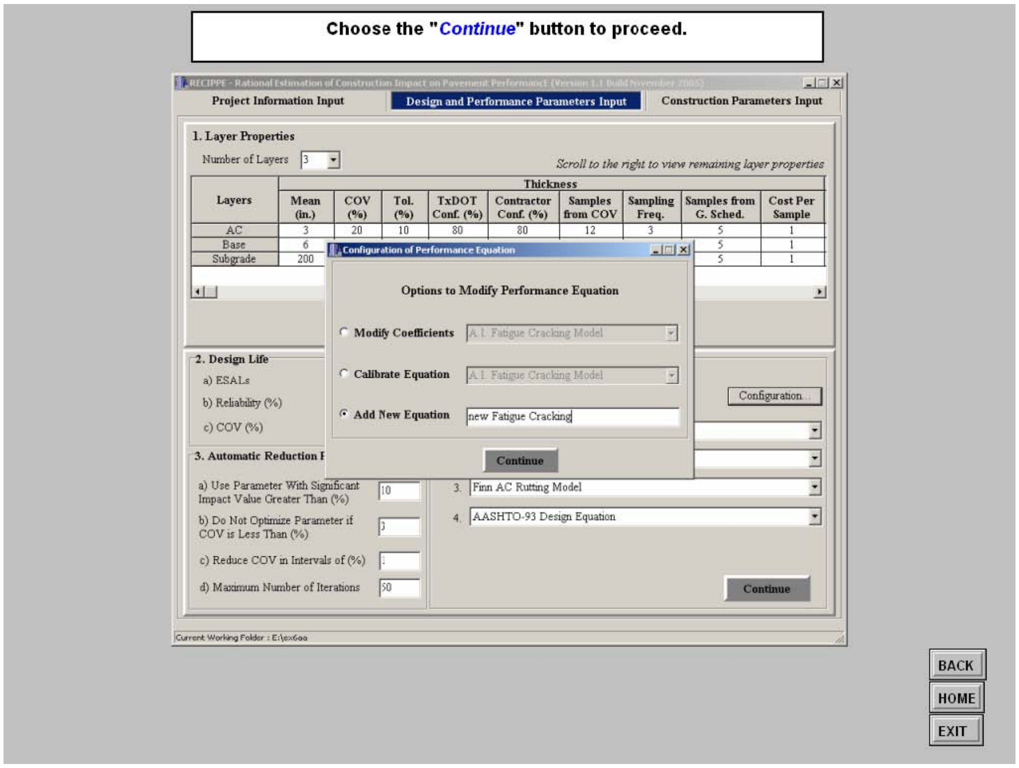


Figure A.101 - Slide 5 of Exercise 6

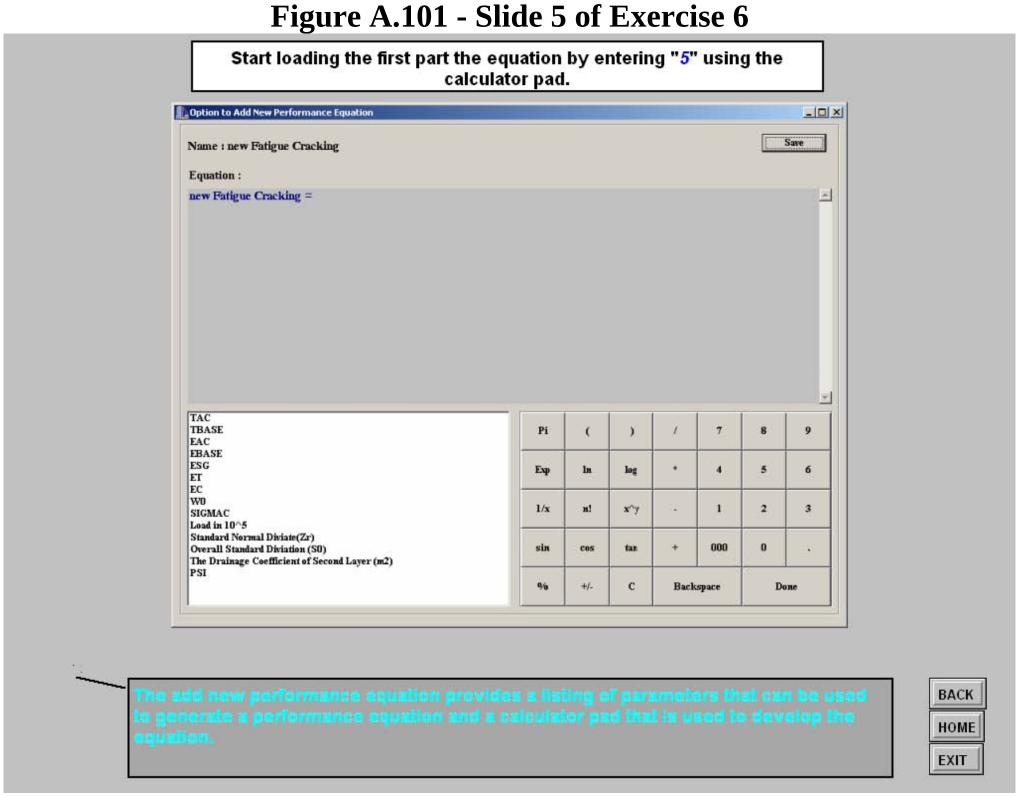


Figure A.102 - Slide 6 of Exercise 6

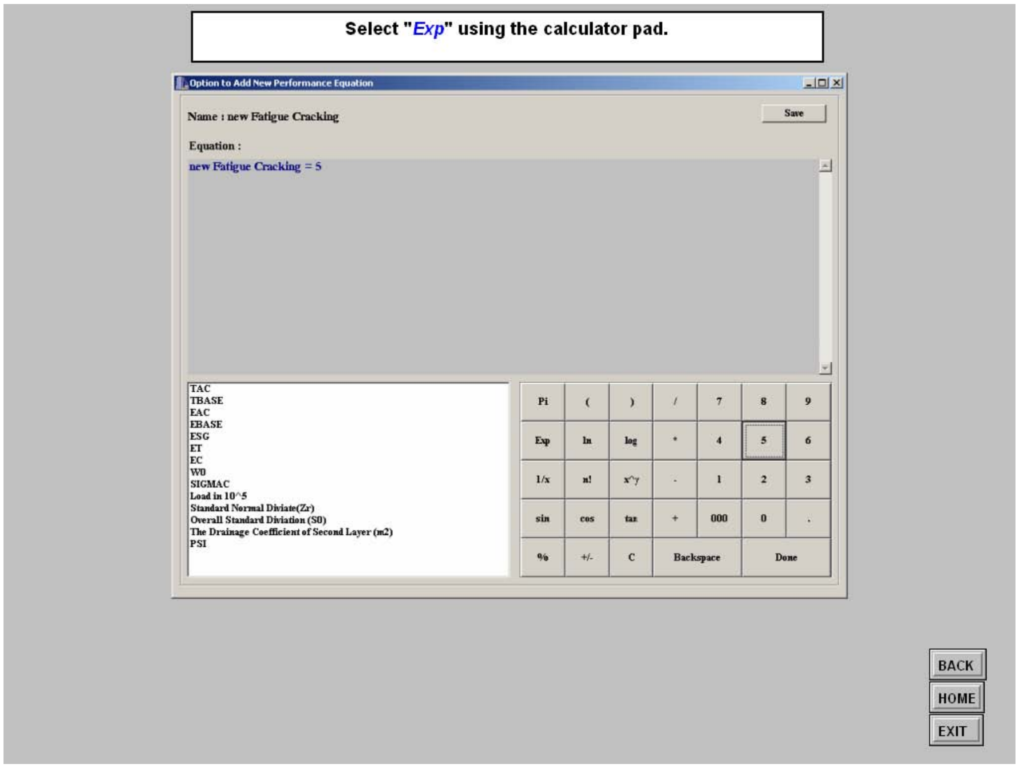


Figure A.103 - Slide 7 of Exercise 6

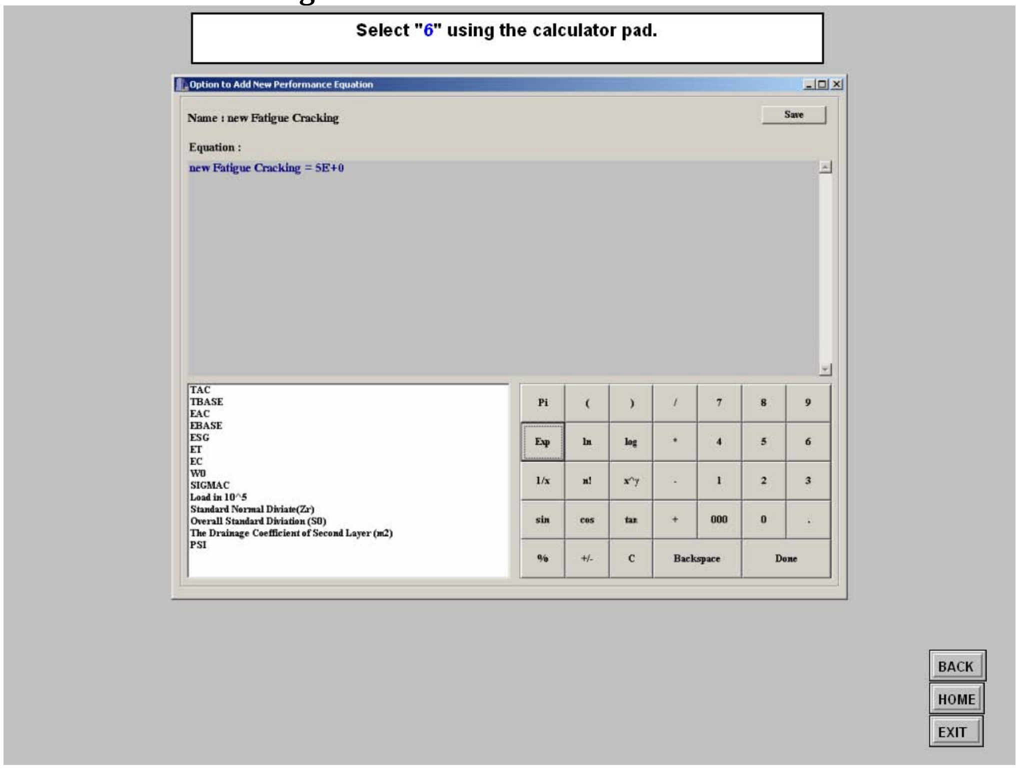


Figure A.104 - Slide 8 of Exercise 6

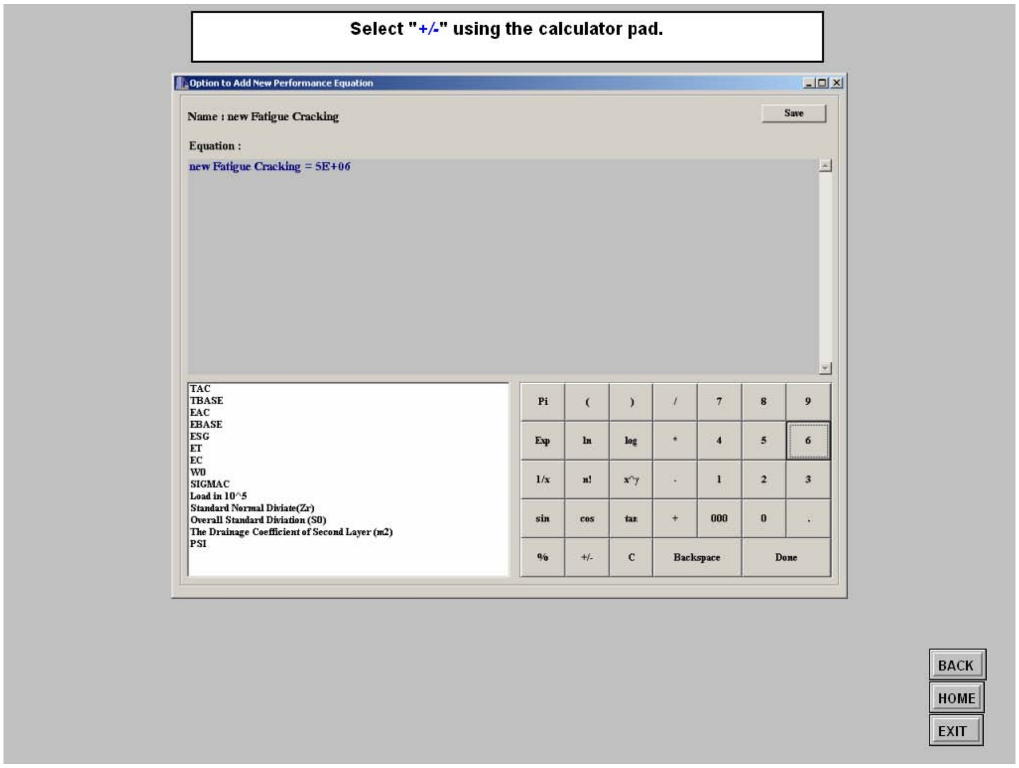


Figure A.105 - Slide 9 of Exercise 6

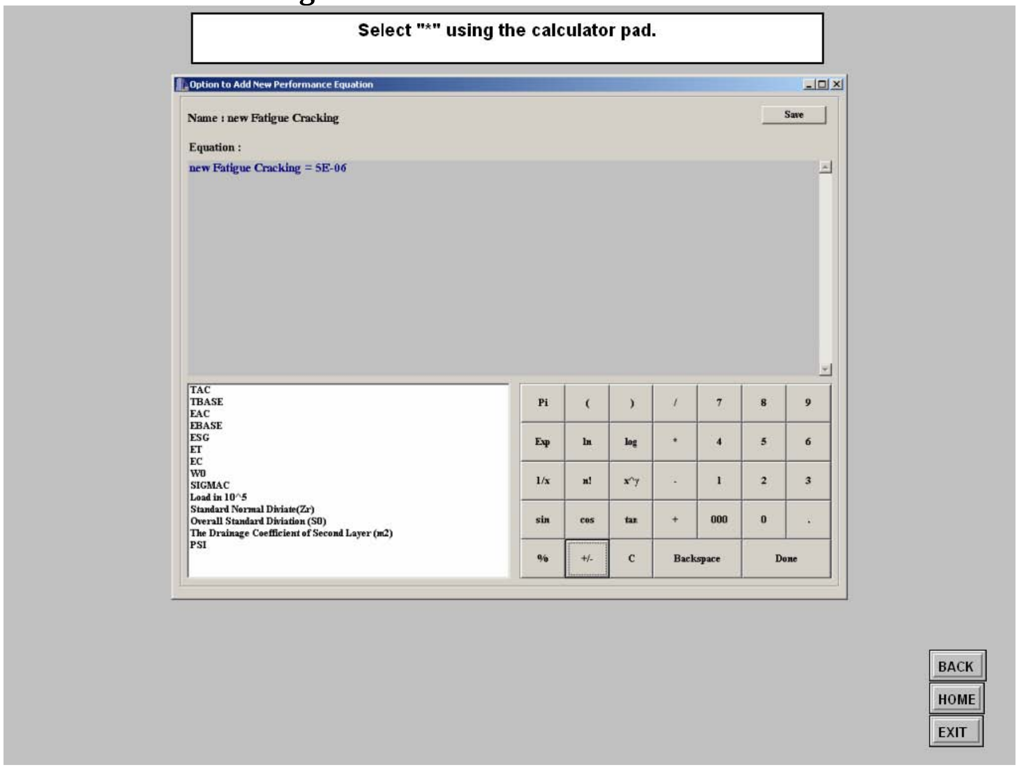


Figure A.106 - Slide 10 of Exercise 6

Figure A.107 - Slide 11 of Exercise 6

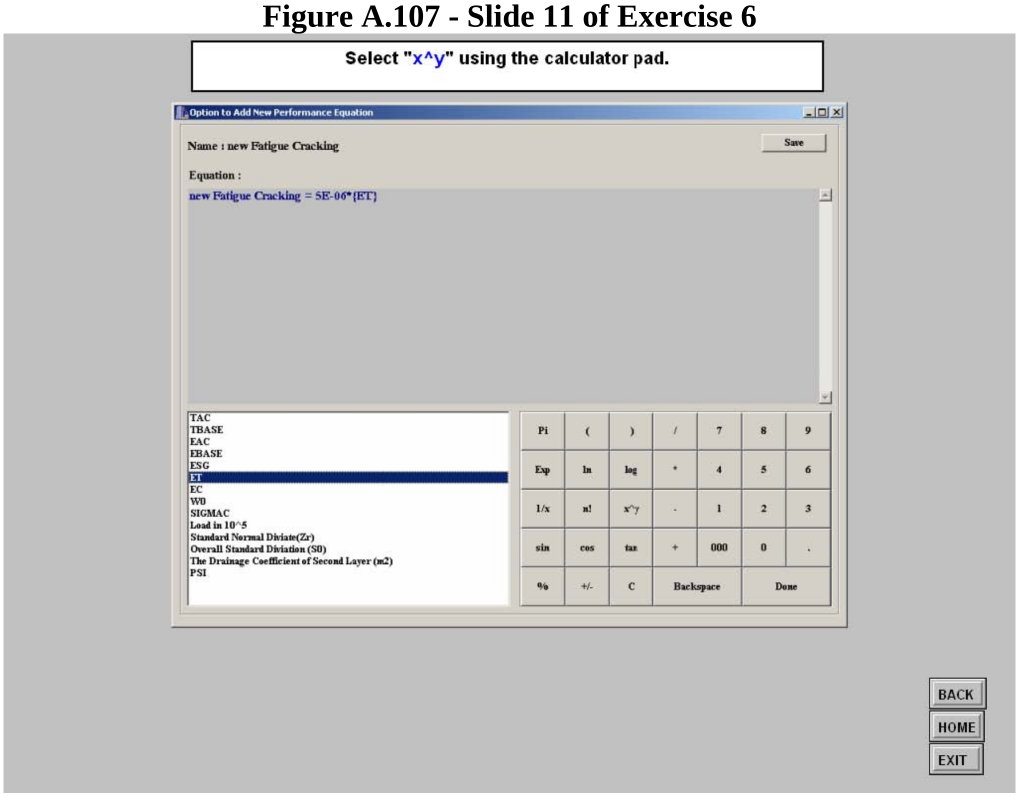


Figure A.108 - Slide 12 of Exercise 6

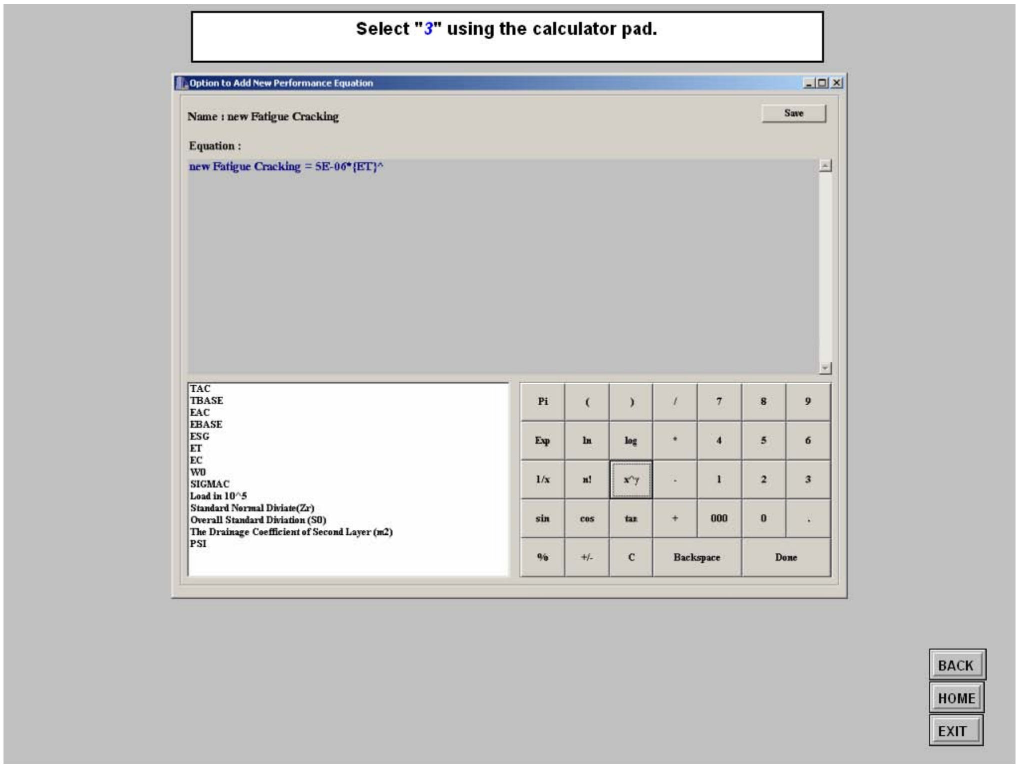


Figure A.109 - Slide 13 of Exercise 6

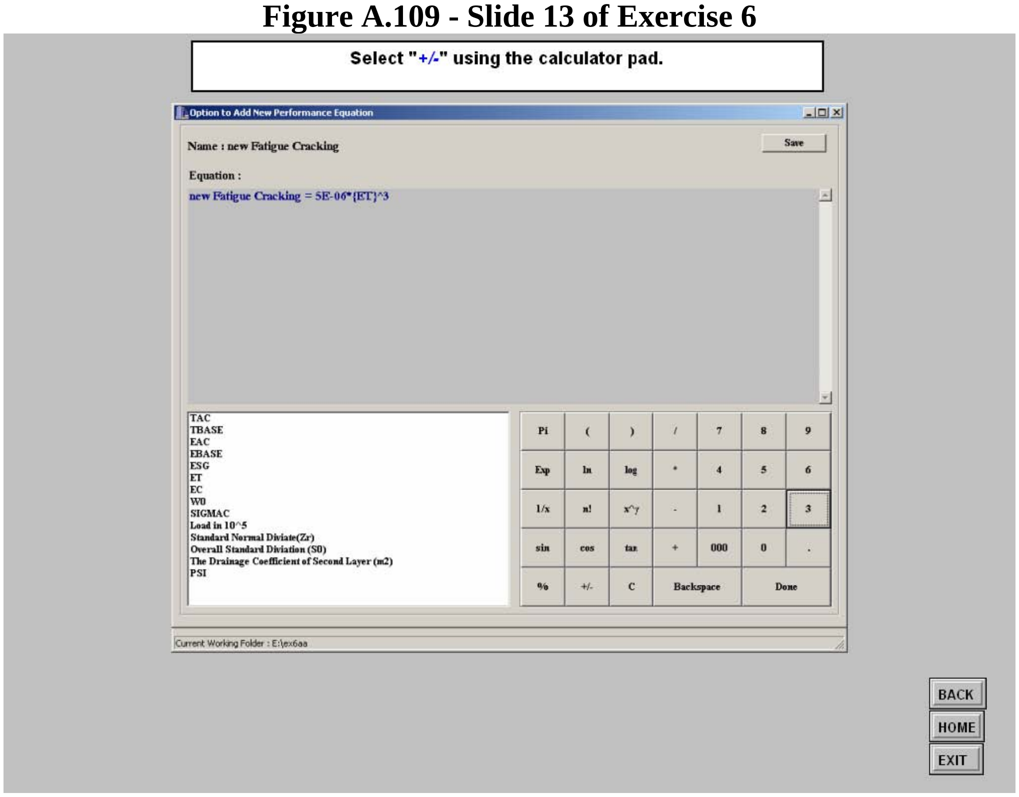


Figure A.110 - Slide 14 of Exercise 6

Figure A.111 - Slide 15 of Exercise 6

Figure A.112 - Slide 16 of Exercise 6

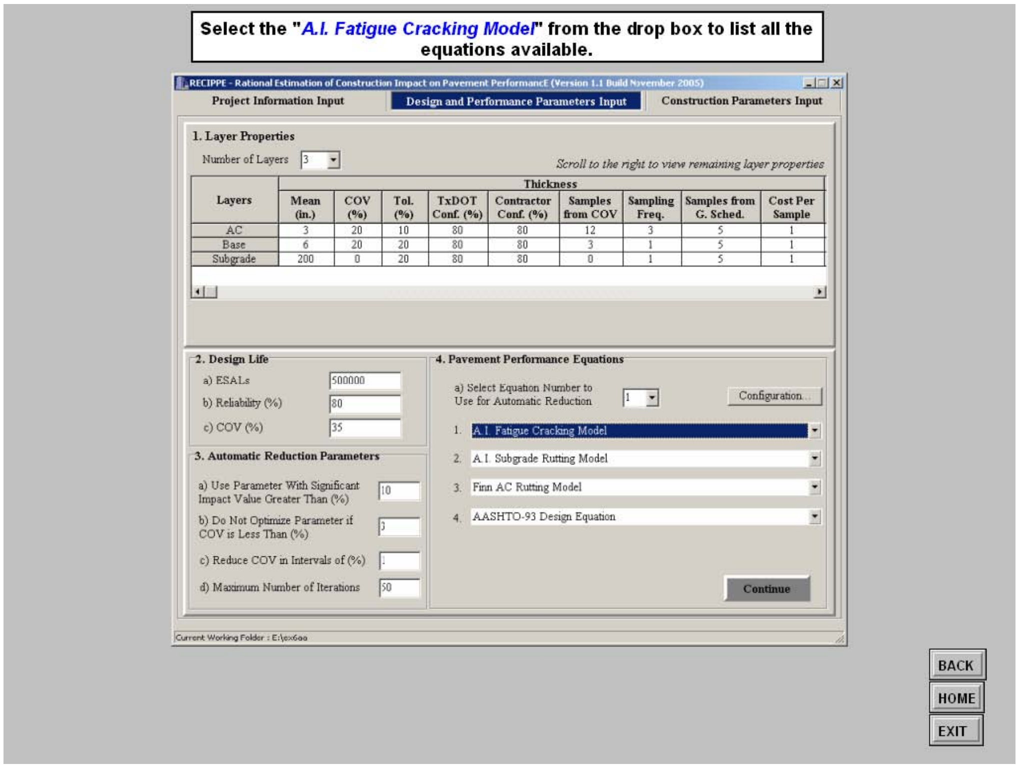


Figure A.113 - Slide 17 of Exercise 6

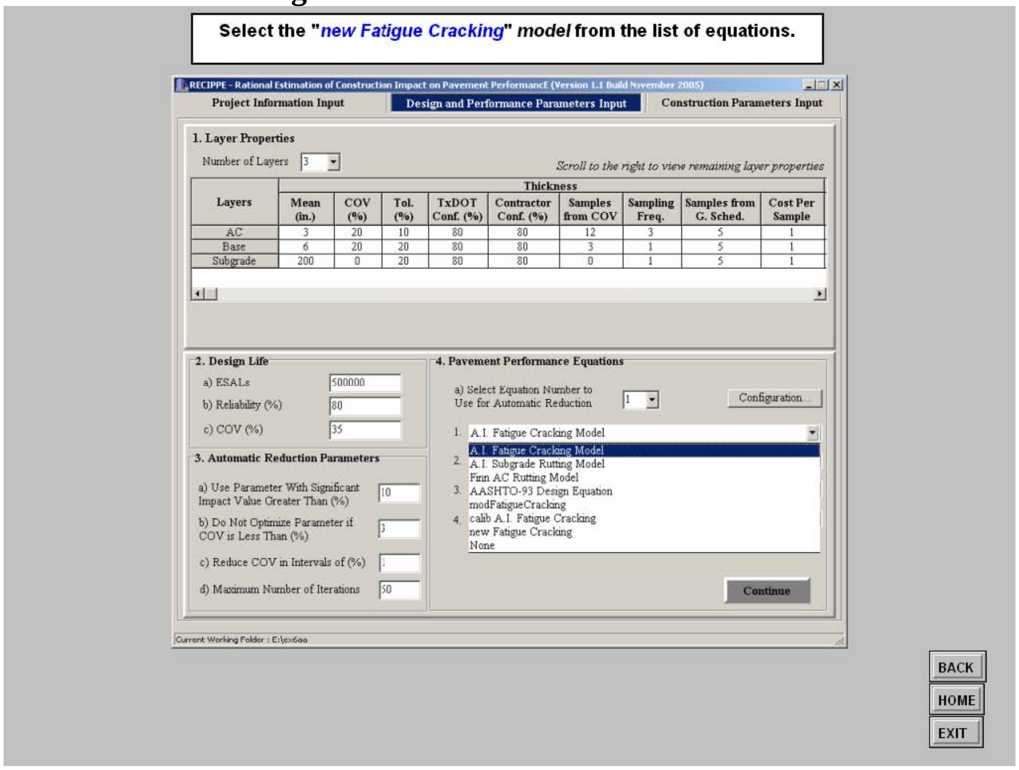


Figure A.114 - Slide 18 of Exercise 6

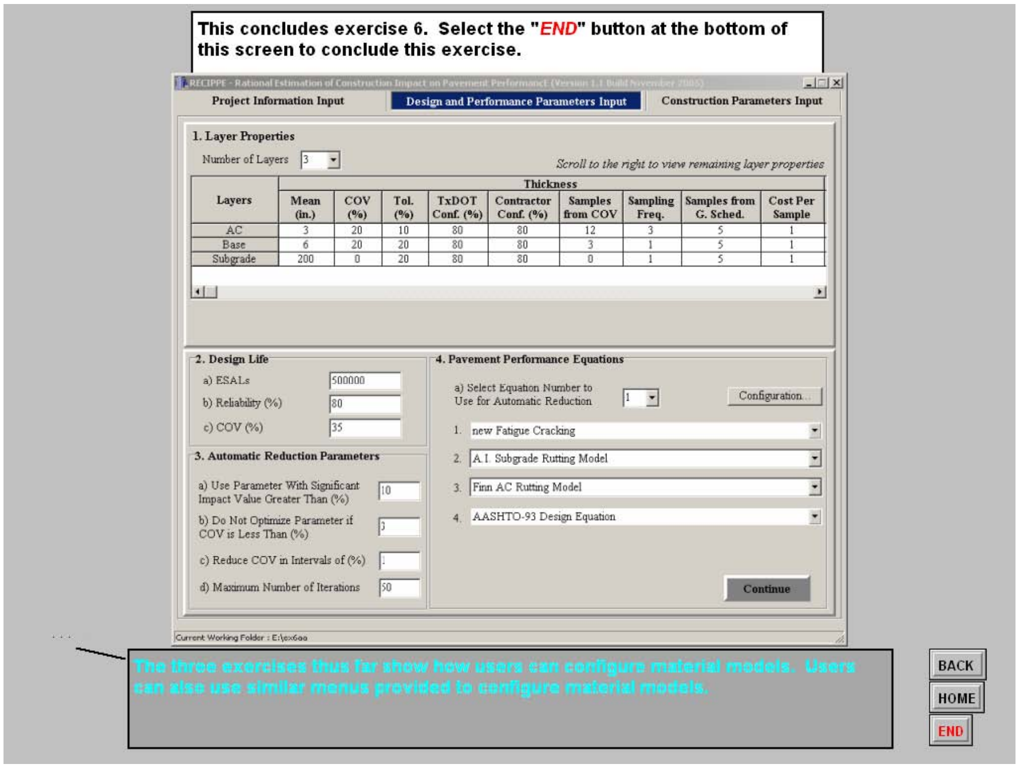


Figure A.115 - Slide 19 of Exercise 6

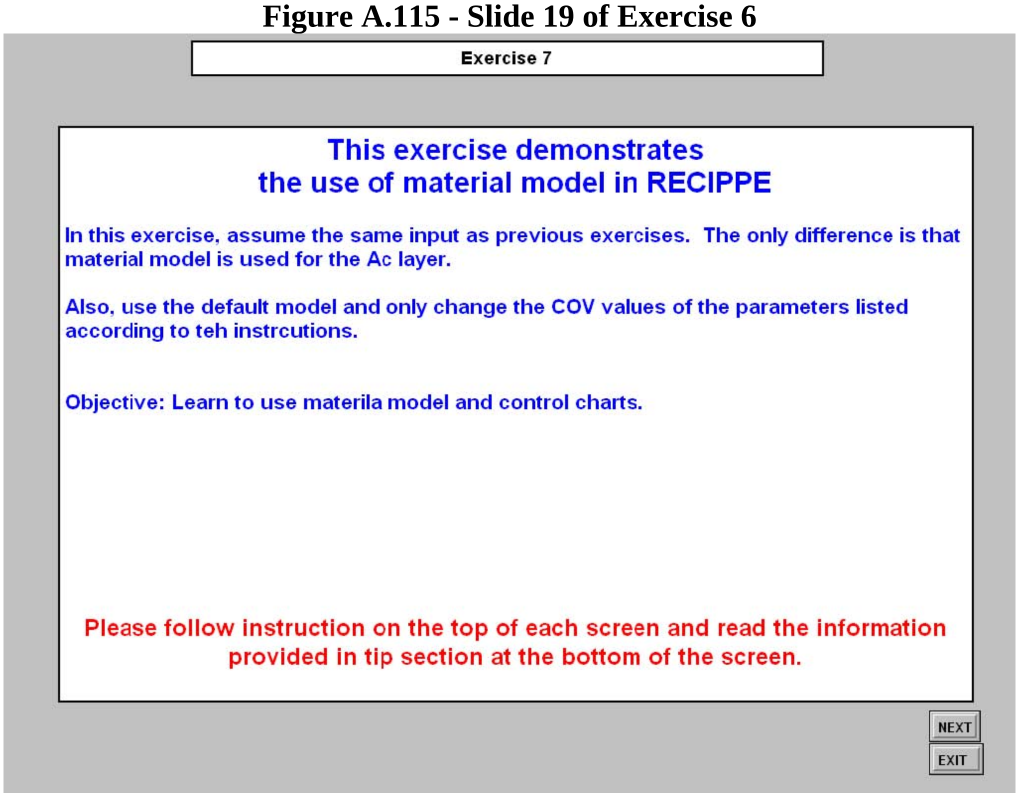


Figure A.116 - Slide 1 of Exercise 7

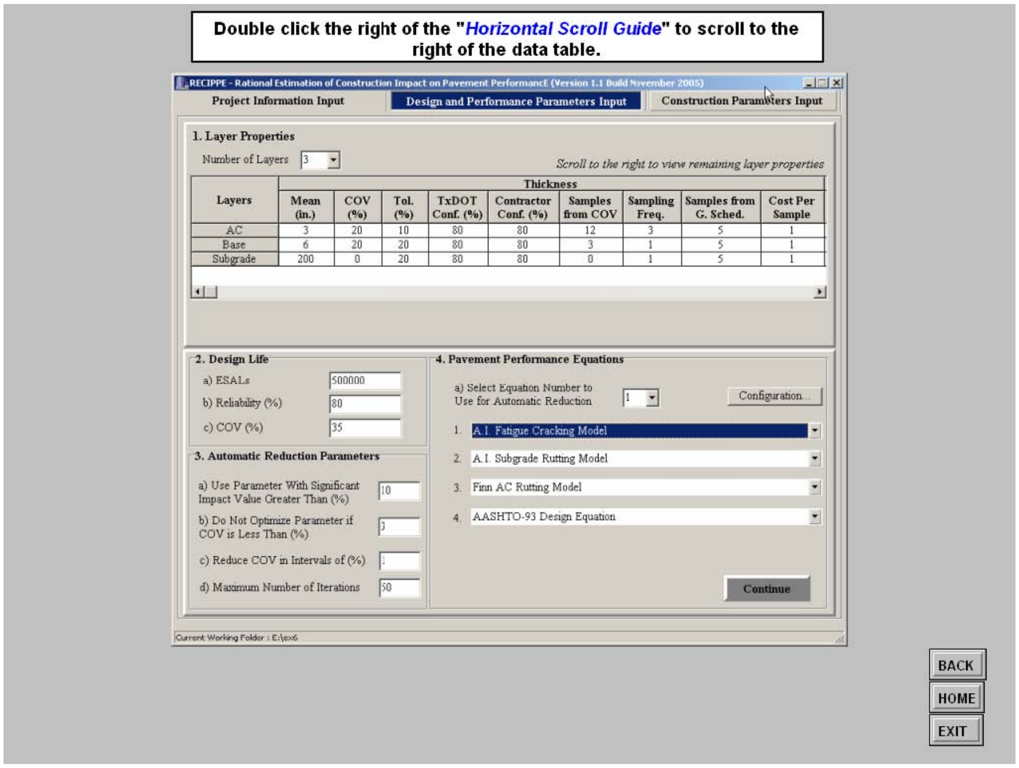


Figure A.117 - Slide 2 of Exercise 7

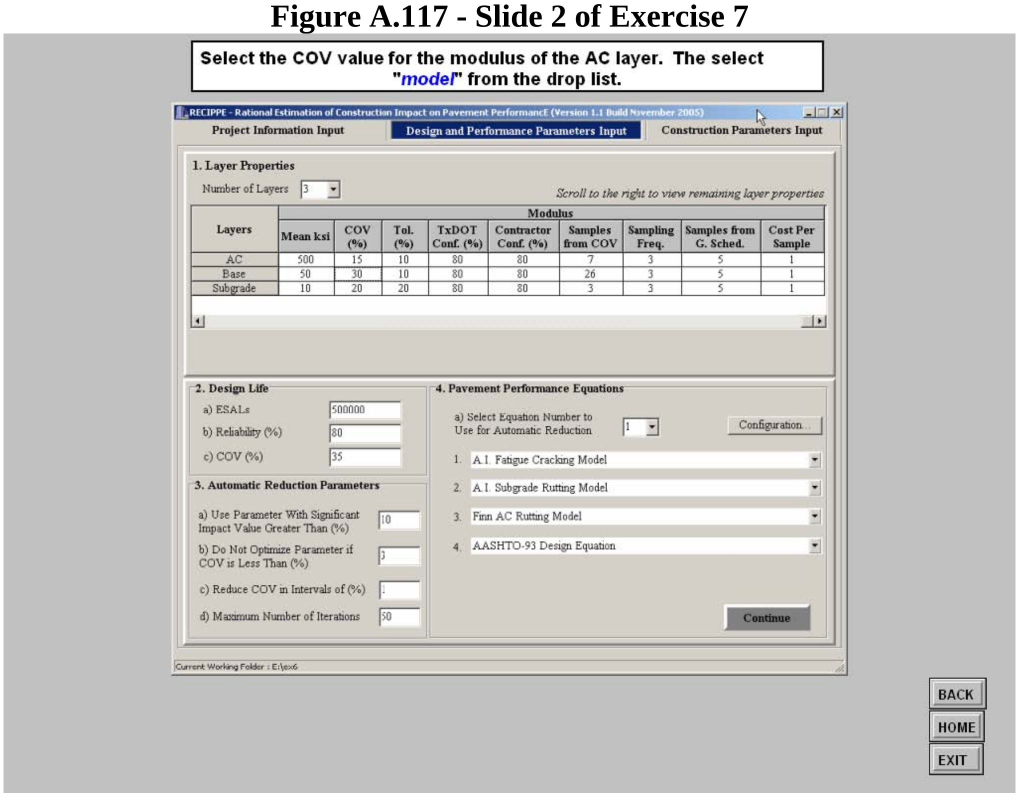


Figure A.118 - Slide 3 of Exercise 7

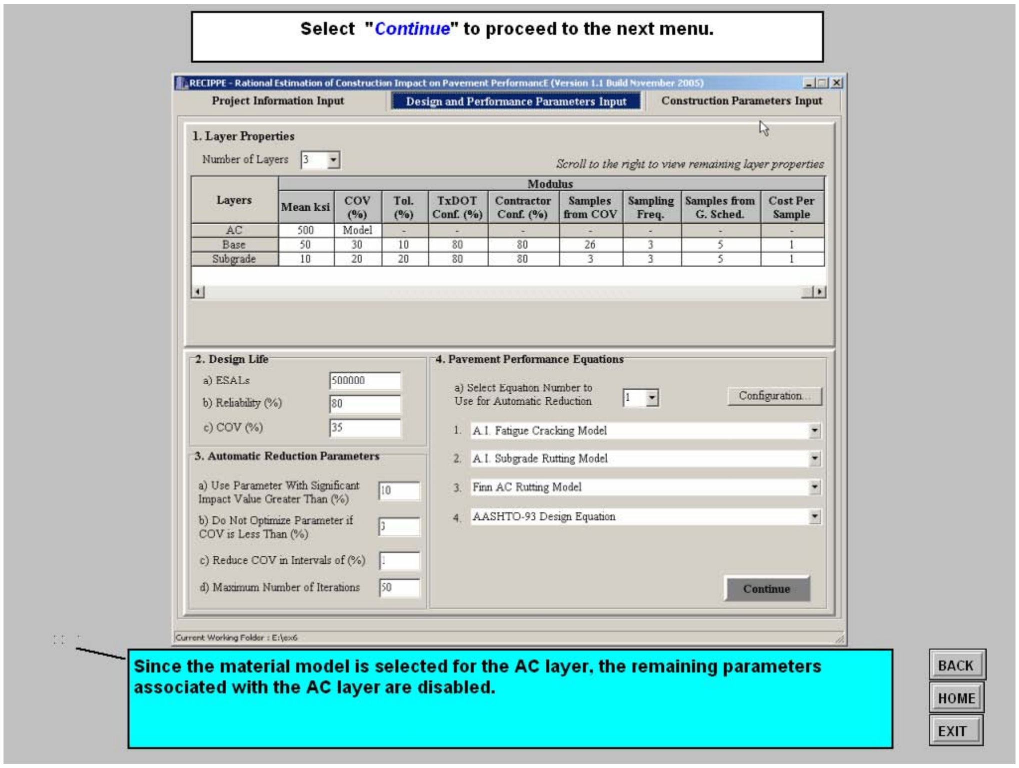


Figure A.119 - Slide 4 of Exercise 7

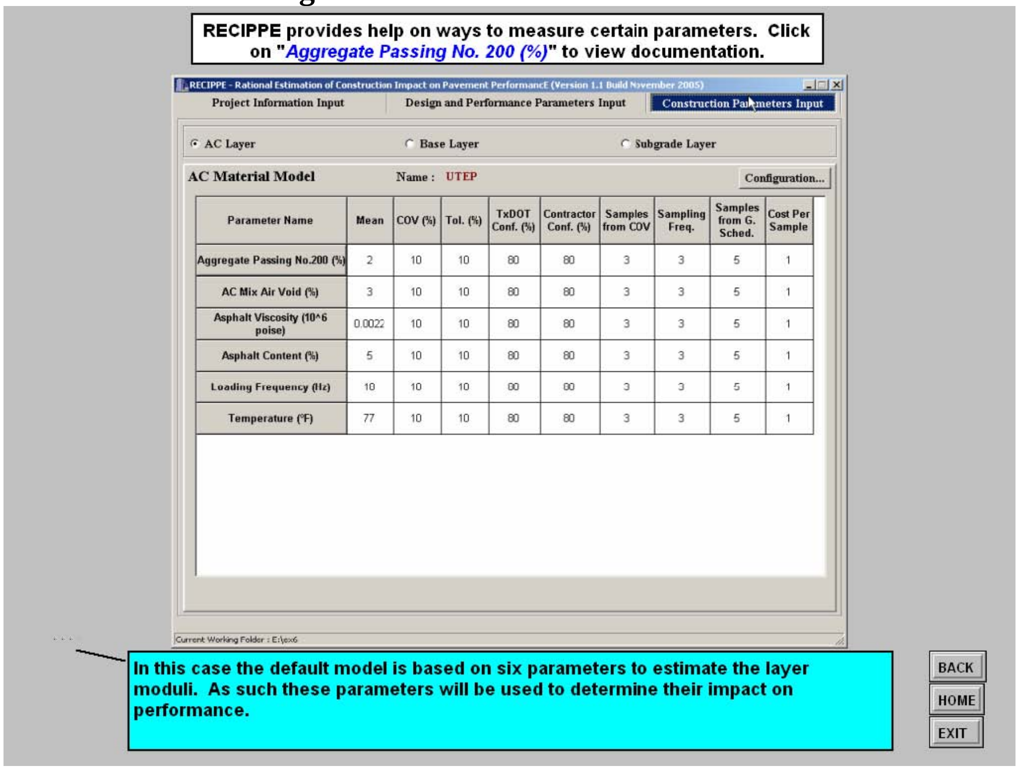


Figure A.120 - Slide 5 of Exercise 7

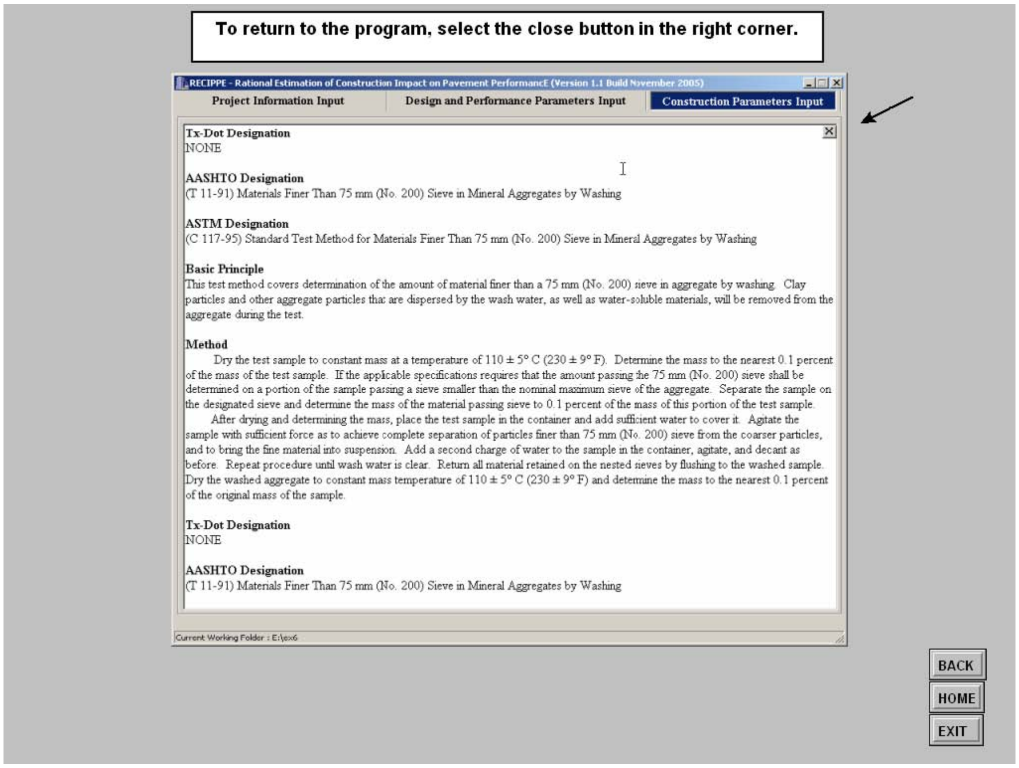


Figure A.121 - Slide 6 of Exercise 7

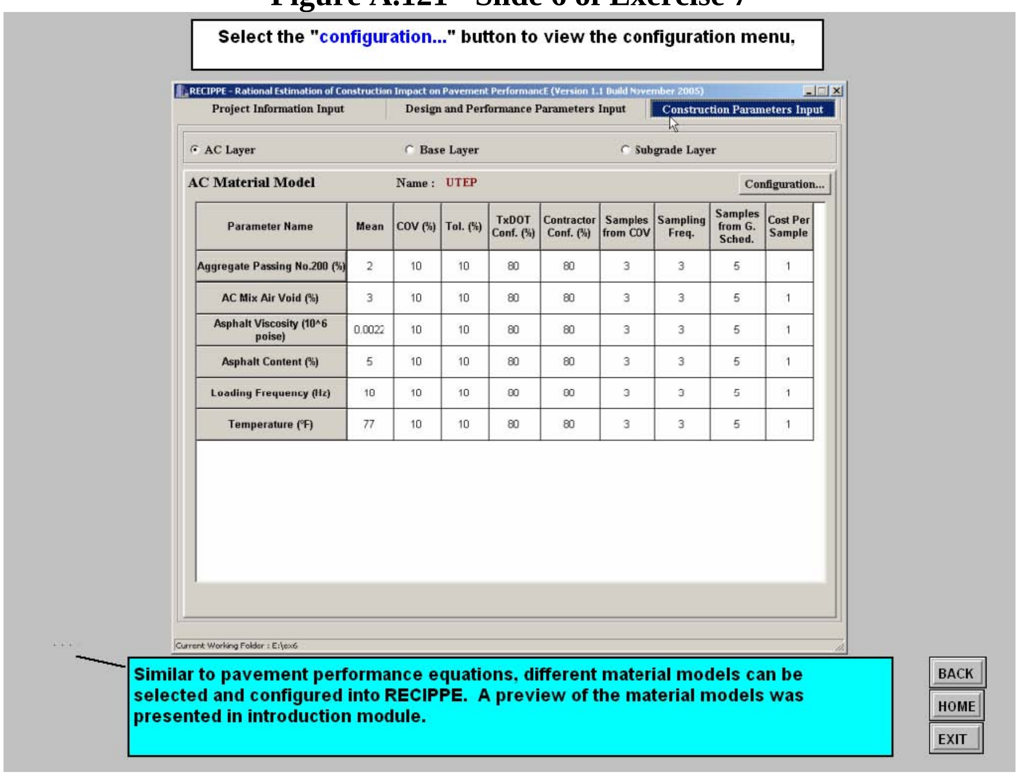


Figure A.122 - Slide 7 of Exercise 7

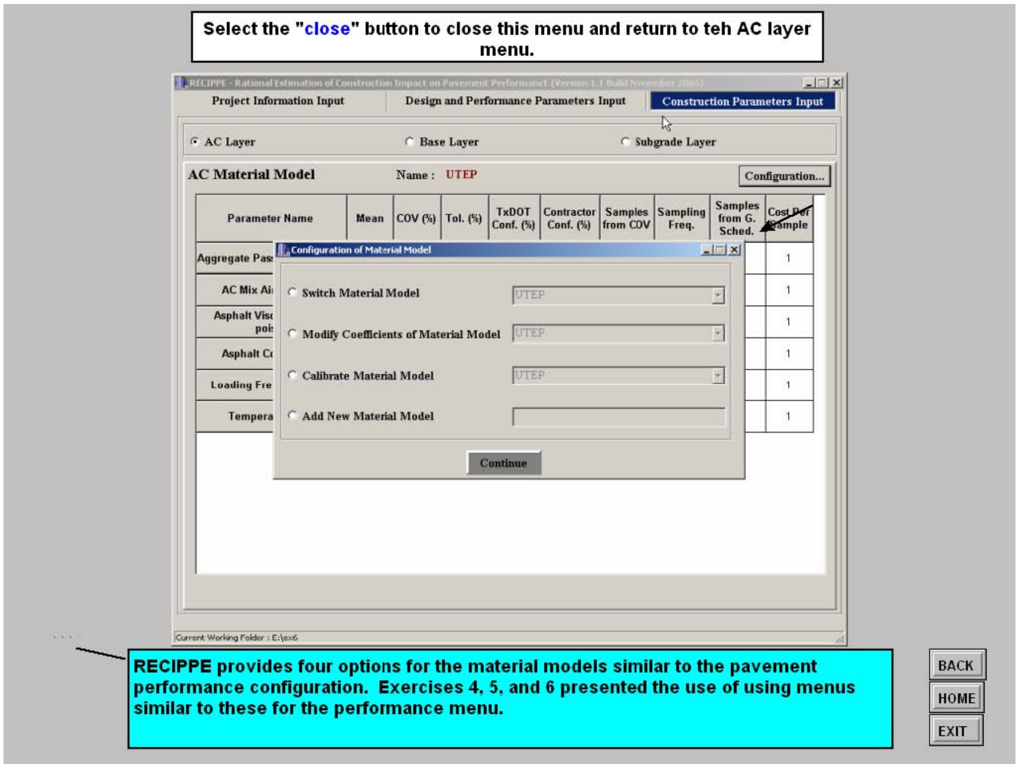


Figure A.123 - Slide 8 of Exercise 7

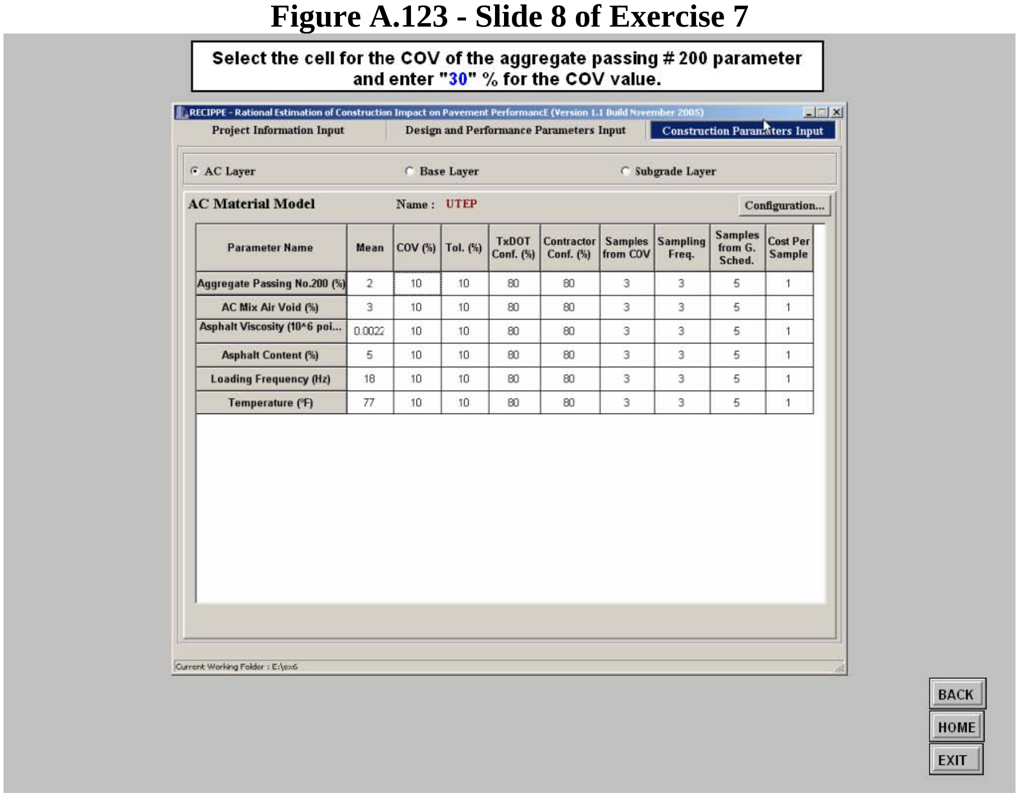


Figure A.124 - Slide 9 of Exercise 7

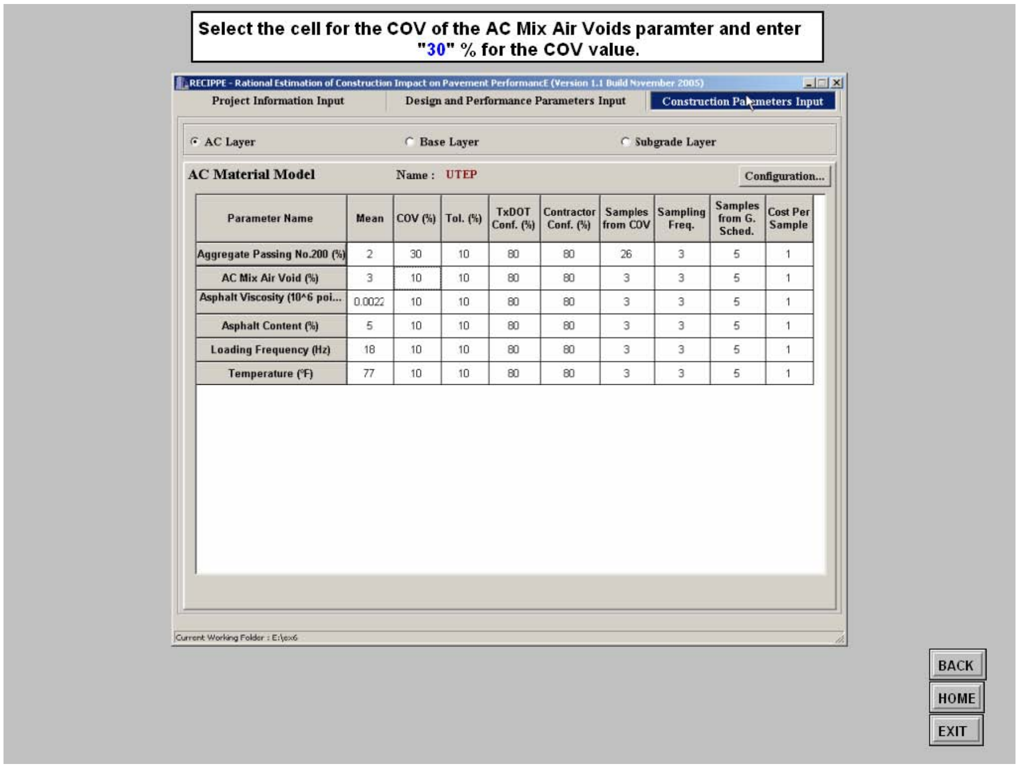


Figure A.125 - Slide 10 of Exercise 7

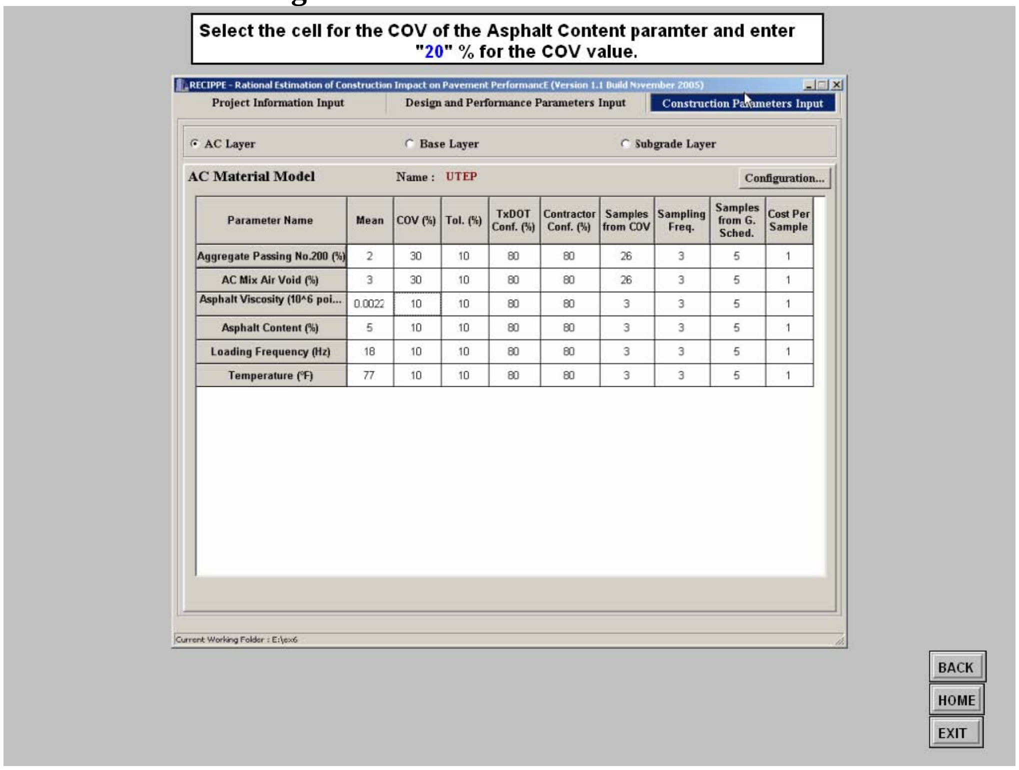


Figure A.126 - Slide 11 of Exercise 7

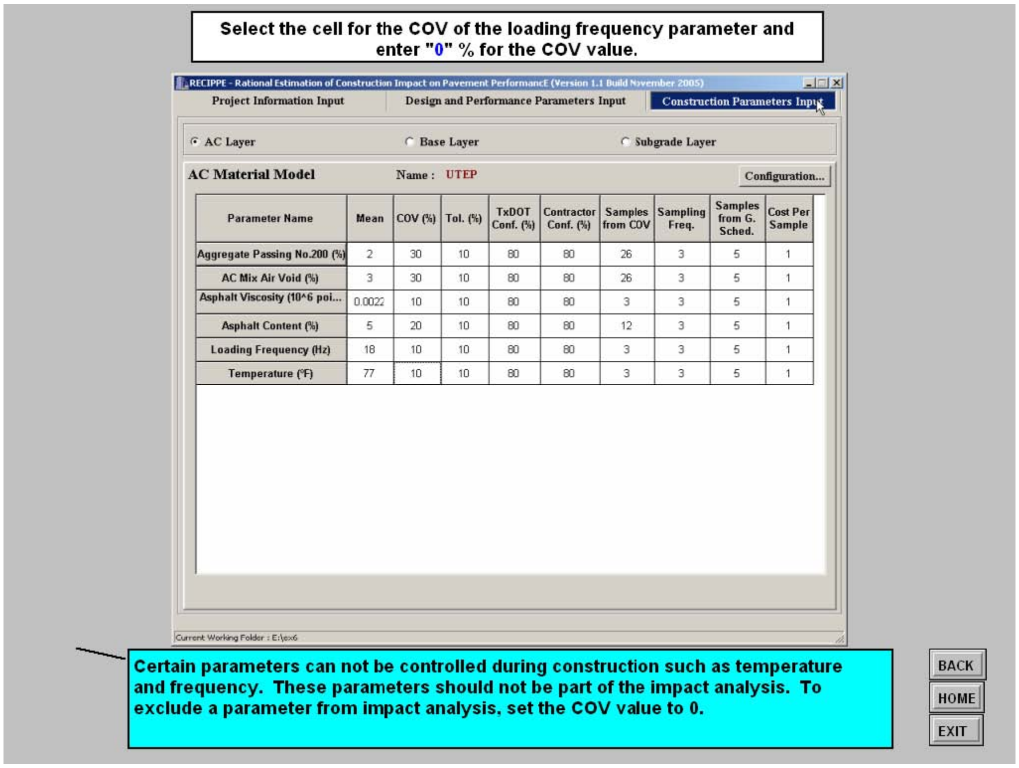


Figure A.127 - Slide 12 of Exercise 7

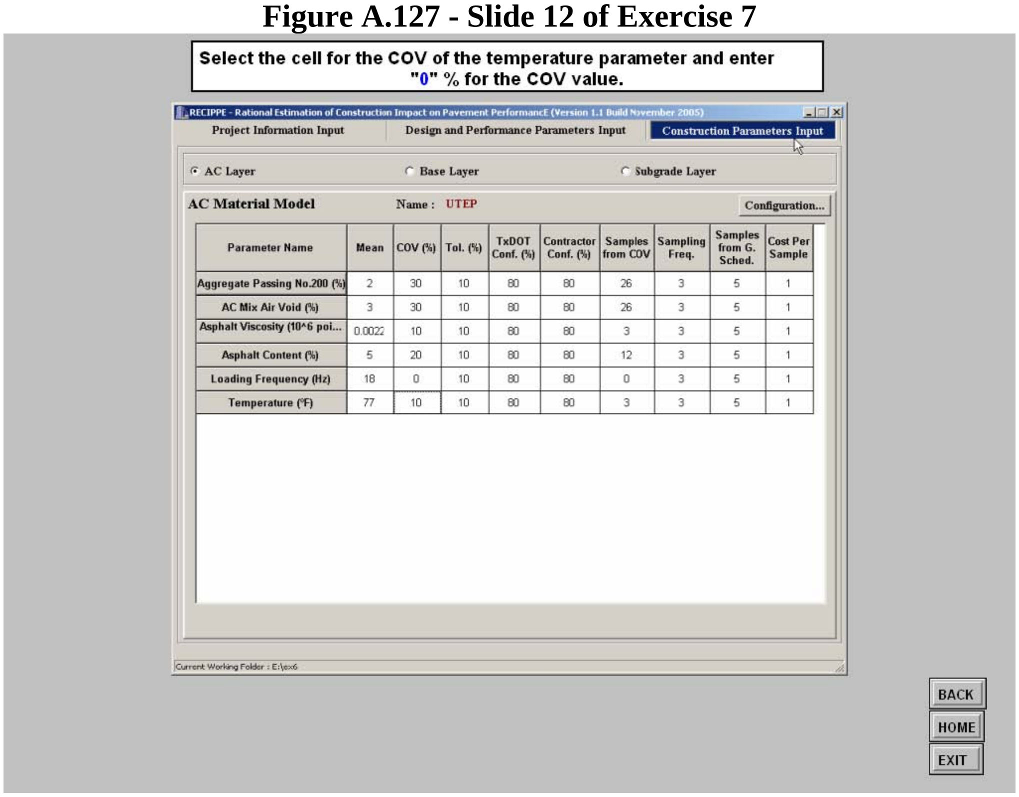


Figure A.128 - Slide 13 of Exercise 7

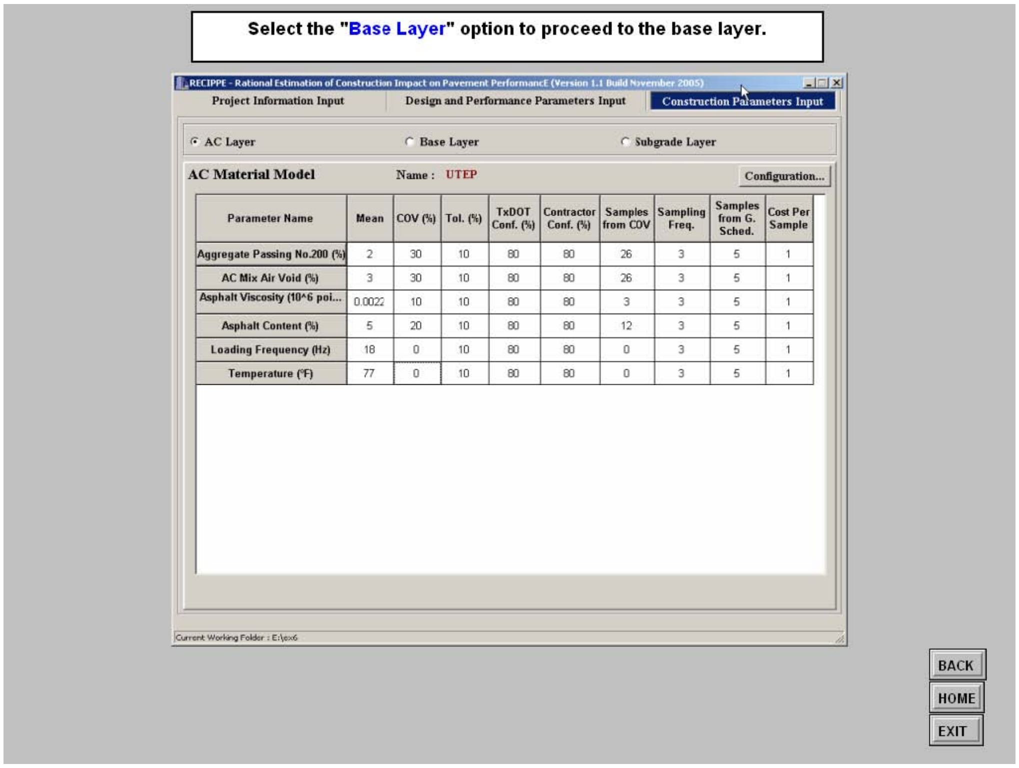


Figure A.129 - Slide 14 of Exercise 7

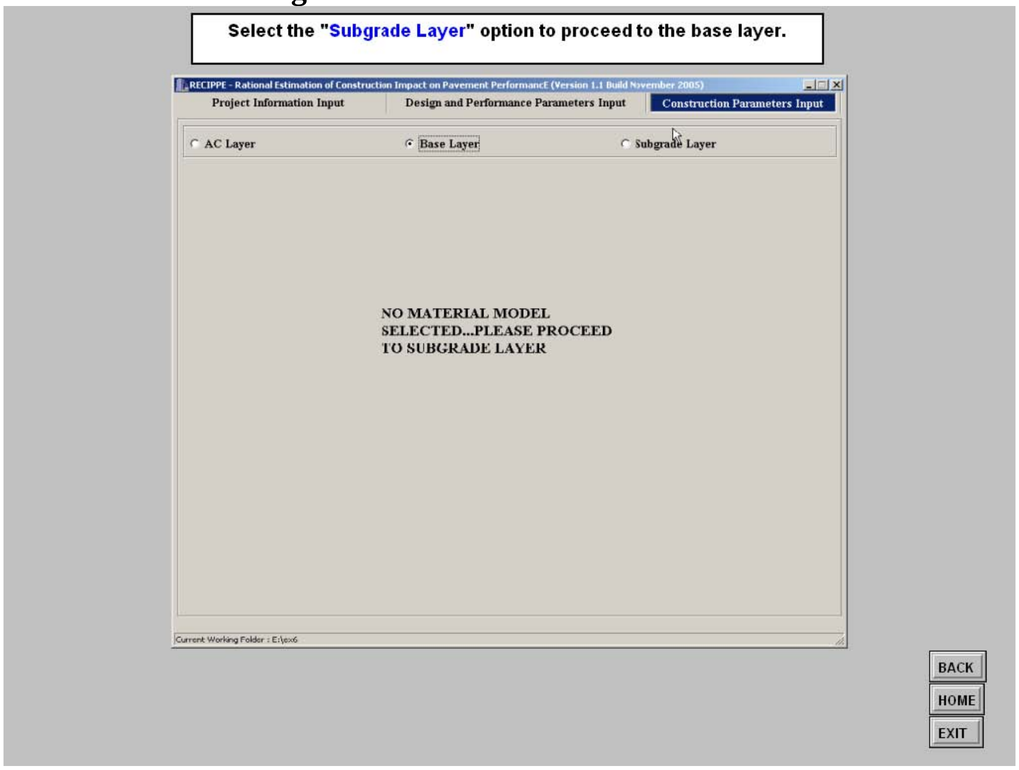


Figure A.130 - Slide 15 of Exercise 7

Figure A.131 - Slide 16 of Exercise 7

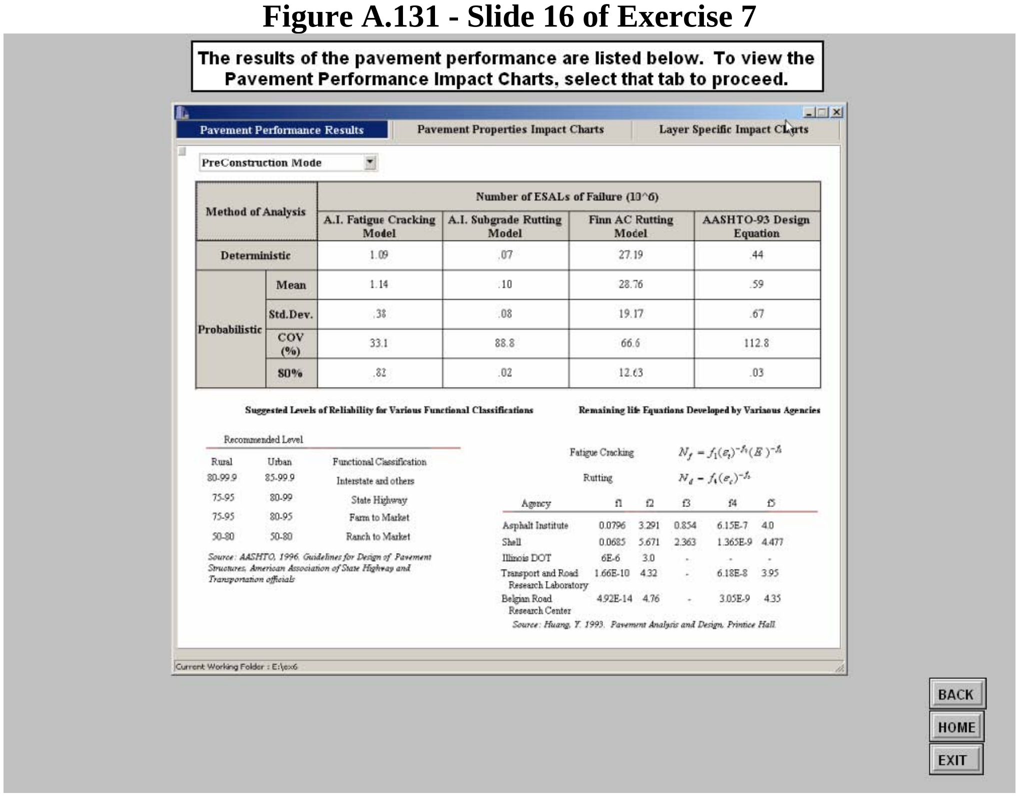


Figure A.132 - Slide 17 of Exercise 7

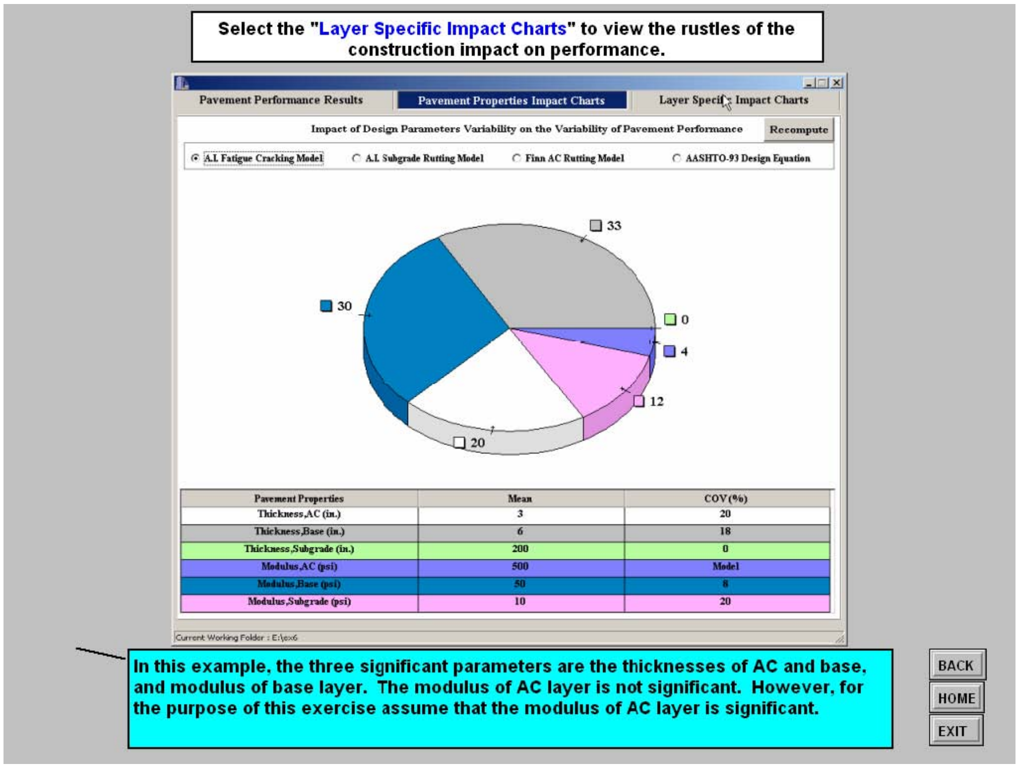


Figure A.133 - Slide 18 of Exercise 7

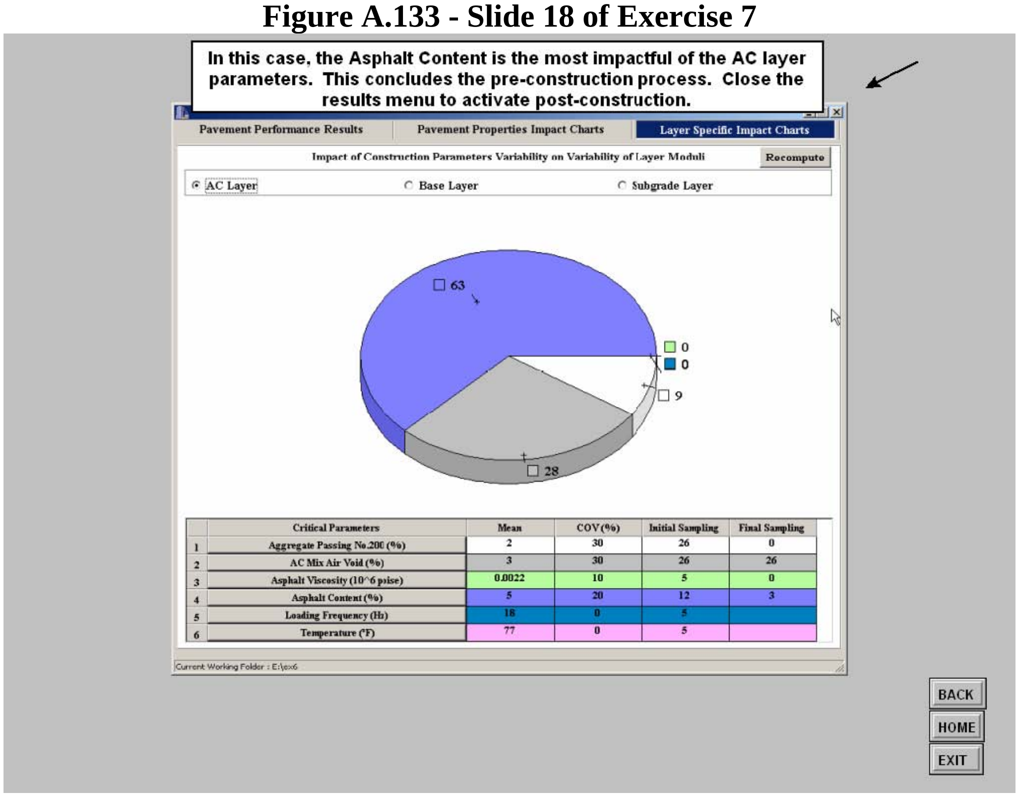


Figure A.134 - Slide 19 of Exercise 7

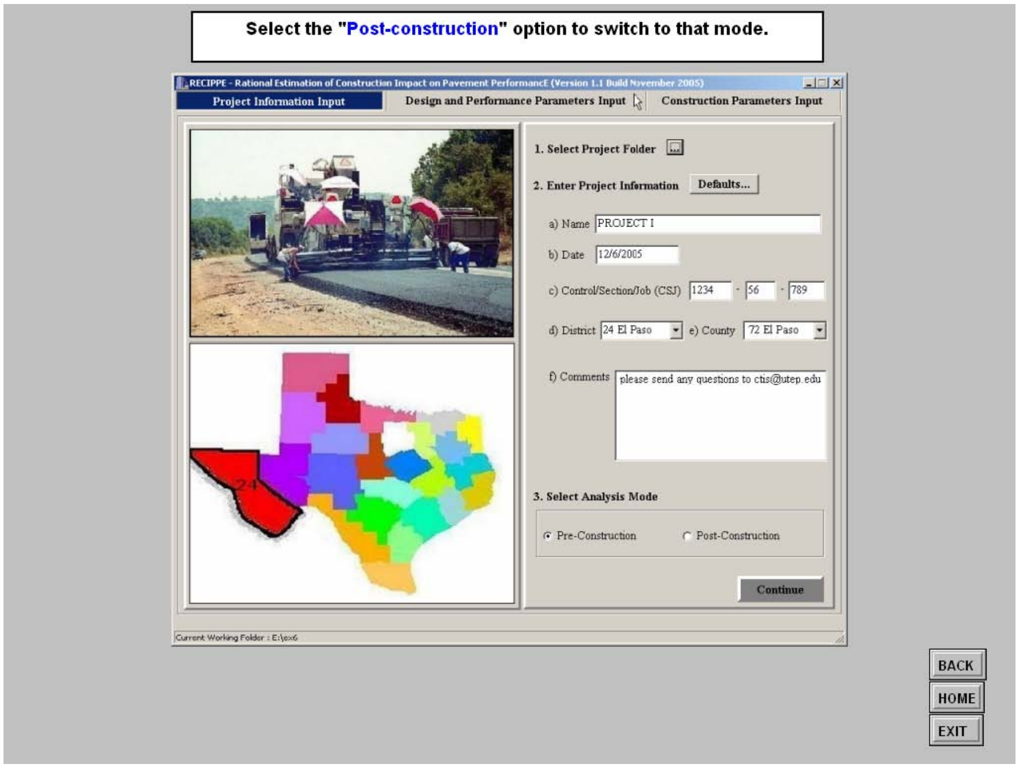


Figure A.135 - Slide 20 of Exercise 7

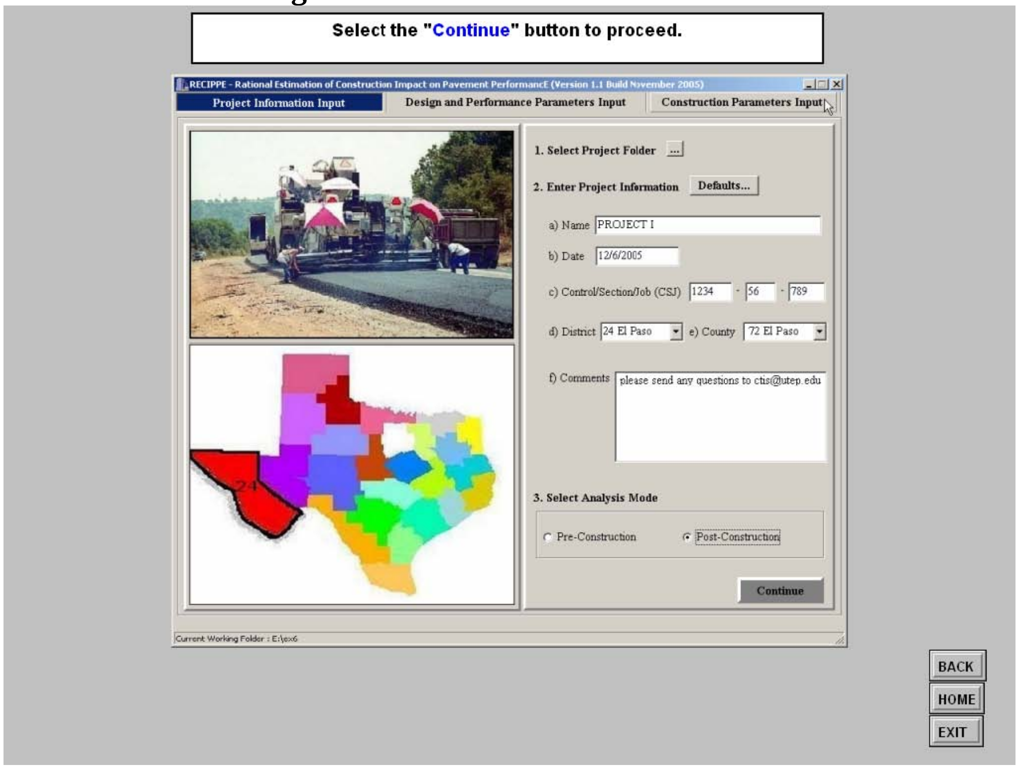


Figure A.136 - Slide 21 of Exercise 7

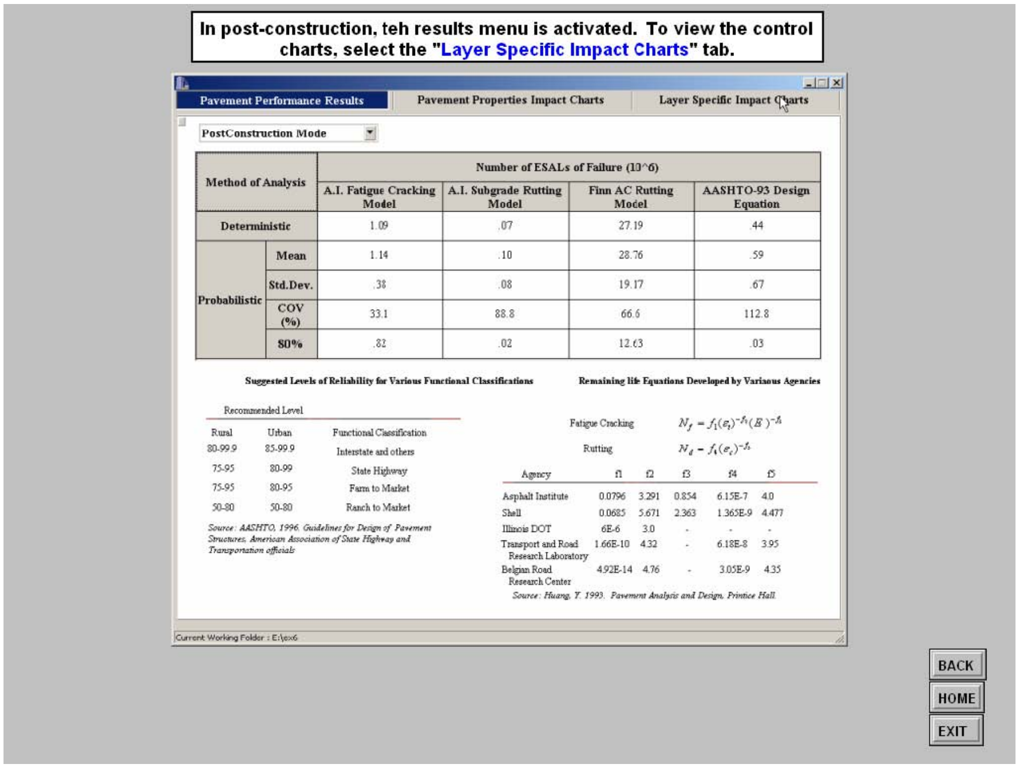


Figure A.137 - Slide 22 of Exercise 7

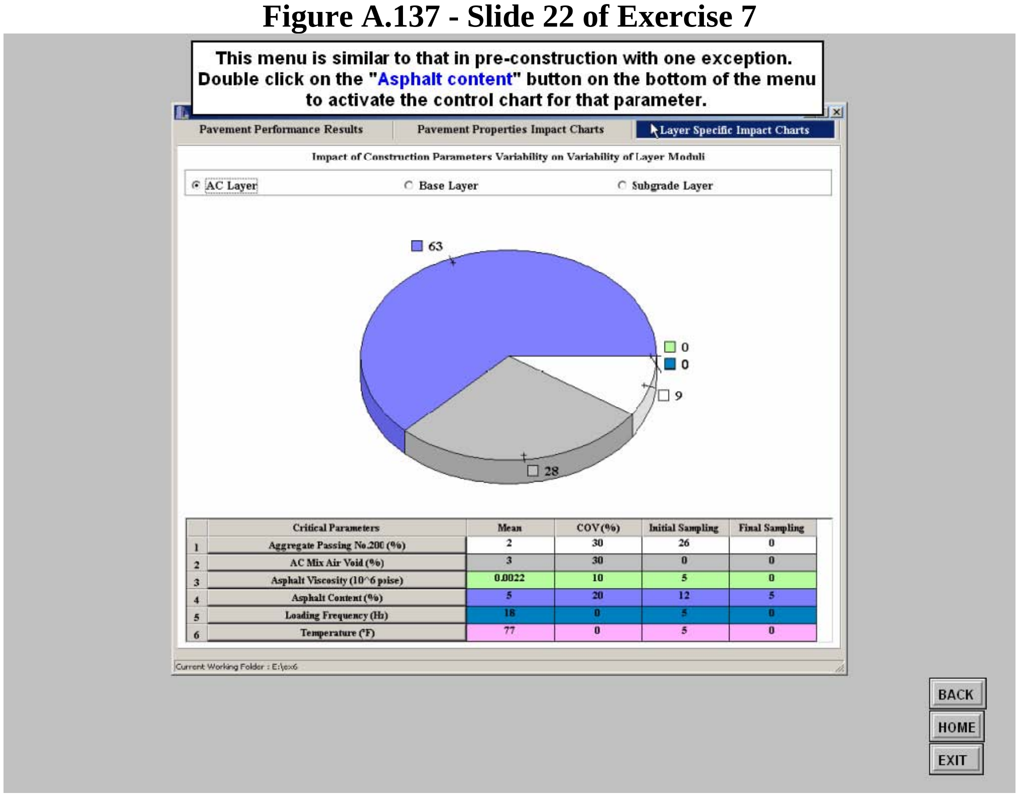


Figure A.138 - Slide 23 of Exercise 7

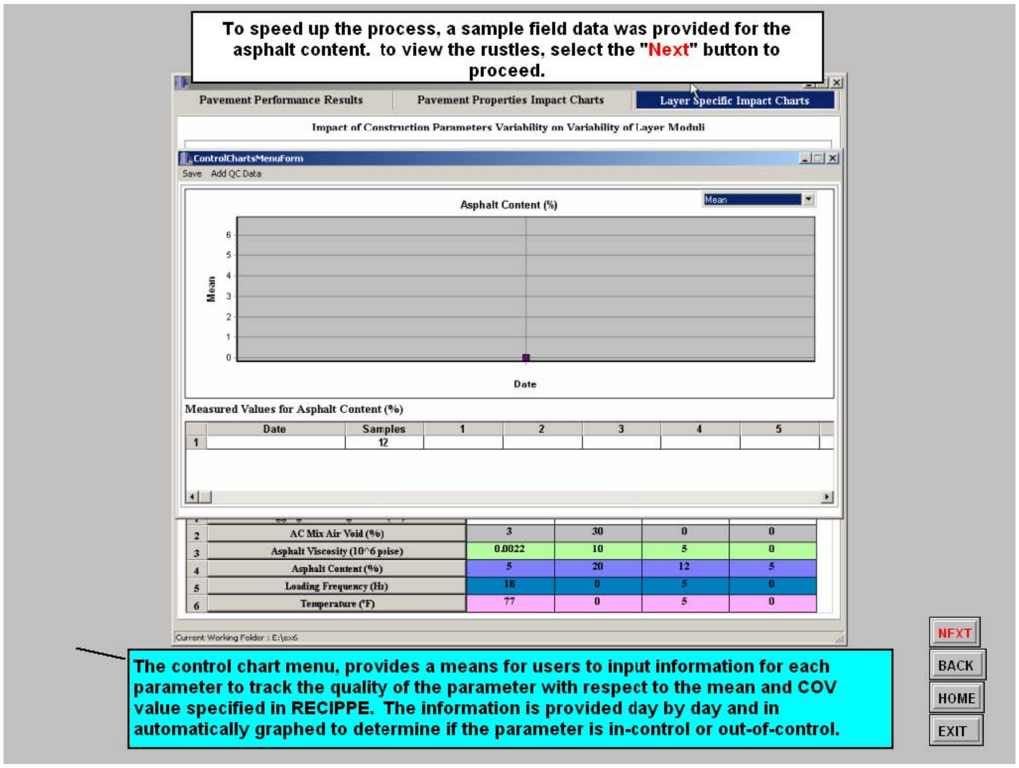


Figure A.139 - Slide 24 of Exercise 7

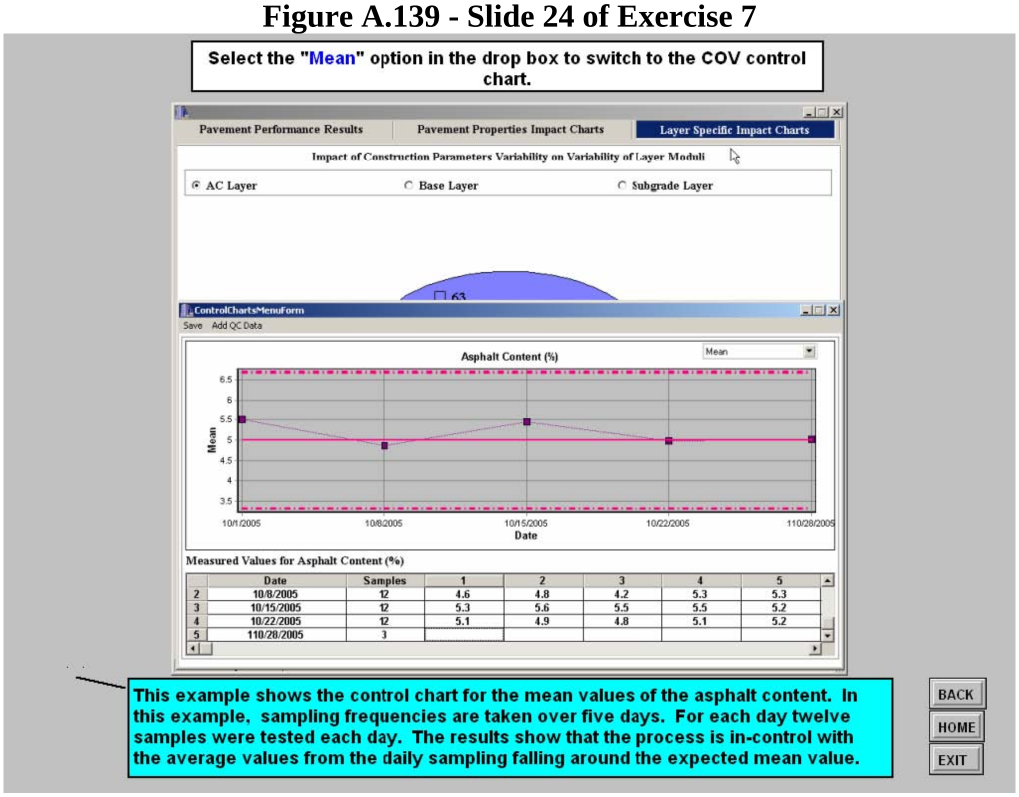


Figure A.140 - Slide 25 of Exercise 7

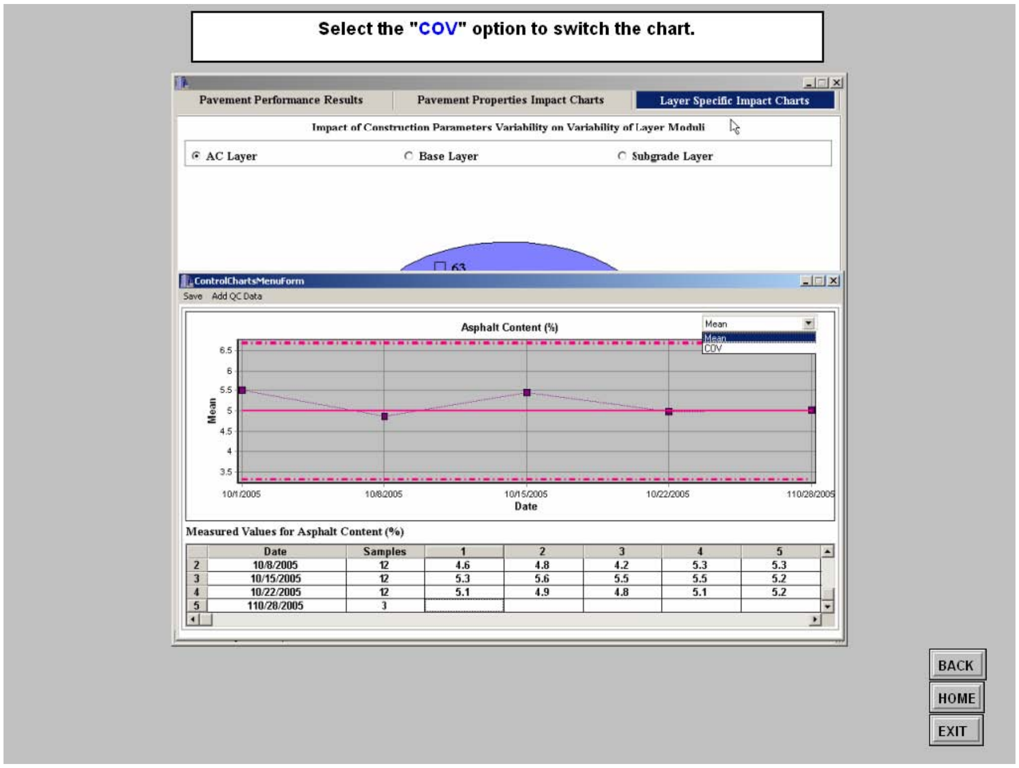


Figure A.141 - Slide 26 of Exercise 7

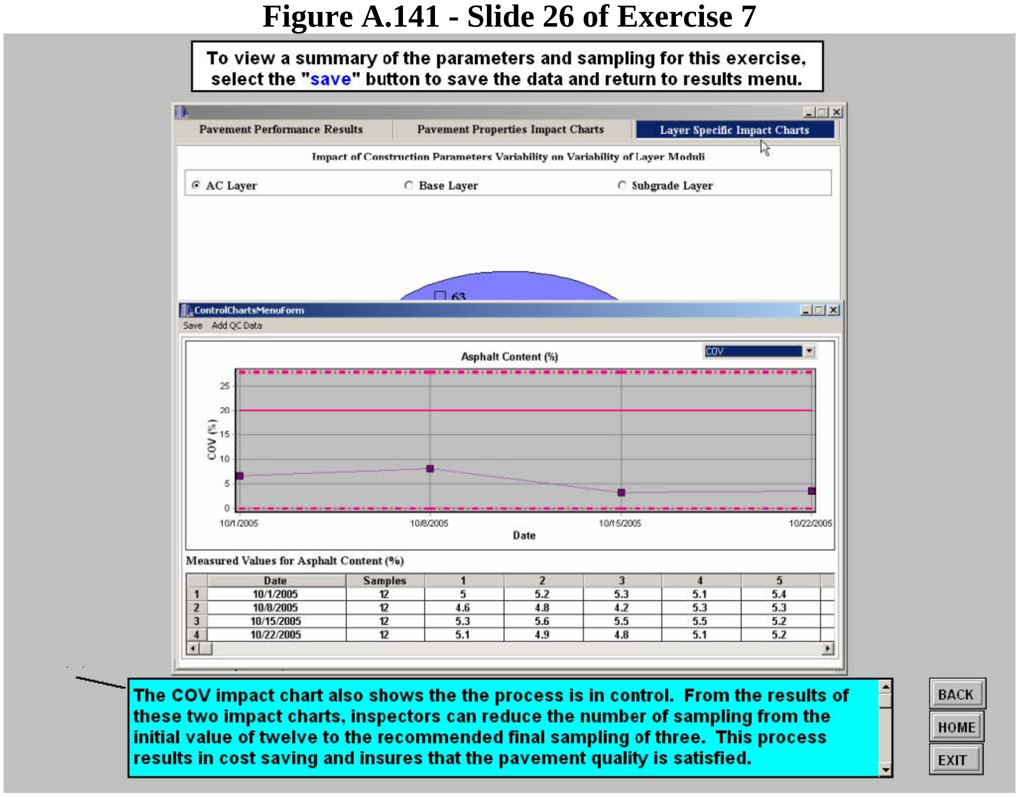


Figure A.142 - Slide 27 of Exercise 7

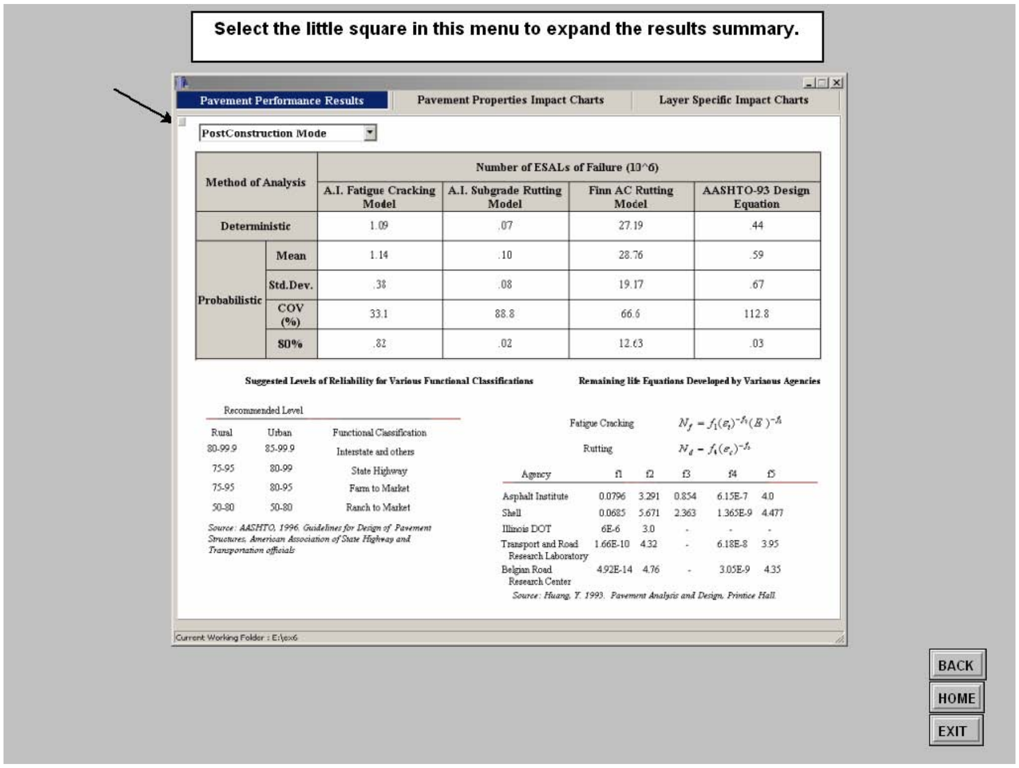


Figure A.143 - Slide 28 of Exercise 7

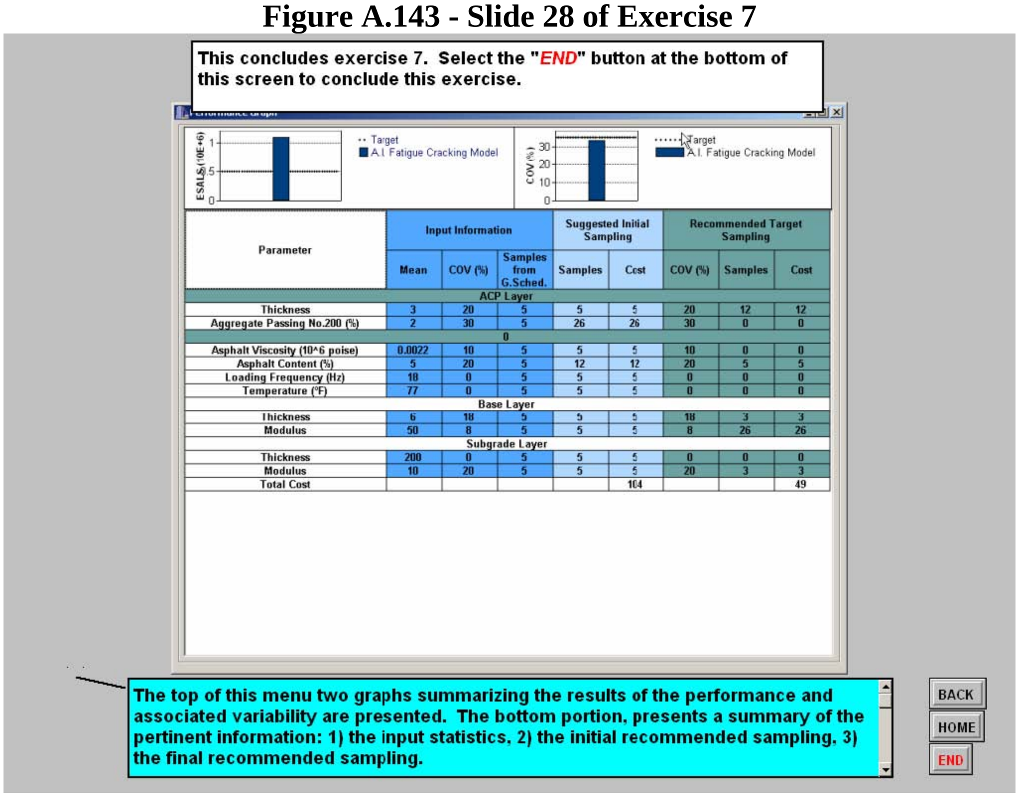


Figure A.144 - Slide 29 of Exercise 7