

**DEVELOPMENT OF A MODELING FRAMEWORK TO
PREDICT AND EVALUATE LOAD GENERATION PROFILES
USED AT FORWARD OPERATING BASES**

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The Academic Faculty

by

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**DEVELOPMENT OF A MODELING FRAMEWORK TO PREDICT
AND EVALUATE LOAD GENERATION PROFILES USED AT
FORWARD OPERATING BASES**

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LIST OF SYMBOLS AND ABBREVIATIONS

FOB	Forward Operating Base
ERPT	Energy Resource Planning Tool
OS	OpenStudio
AWS	Amazon Web Services
EEOMC	Energy Efficient Outpost Modeling Consortium
NREL	National Renewable Energy Laboratories
CERL	U.S. Army Construction Engineering Research Laboratory
CORSO	Center for Optimally Resource-Secure Outposts
ECU	Environmental Control Unit
HVAC	Heating, Ventilation and Air Conditioning
LHS	Latin Hypercube Sampling
OSM	OpenStudio Model
OSC	OpenStudio Component
IDF	EnergyPlus Model File
IDD	Input Data Dictionary
TPEX	Technology Performance Exchange
OAT	One-at-a-Time
EES	Elementary Effects
TEI	Total Electricity Intensity

SUMMARY

The military is facing a significant issue of increasing fuel cost to deploy troops overseas and establish and maintain Forward Operating Bases (FOBs) or outposts. Liquid fuel is one of the primary energy source for these FOBs, which is a non-renewable source, flammable, and needs large convoys with specialized equipment to transport, therefore being both unsafe and expensive for the operation of FOBs. To help reduce energy consumption, transportation, and cost an Energy Resource Planning Tool (ERPT) is needed. This ERPT will help the military in making crucial decisions about the optimal shelter and equipment configuration for their Forward Operating Bases (FOBs) prior to deployment. To make this tool effective, load profile data of shelters needs to be simulated and uploaded into a database, so that it can be easily available when outposts need to be configured and optimized with respect to energy consumption for a given set of constraints. This research has developed a programmatic modeling framework to generate load profiles for shelters of interest for outposts for different weather profiles, equipment, occupancy, and other relevant parameters of interest, and upload data points into a database. The modeling framework is developed using the programming language Ruby and simulation platforms OpenStudio and EnergyPlus. In order to make sure the ERPT estimates reasonably accurate load profiles for a shelter through regression techniques, a large set of data points, on the order of around 500,000 data points, needs to be uploaded into the database. The database is named DEnCity and is established using Amazon Web Services (AWS). This research developed programmatic workflow to perform Sensitivity analyses along with Sampling analyses to generate and upload the

data points needed into the DEnCity database. It analyzes different Sensitivity methods for creating and uploading data points. It compares these computational methods and discusses their pros and cons in context of the load generation profile for shelters used in FOBs. This thesis provides details of the creation of the programmatic workflows and uses generated data to evaluate the analysis methods finally selected to create and upload data points to the DEnCity database. This research will enable the simulation of large number of data points corresponding to different shelters of interest, making it a valuable tool for providing the necessary inputs for an energy efficient design of Forward Operating Bases.

CHAPTER 1. INTRODUCTION

The cost of sending a single military troop overseas has been increasing since 2014. Based on data collected by the Center for Strategic and Budgetary Assessments, the cost of sending a single service member steadily increased between 2008 to 2014 from about 1.25 million USD to about 2.1 million USD [1]. One cause for this increase is the lack of planning in allocating mission supplies in the most cost effective manner. Another cause for this increase is the current necessity of using liquid fuel. Liquid fuel can be very expensive to transport, usually needing large convoys to protect the liquid fuel asset and expensive materials to handle the flammable fuel. Due to the large costs incurred by the lack of planning and by using liquid fuel, the military is aiming to create an Energy Resource Planning Tool (ERPT). [1, 2]

This ERPT will take generated Forward Operating Base (FOB) energy consumption data as an input and use it to help the military plan their FOBs in advance, to help distribute resources cost effectively as well as to help transition from using liquid fuels to using renewable resources. The ERPT will be an application that helps make decisions about the optimal quantity, sizing, and type of equipment prior to deployment to other countries. This project is being pursued by the Energy Efficient Outpost Modeling Consortium (EEOMC), a collaborative effort funded by the U.S. Department of Defense and the Office of Naval Research (ONR). The consortium consists of entities such as the National Renewable Energy Laboratory (NREL), Communications-Electronics Research and Engineering Center (CERDEC), U.S. Army Construction Engineering Research Laboratory (CERL), Colorado School of Mines, Naval Surface

Warfare Center in Philadelphia (NSWC-PA), and other entities including Georgia Institute of Technology. The Georgia Institute of Technology team involved in this project, the Center for Optimally Resource-Secure Outposts (CORSO), is responsible for developing a modeling framework to predict load profiles of military shelters considering all necessary inputs such as shelter models, Environmental Control Units (ECUs), internal equipment loads, infiltration loads, location, and other parameters. The CORSO team is tasked to use the modeled inputs to generate shelter load profile data and upload the data into the DEnCity Database, a database designed to store a large number of building energy models and related data. NREL is tasked with taking this information and perform a regression analysis on the data to accurately extrapolate a larger set of data on a full spectrum of shelter energy models. This information will then be inputted into the ERPT, providing the ERPT with the necessary information it needs to accurately predict energy usage in military FOBs. This process can be visualized with the Project Flow Diagram displayed in Figure 1. The tasks for the CORSO team are in green while tasks not assigned to the CORSO team are shown in red.

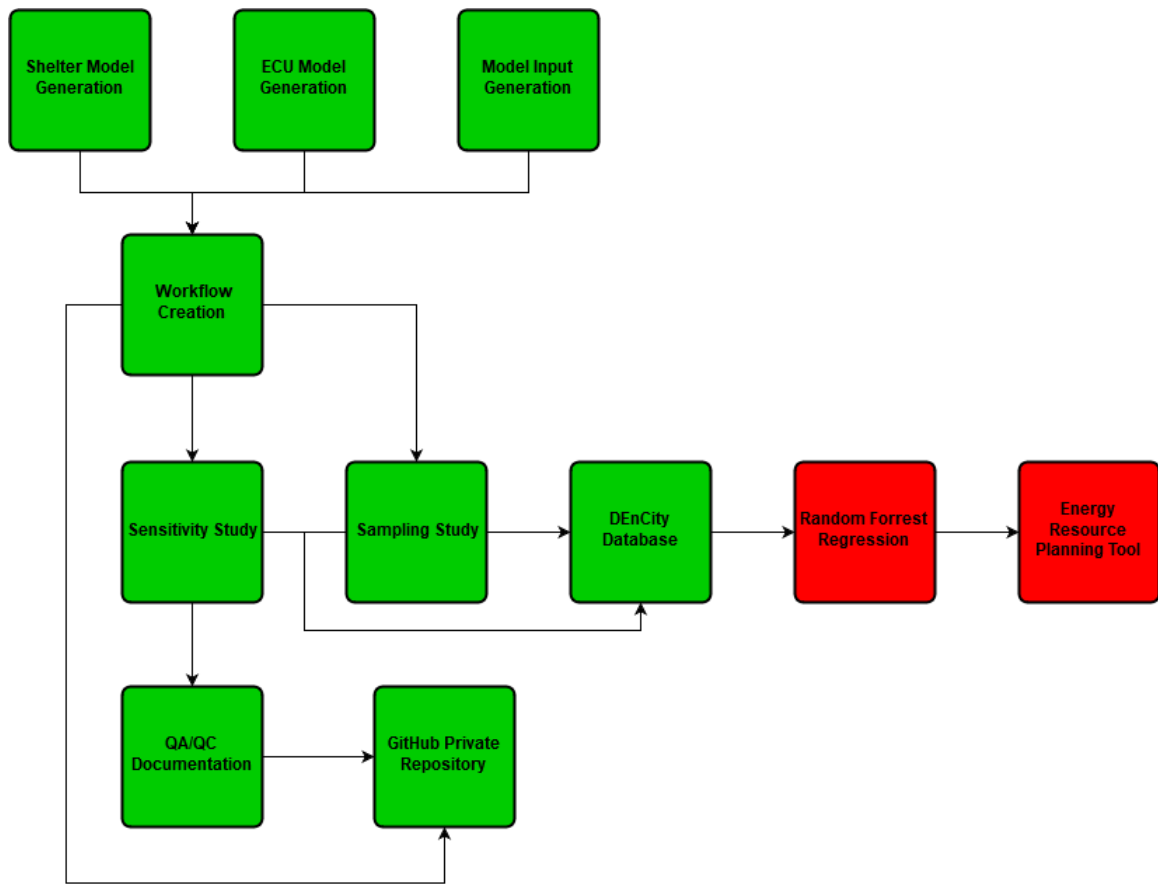


Figure 1 - CORSO Project Flow Diagram

Due to the wide variety of shelters, mission supplies, weather locations, and other factors to consider, it is important to create a programmatic modeling framework to efficiently generate a wide spectrum of shelter energy models to populate the DEnCity Database. This thesis further develops a load generation tool previously created by KamYu Lee, described in “Programmatic Modeling of Shelters Used In The Forward Operating Bases”, integrates the full set of modeling inputs into the tool, performs sensitivity studies to analyze the shelter modeling parameters, performs sampling studies to upload the necessary data into the DEnCity Database for the population of the ERPT,

performs additional sensitivity studies to evaluate the performance of the sensitivity study required by the EEOMC, and details an automated documentation generation process used for the project.

In Chapter 2, a literature review of the simulation tools, simulation inputs, and methods used for this thesis are described. The simulation tools include OpenStudio, EnergyPlus, Measures, and the DEnCity Database. The simulation inputs include shelter models, Environmental Control Units (ECUs), Internal Equipment Load Profiles, and Weather Location Profiles. The methods used in this study include the Morris Sensitivity Method, the Sobol Sensitivity Method, and the Latin Hypercube Sampling (LHS) Method.

In Chapter 3, the computational methodology used for modeling is presented. A detailed explanation of the workflow development is presented along with each of the method's workflows. The Morris Method is described in this section along with the Morris Method workflow. The Sobol Method along with its workflow is presented in this section. The Latin Hypercube Sampling Method as well as the LHS workflow is also detailed in this chapter.

Chapter 4 details the results of the full sensitivity study. This chapter starts with an overview of the sensitivity study. Then the chapter details the Morris Method Sensitivity Study results for each shelter used in this thesis and presents the overall conclusions for the Morris Method Study. Then the chapter details the results of the Sobol Method Sensitivity Comparative Study performed to determine which method is more cost effective for shelter sensitivity studies. These sensitivity studies are important to perform

to better understand the parameters involved in shelter modeling, and specifically to understand the effect of model inputs this project has considered, along with informing which parameters and which models to include in a full sampling study.

Chapter 5 presents a detailed overview of the full sampling study performed for this thesis. Then the chapter details the sampling study results and conclusions derived from the study. This study, as shown in Figure 1, serves to populate the DEnCity Database and serve as the inputs to the ERPT. Then the chapter details the automated documentation process that was created for Quality Assurance/Quality Control Documentation for the sensitivity study.

Chapter 6 presents conclusions derived from this thesis as well as suggests future work that can be done for this effort.

CHAPTER 2. LITERATURE REVIEW

This chapter presents a detailed literature review of the simulation tools used in the Shelter Energy Modeling process: EnergyPlus, OpenStudio, and Measures, along with the sensitivity analysis and sampling analysis methods used. The chapter is divided into two sections: the building energy modeling tools followed by the sensitivity and sampling analysis methods.

2.1 Shelter Energy Modeling Tools

Shelter energy modeling requires sophisticated tools in order to accurately model building loads, electric loads, heat and energy flows that occur in buildings. The Shelter Energy Modeling Tools section of the Literature Review is divided into sections describing the OpenStudio tool, EnergyPlus tool, and Measures.

2.1.1 *OpenStudio*

OpenStudio (OS) is an open source platform developed by National Renewable Energy Laboratory (NREL), Argonne National Laboratory (ANL), Lawrence Berkeley National Laboratory (LBNL), Oak Ridge National Laboratory (ORNL), and Pacific Northwest Laboratory (PNNL). OS is an integrated analysis tool, combining EnergyPlus and Radiance, designed to support the U.S. Department of Energy's (U.S. DoE) efforts for whole building energy modeling. OS is written in C++ and can be used across multiple platforms such as Windows, Mac, and Linux.

OpenStudio aids in the whole building energy modeling process from creating building geometries to results analysis. Through the OS SketchUp Plug-in, a user can create and load a building geometry into OS. Then the user can add to the model weather profiles, internal loads (people, lighting, electric, etc.), operation schedules,

Environmental Control Units (ECUs), and other factors involved in building energy modeling. The user adds these factors to the model by adding in separate objects for each of these factors. An OS Model can be broken down into Model Objects which interact together in order to help translate the OS Model into multiple EnergyPlus Input Data Dictionary (IDD) objects to be compiled into an EnergyPlus IDF file to run through EnergyPlus. After the OS Model is made, the model is translated into EnergyPlus and then the simulation is run and the results can be viewed through the OS program, the OS Results Viewer application, the OS report, or the EnergyPlus Report. [3, 4, 5]

2.1.2 EnergyPlus

EnergyPlus is an energy analysis and thermal load modeling program developed through the U.S. government's efforts for whole-building energy simulation. EnergyPlus was created by combining BLAST, Building Loads Analysis and System Thermodynamics, and DOE-2 through joint efforts by the U.S. DoE, the U.S. Army Construction Engineering Research Laboratory (CERL), the University of Illinois, LBNL, Oklahoma State University, and Gaud Analytics. EnergyPlus was originally released in 2001 and then switched from being written in Fortran to C++ in 2014.

EnergyPlus aids in whole-building energy modeling by being able to calculate energy consumption and water use in buildings. EnergyPlus can perform integrated simultaneous solutions of thermal zone conditions and HVAC system responsiveness, heat balanced solutions from radiation and convection effects, as well as heat and mass transfer between different building zones. EnergyPlus uses advanced fenestration models, glare calculations, component-based systems, and HVAC and lighting control strategies to create advanced building energy solutions. EnergyPlus also uses user defined time steps for calculations and for reporting. Users can also generate detailed output reports for averaged calculations as well as time step calculations. [6, 7, 8]

2.1.3 Measures

A measure is a set of flexible programmatic instructions that can be used to make changes in any building energy model. Effortless parametric, sensitivity, and uncertainty analyses studies can be performed as a result of the measure's flexibility, as the input values of the simulation model can be easily modified through the measures. Measures not only allow for effortless studies, but measures also reduce the modeling time and cost, increase the quality and consistency, as well as allow for automated reporting and documenting across the many simulations done in these studies. There are three types of measures, all written in Ruby 2.0, which are used for the generation of load profiles for the ERPT: OpenStudio, EnergyPlus, and Reporting measures. These measures facilitate the building energy modeling process from creating objects and models in OpenStudio to translating the model into EnergyPlus to running simulations and creating the simulation output reports. There are multiple sources to obtain measures for building energy modeling. The Building Components Library (<http://bcl.nrel.gov>), created by NREL, is a public repository containing more than 200 measures and more than 45,000 components. NREL has also published multiple resources to assist in writing measures so individuals can create their own measures. The measures used for load profile generation for the ERPT are located in the Shelter_Corso GitHub Repository (https://github.com/satishkumar33/Shelter_Corso/tree/master/shelter_modeling/measures). [7, 9]

An OpenStudio measure interfaces with OpenStudio Models through the OpenStudio program. A measure uses an OpenStudio Model as an input and outputs a modified OpenStudio Model. Since the OpenStudio program works based on objects, the modifications OpenStudio measures make are object oriented, such as adding, altering, replacing, or removing objects in an OpenStudio Model. OpenStudio measures can add in people objects into a shelter, alter operating schedules, replace one ECU with another,

remove material or construction objects, etc. These measures also have user specified arguments, allowing a user to control which objects are modified and what the objects are modified to. [7, 9]

EnergyPlus measures, like OpenStudio measures, modify building energy models, but instead of working with object oriented code to interface with the OpenStudio program, EnergyPlus measures deal with adding, altering, replacing, or removing ASCII text blocks. Since EnergyPlus measures are entirely text or string based, they do not necessarily work for all buildings or shelters. Therefore, each EnergyPlus measure has to be specifically made for the input of a specific building energy model; for the ERPT, there are EnergyPlus measures specific for each shelter. Due to the inflexibility, the use of EnergyPlus measures have been confined to building energy objects that cannot be changed by OpenStudio, such as Surface Boundary Conditions and EnergyPlus' Energy Management System. [7, 9]

The EnergyPlus measures used for each shelter can be found listed in the shelter's EnergyPlus measures sheet in the Excel Matrix. The sheets in between and including 'milvanepius' and 'mgptsleplus' list the EnergyPlus measures and their arguments for each shelter currently considered in the ERPT. The EnergyPlus measures can also be found within the measures folder in the GitHub repository. [7, 9]

https://github.com/satishkumar33/Shelter_Corso/blob/master/shelter_modeling/projects/matrix.xlsx

https://github.com/satishkumar33/Shelter_Corso/tree/master/shelter_modeling/measures

Reporting measures take in EnergyPlus and OpenStudio simulation results and allow users to customize those reports or create new custom reports, figures, tables, etc. These measures, like OpenStudio measures, not only are similar in format, but are also flexible and can work with most building energy models. Unlike OpenStudio and EnergyPlus measures, Reporting measures do not usually need, or at least can use the default, user specified arguments. The Reporting measures can be found in the measures folder in the GitHub repository. [7, 9]

2.1.4 DEnCity Database

DEnCity, the Department of Energy's Energy City, is an open, database where the public can store and share building energy simulation inputs and results. NREL created DEnCity for building energy modelers can compare their data to other modelers' data to help reduce cost and increase data resolution of analyses and simulations. The database can store input model files, simulation attributes, and hourly simulation data, allowing users to quickly find the data they need. [10]

DEnCity is implemented through mongoDB, an open source database for document storage, and the Department of Energy's Building Performance Database (DBPD), a database for building consumption data and building characteristic information. The DEnCity Database also provides a convenient API, application program interface, to let users to easily search through the uploaded data and building information. The DEnCity Database is implemented using an Amazon Web Services server instance. Amazon Web Services (AWS) allows users to establish virtual servers in the cloud through the use of EC2 instances. The service allows users to establish servers and workers on demand with control over the amount of vCPUs (virtual CPUs), memory,

and storage. Users have complete control over these instances, with Amazon's security level. [10]

2.2 Simulation Inputs

For military shelter energy modeling, and building energy modeling in general, the simulations need verified and validated inputs. For shelter energy modeling, these inputs include validated shelter models, Environmental Control Units (ECUs), internal equipment load profiles, environmental conditions, and other inputs. This section details the major inputs that have been verified and validated for the shelter energy modeling performed in this thesis.

2.2.1 Shelters

Military forward operating bases contain multiple shelters that can be used for a wide variety of purposes. The use of the shelters, the dimensions of shelters, and the materials used in these shelters can affect their energy usage characteristics. In general shelters used in forward operating bases can be classified in two general categories based on their materials; hard shelters and soft shelters. There are 12 shelters used in this study. The 12 shelters are listed below in Table 1. Also listed in the table are the shelter dimensions, the floorplan area, and whether the shelter is a soft shelter or hard shelter. [11, 12, 13, 14, 15, 16, 17, 18, 19, 20]

Table 1 - List of Military Shelters Integrated

Shelter Name	Shelter Manufacturer	Shelter Dimensions (LxWxH)	Shelter Floor Area (ft²)	Hard or Soft
Airbeam	HDT	20' x 32' x 11'6"	640.0	Soft
B-Hut	-	36' x 18' x 8'	648.0	Hard
MILVAN	-	20' x 8' x 8'	160.0	Hard
ArctiX	HDT	19' x 19' x 7'10"	310.0	Soft
TM60	Utilis	34' x 19' x 9'	646.0	Soft
Base X203	HDT	14' x 15' x 9'5"	210	Soft
Base X305	HDT	18' x 25' x 10'6"	450.0	Soft
Base X307	HDT	18' x 35' x 10'6"	630.0	Soft
Base X6D31	HDT	27' x 31' x 14'7"	615.0	Soft
Base X8D36	HDT	31' x 37' x 14'7"	935.0	Soft
MGPTS-M	Eureka	18' x 36' x 11'5"	648.0	Soft
MGPTS-L	Eureka	18' x 54' x 11'5"	972.0	Soft

The shelter models were created and validated through collaboration between NREL and the Georgia Institute of Technology's CORSO initiative. NREL sent CORSO validated shelter EnergyPlus models, CORSO converted the shelter models into OpenStudio models (OSMs), and then NREL validated the OSM shelter models. These shelter models were then integrated into the workflows through the process explained in Section 3.1.1.

2.2.2 Environmental Control Units (ECUs)

A wide variety of Environmental Control Units (ECUs), also known as HVAC Systems, are used in military shelters. For this study, six ECUs are used. Five of the ECUs are military grade ECUs while one unit, the Carrier brand unit, is a commercial grade unit. The military grade units are HDT Global and Mainstream units. The six units are listed in Table 2. The table also lists relevant parameters that were used to create the OpenStudio Model files for each ECU. The main parameters used for ECU performance are Cooling Capacity, Heating Capacity, Evaporator Air Flow, Condenser Air Flow, and the Operating Temperatures. Table 2 lists each ECU used in the study along with the main parameters listed in the previous sentence. For the study, doubled versions of the units were also used to obtain higher tonnage units. The doubled versions of the units are designated with a "-D" at the end of the name. The doubled versions are also included in Table 2. [21, 22, 23, 24]

Table 2 - List of Environmental Control Units Integrated

ECU Name	Cooling Capacity (Btu/Hr)	Heating Capacity (Btu/Hr)	Evaporator Air Flow (SCFM)	Condenser Air Flow (SCFM)	Operating Temperatures (°F)
Carrier	12k	12k	425	1,000	Cooling: 55 – 125 Heating: 5 – 75
Carrier-D	24k	24k	850	2,000	Cooling: 55 – 125 Heating: 5 – 75
HDT EEECU36K	38k	31k			Cooling: 20 – 125
HDT EEECU36K-D	76k	62k			Cooling: 20 – 125
HDT F100	58k	34.14k	1,900	6,000	Cooling: 40 – 130 Heating: -50 - 80
HDT F100-D	116k	68.28	3,800	12,000	Cooling: 40 – 130 Heating: -50 – 80
HDT USMC60K	62k	37k	1,900	6,000	Cooling: 20 – 125
HDT USMC60K-D	124k	74k	3,800	12,000	Cooling: 20 – 125
Mainstream E2CU	60k	72k	2,000/1,100	4,800	Cooling: 50 – 125 Heating: -25 – 80
Mainstream E2CU-D	120k	144k	4,000/2,200	9,600	Cooling: 50 – 125 Heating: -25 – 80
DRS IECU	62k	30k	1,700	-	Cooling: 40 – 125 Heating: -50 - 70
DRS IECU-D	124k	60k	3,400	-	Cooling: 40 – 125 Heating: -50 - 70

The ECU models were created and validated through collaboration between NREL and the CORSO initiative. CORSO contacted the manufacturers for ECU data sheets and took the information and put the information into NREL's Technology Performance Exchange (TPEX) [25]. The information is input into TPEX through a series of performance maps, specifically the Rooftop Unit Cooling Performance Map, the Rooftop Unit Heat Pump Performance Map, and the Rooftop Unit Gas or Electric Heating Performance Map. For some ECUs, there was not enough information to fill out the performance maps, making it necessary for the CORSO initiative to model the performance of some ECUs using CoilDesigner and VapCyc. Once the TPEX performance forms are filled out, then the TPEX forms are submitted to TPEX, and TPEX returns an OpenStudio Model (OSM) modeling the ECU in OS and EnergyPlus. Once the unit is converted into the OSM, then the model is integrated into the workflows. This process is detailed in Section 3.1.2.

2.2.3 Internal Loads

Forward Operating Base shelters are used for various reasons such as Billeting, Maintenance, Mission Support, and Medical Support. Each of these facility types has its own equipment associated with the purpose. These pieces of equipment have their own electrical power consumption requirements which affect the energy flow throughout the shelter. There are 42 facility equipment load profiles, provided by CERL, that are modeled through OS Component files (.osc files). These OSC files are modeled with a Peak Power Design Level that is fractionally varied over time based on the information in

the OSC files. The 42 facility equipment loads are listed in Table 3 along with their corresponding Peak Power Design Levels in kilowatts. These values range from 0 kW to around 20.2 kW. Due to this range in variability, lighting loads which are around 0.4 kW are considered negligible and were not modeled in this study.

Table 3 - List of Internal Loads Integrated

Facility Load	Design Level (kW)	Facility Load	Design Level (kW)	Facility Load	Design Level (kW)
AAFES	0.144	Laundry Milvan	0.000	Shower Changing Tent A	1.009
Aid Station	0.204	LCMR	5.361	Shower Gray Water Blivet A	0.216
Battalion TAC	11.487	M7 Repair System	0.300	Shower Supply Blivet A	0.000
Billeting Tent A	0.211	Maintenance MILVAN	0.000	STT	0.000
Dining Tent	0.408	Maintenance Tent	0.144	Supply Office	5.800
ECP A	0.408	MTRCS Freezer	0.288	Supply Tent	0.144
ET Kitchen	1.000	MTRCS Fuel Supply	0.000	Support Vehicle Fuel Supply	0.200
Fires CP	20.175	MTRCS Mixed	0.000	Support Vehicles	0.000
Fuel Powered Light Set	5.153	MTRCS Refer	0.000	Transient	0.000
Genset 1	0.000	MWR	0.000	TriCold	0.408
Gray Water Recycling	0.000	Perimeter Light Set	0.408	Utility Fuel	2.000
Latrine A	2.400	RAID	0.000	Utility Water	0.000
Latrine Black Water Blivet A	0.862	Rifles CP	0.000	VIP	0.000
Latrine Supply Blivet A	0.000	Shower A	10.700	Wash Rack Assembly	0.000

2.2.4 Weather Files

Building energy simulations are run under a certain set of shelter, ECU, internal loads, and weather file location combination. For this study, three locations are used: Kharga, Egypt, Chongjin, DPRK, and Singapore. These locations represent three different types of climates. They are respectively Hot Dry, Cold, and Hot Humid. This distribution of weather climates allows for a good distribution of weather climates, allowing the regression that NREL will perform with the simulation data uploaded into the DEnCity Database. The monthly weather profiles for the three locations are shown in Figure 2. Figure 2 plots the monthly Average Dry Bulb Temperature of each location for a full year. [26]

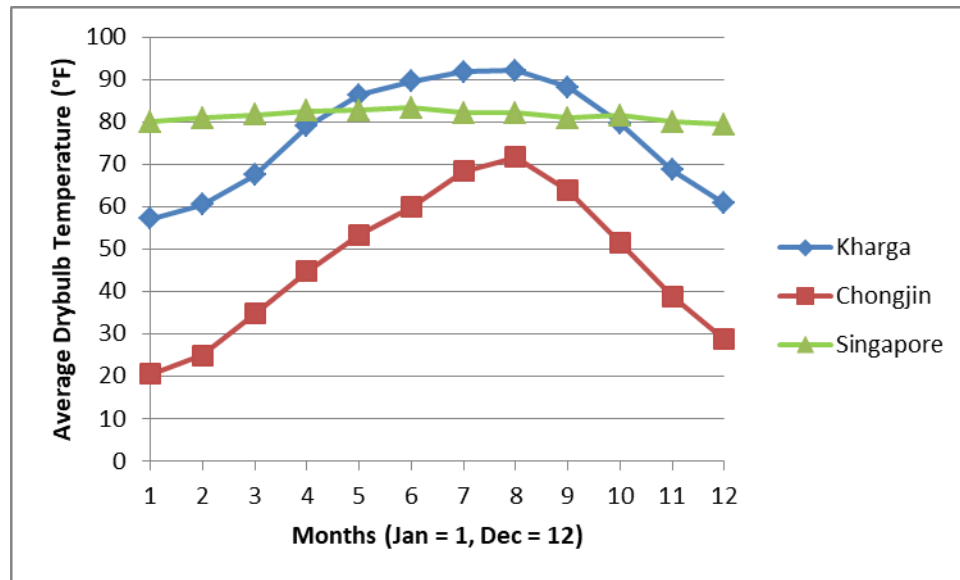


Figure 2 - EnergyPlus Weather Profiles

2.3 Analysis Methods

Sampling and sensitivity analyses are important in modeling processes in order to help make engineering decisions while consider the influence of parameters in a model [27]. There are primarily two different types of sensitivity analyses, local and global. Local sensitivity methods focus on calculating partial derivatives to measure the impact of a single parameter to its output. On the other hand, global methods are used to evaluate multiple parameters to consider the overall impact of each factor on its output. Sampling studies are used to generate a subset of data in order to estimate or interpolate and extrapolate the characteristics of a whole population. With sampling studies and regression to extrapolate the population's characteristics, a small amount of data can be used to represent a large amount of data at a relatively low computing cost. This thesis uses two sensitivity methods, the Morris Method and the Sobol Method, along with one sampling method, the Latin Hypercube Sampling Method. [27, 28]

The Morris Method is a global sensitivity analysis method that is derived from One-factor-at-a-time (OAT) technique, which varies one factor of a model at a time to calculate the variance in the outputs of the model. To better model factors with high uncertainty, Max D. Morris created the Morris Method in 1991. The method characterizes the sensitivity of different factors in a model with Elementary Effects (EEs). The EEs are approximations of the first order partial derivatives of the model. The Morris Method randomly selects initial sample points and compares those points with changes of a p-value regular grid. The averages and standard derivations of EEs indicate the effect that the specific parameter has on the output of the model and the effect that the parameter has on other parameters respectively. The Morris Method has been used in

many fields for large data analysis. [28] For instance, the Morris Method has been used in building energy simulations by Corrado and Mechri. Sensitivity analyses were performed to analyze HVAC loads in a house. The analysis showed the most influential parameters on the HVAC loads were the indoor air temperature, the air flow rate, the number of people, the people activity level, and the equipment loads. [28]

The Sobol Method, also referred to as Sobol Indices or the variance-based sensitivity indices, is another global sensitivity analysis method. The method was developed by Ilya M. Sobol in 1967 during his development of Sobol Sequences. This method does not make any assumptions between the input and output of the model and it evaluates the effects of the full range of each input as well as the interactions between inputs through Sobol Indices. First order Sobol Indices represent the effect that an input has on the output while Second order Sobol Indices represent the effect that an input has on another input. [29] This method does provide more accurate information, but at a higher computational cost compared to the Morris Method. For example, for a 12 parameter analysis, the Morris Method would only require 130 data points, the Sobol Method could require as much as 14,000 data points. The Sobol Method also has the possibility of never converging. [7, 29]

The Latin Hypercube Sampling (LHS) method is a sampling method that is used to generate a near random sample of parameters in a multidimensional distribution. The LHS method was developed by M.D. McKay in 1979 and by Eglajs in 1977. Ronald L. Inman expanded upon the method in 1981. LHS was developed to generate distributions of collections of parameter values for multidimensional distributions. This method creates a gridded sample space and then samples the grid so that there is only one sample

in each grid space. This, while not a truly random sampling, ensures a sampling that uniformly covers a desired sample space. This method generates more efficient sampling than other sampling methods such as Monte Carlo Sampling. [30]

CHAPTER 3. COMPUTATIONAL METHODOLOGY

This chapter presents the computational methodology used for the sensitivity and sampling analyses. This chapter describes the Sensitivity Methods in detail, the Sensitivity Workflows, the Sampling Method, and Sampling Method Workflow.

3.1 Workflow Development

One of the project's objectives is to generate a database of shelter energy models for multiple shelter types while considering variations of different parameters. In total there are nine different parameters considered in this study: Internal Loads, Environmental Control Units, Number of People in the shelter, Changes in Cooling and Heating Thermostat Setpoints, Door Openings per Person, Pressure Difference across the Door, Shelter Rotation, and People Activity Level. Due to the large number of parameters that need to be varied, the large variations in the parameters, along with the large number of shelters, using OS and EnergyPlus by themselves would be very ineffective at generating the database. Due to the ineffectiveness, it is necessary to develop a workflow based on OS and EnergyPlus measures and an Excel Matrix to have a user generate the amount of data needed to full populate the DEnCity Database. [7]

The workflow developed has at least one measure per parameter, in a sequential order, in order to have the workflow vary each parameter effectively. Due to the many shelters with different geometries, the workflow initializes an empty OpenStudio seed model and has the specific shelter's geometry desired for the facility. These geometries have a default construction modeled in the OpenStudio Model (OSM). The next step is to input the internal load, occupancy schedule, people loads, and schedules. These

components are generated from other measures that input the load profiles and schedules from OpenStudio Component files (.osc files). Then the workflow inputs the Environmental Control Unit (ECU), the location, and infiltration information into the model. Then the EnergyPlus measures are run through in the workflows, for all of the inputs that are not supported by OS. EnergyPlus measures are applied after applying all OpenStudio measures, once the model is converted from an OSM to an EnergyPlus model.

Infiltration and ground temperature objects are some of the parameters that can only be modeled through EnergyPlus. Also, due to the uniqueness of each shelter, there has to be individual EnergyPlus measures for each shelter. In order to effectively accomplish this, an Excel Matrix has to be included into the workflow as a user input.

The Excel Matrix also allows users to run the workflow using a simple interface. This process requires a Ruby script to read the Matrix and translate the values into measure inputs. After the model has been created and run, reporting measures compile the necessary data and push the completed simulation data points into the DEnCity Database created by NREL. The workflows for each simulation are diagrammed in the following sections.

3.2 Sensitivity Study Methodologies

The objective of the Sensitivity Study is to determine which variables are the most sensitive in order to determine what variables should be included as variables in the Sampling Study to upload into the DEnCity Database. The Sensitivity Study covers all 12

shelters listed in Table 2, ran across all of three weather locations listed in Section 2.2.4, utilizing all 12 ECU models listed in Table 3.

Two different Sensitivity Studies have been performed. The first study uses the Morris Method. This method is commonly used for sensitivity analyses that are performed on large sets of data and calculates information on how inputs affect the output and how different inputs interact together. The second study uses the Sobol Method. The Sobol Method, like the Morris Method, is another global sensitivity method that can also calculate both the inputs' effects on the output and the interactions between inputs. The Sobol Method though is a Variance-based decomposition method, a type of method that can be used for non-monotonic and non-linear models. While both can calculate the sensitivities of inputs, the Sobol Method in general is more accurate than the Morris Method, but is susceptible to high computational costs. For this thesis, the Morris Method is used to calculate the sensitivities used to inform the Sampling Study, while the Sobol Method is used to determine which of the two methods is the better method for sensitivity studies on military shelters. [29]

3.2.1 Morris Method

The Morris Method focuses on calculating the elementary effects (EEs), the impact of a standardized perturbation, for each factor in a model. In this study, the shelter's Total Electricity Intensity/Consumption (TEI) was the output of interest in the building model. The TEI can be represented by a function $y(x)$ where x is a vector of input variables and factors (i). The EEs for a single input can be characterized through the following equation, Equation 1. [7, 28]

$$EE_i = \frac{y(x \pm \Delta_i) - y(x)}{\Delta_i} \quad (1)$$

The EEs calculated are comparable to the first order partial derivatives of each variable. After calculating the EEs of each of the inputs, the mean (μ), absolute mean (μ^*), and the standard deviation (σ) of each of the inputs EEs is calculated as shown in Equations 2, 3, and 4 respectively

$$\mu_i = \frac{1}{r} \sum_{w=1}^r EE_{iw} \quad (2)$$

$$\mu_i^* = \frac{1}{r} \sum_{w=1}^r |EE_{iw}| \quad (3)$$

$$\sigma_i = \sqrt{\frac{1}{(r-1)} \sum_{w=1}^r (EE_{iw} - \mu_i)^2} \quad (4)$$

where r is a user defined variable that is used to determine how many trajectories used in the calculations of the EEs, and w is a specific trajectory. Calculating the mean though can be influenced by negative EE values, which is why the absolute mean is calculated, in order to more accurately reflect the magnitude of the sensitivity of the variables. The absolute mean is a characteristic of how sensitive the output is to change based on the change of an input, while the standard deviation is a characteristic of the dependence of the input to other inputs. Inputs with high absolute means have a high influence on the output of a model, and inputs with high standard deviations have elementary effects that have a high dependence on other inputs. [7, 28]

The benefit of the Morris Method is that the user can pre-define how much an analysis is going to cost computationally. The user has control over the r value, the

number of trajectories and the k value, which is just the total number of variables or inputs. Based on Equation 5, the user can predict how many samples the Morris Method will generate.[7, 28]

$$\# \text{ of Samples} = r(k + 1) \tag{5}$$

For instance if a user defined an r value of two with three variables in a model, the Morris Method will generate eight samples, as demonstrated in Figure 3 below.

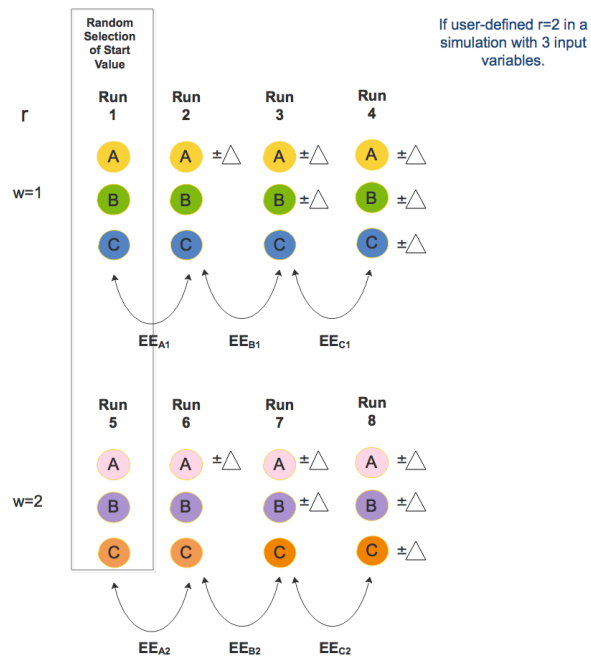


Figure 3 - Morris Method Example [7]

3.2.2 Morris Method Workflow

The Sensitivity Study analyses how the Total Site Energy [GJ] changes based on changes in variable parameters. There are nine different parameters, listed in Table 4 considered in the study, along with their minimum and maximum values.

Table 4 - List of Parameters

Parameter	Minimum	Maximum
Internal Load Level	0.00 kW	20.175 kW
ECU/HVAC System	0	0.999
Number of People	0	32
Adjust Cooling Setpoint	20.9 [°C]	24.9 [°C]
Adjust Heating Setpoint	16.2 [°C]	20.2 [°C]
Door Opening Per Person	2	6
Pressure Gap Across Door	15 [Pa]	30 [Pa]
Building Rotation	0 [°]	270 [°]
People Activity Level	100 [W/Person]	160 [W/Person]

The ECUs were added in as a variable in the study through the use of an ordered set, shown in Figure 4, where the ECUs were ordered based on both ECU Refrigeration Tonnage and Efficiency obtained from manufacturer specifications. Then the ECUs were put in an ordered set with values ranging from 0 to 0.999 (see Fig. 4).

```
if hvacsystem >=1 || hvacsystem < 0
  runner.registerError("Only values in the interval [0,1) are allowed. The values supplied was #{hvacsystem}")
end
ordered_hvacsystem_set = [
  'Carrier', 'Carrier-D', 'HDT EEECU36K', 'HDT F100', 'Mainstream E2CU', 'IECU', 'HDT USMC60K',
  'HDT EEECU36K-D', 'HDT F100-D', 'Mainstream E2CU-D', 'IECU-D', 'HDT USMC60K-D'
]
hvacsystem = ordered_hvacsystem_set[(hvacsystem.to_f * ordered_hvacsystem_set.length).floor]
```

Figure 4 - Example of Code for ECU Ordered Set

There are three weather locations used in the study, as mentioned in Section 2.2.4, which are Kharga, Egypt, Chongjin, DPRK, and Singapore. The Heating and Cooling Thermostat Setpoint ranges were determined by MIL-STD-1472G, where the Cooling Setpoint is 22.9 °C and the Heating Setpoint is 18.2 °C, and by adjusting the setpoints between -2 °C to 2 °C [31]. The internal loads presented in Table 3 were used to make the boundaries for the Internal Load Level parameter. These parameters are varied through the Morris Method workflow shown in Figure 5 below.

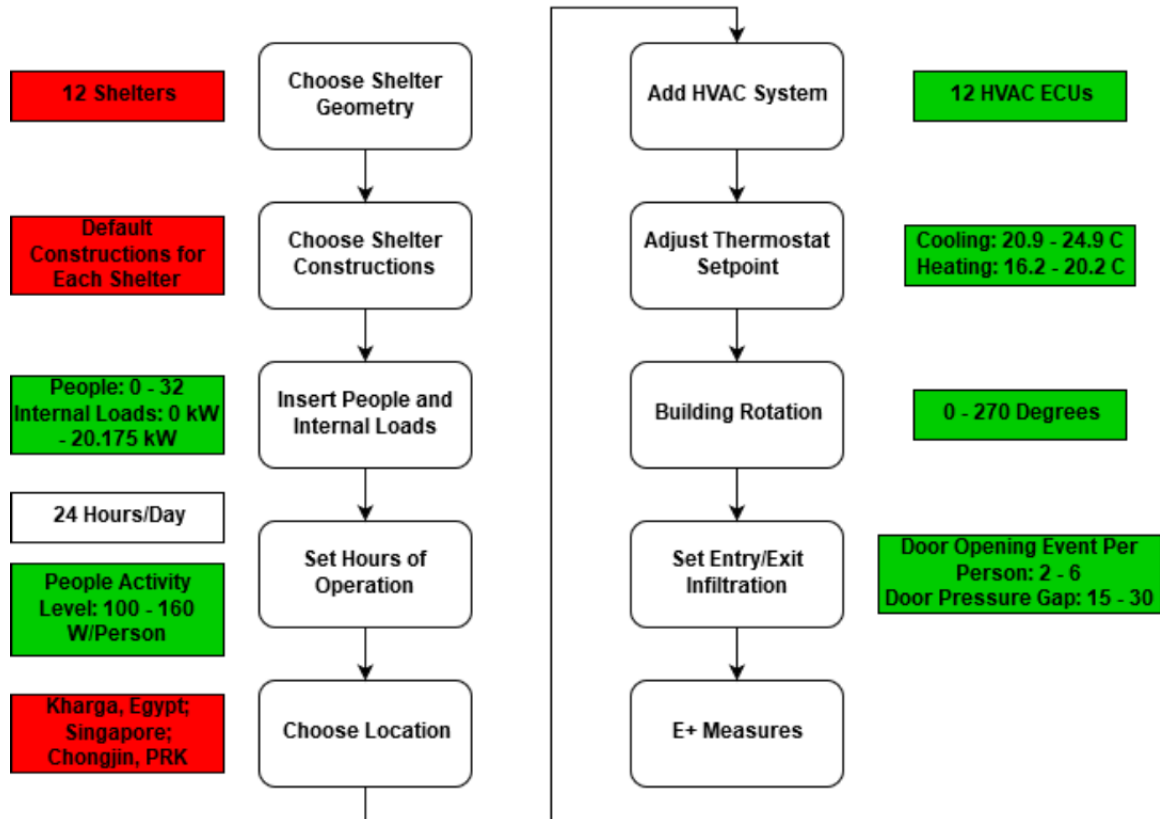


Figure 5 - Morris Method Workflow

To the side of each workflow block, the rounded rectangles, is the variable or parameter that goes along with the workflow block. The parameters in red are for the Shelter or Location blocks which are not varied in an analysis. The variables in green are varied in an analysis. The Morris Method Workflow is structured to work on any Shelter/Location combination. For instance, if a full Sensitivity Study were to be done for this project on the HDT Airbeam shelter, three Morris Method analyses would have to be run, one for each weather location.

The workflow goes from an empty seed OSM file to a complete model that is translated into an EnergyPlus model, which is run to obtain the simulation results and

upload the results into the DEnCity Database. The workflow is a collection of OS and EnergyPlus Measures run in a certain order [7]. The Morris Method Workflow's measures are listed in Table 5 along with each measures description and arguments. The workflow starts by selecting which shelter geometry type to use, a user specified argument set through the Excel Matrix [7]. Then the workflow adds in the shelter construction materials into the model if the user specifies different constructions from the default constructions in the shelter geometry files. In this study the shelter geometry files are not varied from the default. The functionality of the measure only works with specific shelter types that have conventional floor/ceiling/wall configurations. Most of the shelters in this analysis are soft shelters that do not have the typical floor/ceiling/wall configurations.

Then the workflow adds in people loads and internal electric loads for the shelters. Lighting loads can also be added in, but due to the range of Internal Loads shown in Table 3, lighting loads, which are usually 0.4 kW in military shelters, are considered negligible. After adding the loads into the shelter, the workflow adds in the shelter's hours of operation and schedules for the different loads. For the Sensitivity Study the facilities were fixed to a 24 hours/day operating schedule. NREL requested the data be on a 24 hours/day schedule for their requirements for their regression. The people activity level is also set in this step. The activity level bounds were made from ASHRAE standards for Average Metabolic Rates for Adults. 100 Watts/Person represents the rate for an adult seated at rest, 160 Watts/Person represents moderate work, and the static value of 130 Watts/Person represents office work [34].

Afterwards the shelter’s location is set. Then the ECU is selected and inserted into the model and the thermostat setpoints are set. The following measure rotates the shelter by either 0, 90, 180, or 270 degrees. The infiltration due to occupant entry and exit is then added into the model, and after the infiltration is added, the OSM is translated into an EnergyPlus model and the EnergyPlus measures for infiltration coefficients and ground temperature boundary conditions are added into the model. The analysis is then run and the results are compiled and pushed into the DEnCity Database.

Table 5 - List of Morris Method Workflow Measures

Measures (Filename)	Description	Arguments
1.Choose Shelter Geometry (Choose Geometry)	Imports the components for the shelter geometry	geometry
2.Choose Shelter Construction (ChooseConstructionIntoModel)	Imports the construction components into the shelter model.	construction_walls construction_roof construction_floor
3.Insert People and Internal Load (add_electric_equipment_into_space_type) (add_people_into_space_type)	Imports the People and Internal Loads into the model.	constpwr number_of_people
4.Set Hours of Operation for Shelter (temp_assign_schedules)	Sets a default schedule where a user can change the start and end hours. The user can specify if all of the schedules follow the Hours of Operation Schedule as well as the People Activity Level.	start_hour end_hour people_activity_level
5.Choose Location (ChangeBuildingLocation)	Selects weather data based on location specified.	weather_file_name
6.Add HVAC System (AddHVACSystemToModelSensitivity)	Imports the ECU Loop into the shelter model. It also sets the Cooling Setpoint to 22.9 °C and the Heating Setpoint to 18.2 °C.	hvacsystem
7.Adjust Thermostat Setpoints (AdjustThermostatSetpointsByDegrees)	Adjusts the thermostat setpoints by the number of degrees specified from the inputs.	cooling_adjustment heating_adjustment
8.Building Rotation (RotateBuilding)	Rotates the shelter based on a specified degree.	relative_building_rotation
9.Set Entry/Exit Infiltration (AedgSmallToMediumOfficeEnvelopeAndEntryInfiltration)	Calculates the entry/exit infiltration schedules based on the Number of People, People Schedule, Door Opening Per Person, and the Pressure Difference Across the Door.	doorOpeningEventsPerPerson pressureDifferenceAcrossDoor_pa

With the Morris Method, the user can control how much the computational cost of the analysis will be as explained in Section 3.2.1. For the Sensitivity Study’s purposes, the r value was chosen to be 20. The number of variables, the k value, is nine. This causes the Morris Method Workflow to generate 200 simulations, using Equation 5, for one Morris Method analysis. The ‘morris’ function in the ‘sensitivity’ R/CRAN package was used in the workflow to perform the Morris Method Study. [32]

3.2.3 Sobol Method

The Sobol Method focuses on calculating Sobol Indices to characterize the sensitivity of inputs to a model. Before running an analysis, the input parameters need to be defined with their lower and upper bounds and be rescaled in order to be dimensionless, on a scale from [0,1]. These parameters are treated as uniformly distributed random variables on the scale from [0,1]. These random variable functions ($f(x)$), that have a mean (f_0) and a variance (D) as shown in the Equations below. [33]

$$f_0 = \int f(x)dx \quad (6)$$

$$D = \int f(x)^2 dx - f_0^2 \quad (7)$$

These distributions help the sample space be more uniformly distributed rather than being random, helping the method converge quicker. The Sobol Method focuses on calculating the effects from a single parameter that combine to form the variance (D). The variable functions can then be decomposed from their form in Equation 8 and broken up into specific terms shown in Equations 9 and 10. [33]

$$f(x) = f_0 + \sum_{i=1}^s f(x_i) + \sum_{i=1}^s \sum_{i \neq j}^s f_{ij}(x_i, x_j) + f_{1...s}(x_1, \dots, x_s) \quad (8)$$

$$f_{ij}(x_i) = \int f(x) \prod_{k \neq i} dx_k - f_0 \quad (9)$$

$$f_{ij}(x_i, x_j) = \int f(x) \prod_{k \neq i, j} dx_k - f_0 - f_i(x_i) - f_j(x_j) \quad (10)$$

This establishes the parameter sets that are used to calculate the Sobol Indices. To decompose the variables into the representations shown in Equations 9 and 10, the following condition has to be satisfied. [33]

$$\int f_{i_1, \dots, i_s}(x_{i_1}, \dots, x_{i_s}) dx_k = 0, \quad k = i_1, \dots, i_s \quad (11)$$

Due to this property, Equation 8 can be squared on both sides and integrated to yield Equation 12 for the variance and its decomposition into different terms that can be used to represent the effects from a single parameter, combined effects, and other types of effects. [33]

$$D = \sum_{i=1}^k D_i + \sum_{i < j} D_{ij} + \sum_{i < j < l} D_{ijl} + \dots + D_{1,2,\dots,k} \quad (12)$$

This can then be used to derive an equation, Equation 13, which represents the partial variance generated by a subset of parameters represented by $f_{i_1 \dots i_s}(x_{i_1}, \dots, x_{i_s})$. [33]

$$D_{i_1 \dots i_s} = \int f_{i_1 \dots i_s}^2(x_{i_1}, \dots, x_{i_s}) dx_{i_1}, \dots, x_{i_s} \quad (13)$$

After obtaining this expression for the variance, the Sobol Indices can be calculated for different subsets of parameters. For a specific subset of parameters,

$$S_{i_1 \dots i_s} = \frac{D_{i_1 \dots i_s}}{D} \quad (14)$$

represents the Sobol Indices for the whole subset. Where S_i are the First Order Sobol Indices, S_{ij} are Second Order Sobol Indices, and S_{Ti} are the Total Order Sobol Indices. [33]

$$S_i = \frac{D_i}{D} \quad (15)$$

$$S_{ij} = \frac{D_{ij}}{D} \quad (16)$$

$$S_{Ti} = S_i + S_{ij_{i \neq j}} + \dots + S_{1\dots i\dots s} \quad (17)$$

The First Order Sobol Indices represent the contribution of variance of the i^{th} parameter on the output, similar to the absolute mean of the Morris Method. The Second Order Indices represent the contribution of interactions between two parameters, the i^{th} and j^{th} parameters. The Total Order Indices is the summation of all of one parameter's contribution to the variance of the output. In general influential parameters are characterized as parameters that have a S_{Ti} over 0.05. [33]

In general this method is very flexible in being able to be used for non-monotonic and non-linear models. For this thesis non-linear and non-monotonic models refer to input parameters' relationship to different shelter energy modeling outputs. For this thesis, the main energy modeling output is the TEI, Total Electricity Intensity, but other outputs could be Occupied Zone Temperature, ECU Unmet Cooling or Heating Hours, or other parameters. Non-linear models refer to the relationship between an input parameter, or multiple parameters, and a model output being non-linear, such as an increase in the Internal Load Level in a shelter having a non-proportional change in the

Total Electricity Intensity. Non-monotonic models refer to the relationship between an input parameter, or multiple parameters, and a model output being non-monotonic, such as an increase in the combined effect of Number of People and the Door Opening per Person not having an entirely increasing or entirely decreasing relationship to the Occupied Zone's Temperature. Although this method is very flexible in dealing with these types of relationships, the Sobol Method has a high computational cost. This method only has a convergence rate of \sqrt{n} , where n is the sample size. Usually sample sizes have to be on the order of 10^4 to actually converge, unless if quasi-Monte Carlo sequences, such as in Latin Hypercube Sampling, are used, in which case sample sizes are usually on the order of 10^3 . [29]

3.2.4 Sobol Method Workflow

In order to perform the Sobol Method Study, 12 samples sets were created, one per shelter model, using the Latin Hypercube Sampling (LHS) Workflow, detailed in Section 3.3.2. All sample sets were generated using the Kharga, Egypt Weather Location. Due to the comparative nature of the study, each sample set consisted of 200 data points, the same amount of data points used in the Morris Method Workflow. These random sample sets were then input into the 'sobol' function of the R/CRAN package 'sensitivity', using up to second order indices. [32]

The LHS Workflow, for the generation of these data sets, varied all of the nine parameters presented in Table 4 and used all of the same measures the Morris Method Workflow used.

3.3 Sampling Study Methodology

The objective of the Sampling Study is to generate a near random sample space and upload the data into the DEnCity Database. The sample space needs to have enough data to be used by the Random Forest Regression Model developed by NREL to extrapolate the characteristics of the full population of military shelters. The Sampling Study covers all 12 shelters listed in Table 1, and ran across all of three weather locations listed in Section 2.2.4, utilizing all 12 ECU models listed in Table 2. The Latin Hypercube sampling method, described in Sections 2.3.3 and 3.3.1, is used to perform the Sampling Study.

3.3.1 Latin Hypercube Sampling Method

The Latin Hypercube Sampling (LHS) Method focuses on generating a distribution of collections of parameter values from a multidimensional distribution. This method generates a Latin Hypercube and uniformly distributed samples across that hypercube. The Latin Hypercube is generated based on the number of samples the user desires to use (n) and the number of variable parameters in the model (k). The method generates a n by k Latin Hypercube matrix that has k columns and n equally probable intervals. The sampling then occurs by generating a random sample within each of the n sections. This sampling method results in n samples being placed in the Latin Hypercube. Since the user specifies n , the number of samples, the user has control over the computational cost of the analysis [30]. The method also places samples one at a time, each sample having the memory of where the previous sample was placed, causing

the sampling to ensure that the Latin Hypercube, and therefore the sample space, is uniformly sampled. This differentiates the LHS method from true Monte Carlo methods, due to Monte Carlo methods generating truly random samples in a sample space, with no memory of placement and no sample space stratification, causing Monte Carlo methods to have a higher computational cost in comparison to the LHS method.

3.3.2 Latin Hypercube Sampling Method Workflow

The Sampling Study aims to fully sample all of the models that were integrated into the workflow. For this Sampling Study, there are five parameters varied, instead of the nine that are varied in the Sensitivity Study, listed in Table 4. Based on the results of the Sensitivity Study presented in Chapter 4, the Cooling Setpoint, Heating Setpoint, Door Opening Event per Person, and the Pressure Gap Across the Door were not varied.

The ECUs were added in as a variable in the study through the use of an ordered array as shown in Figure 6 below.

```
variables << {name: 'hvacsystem', desc: 'Chose HVAC System Component to Import.',
static_value: 'HDT F100', :value => {type: 'discrete', minimum: 'Carrier', ...
maximum: 'Mainstream E2CU-D', mean: 'Carrier', values: ['Carrier', 'Carrier-D',...
'HDT EEECU36K', 'HDT F100', 'Mainstream E2CU', 'IECU', 'HDT USMC60K',...
'HDT EEECU36K-D', 'HDT F100-D', 'Mainstream E2CU-D', 'IECU-D', 'HDT USMC60K-D']}}
```

Figure 6 - ECU Ordered Array

There are three weather locations used in the study, as mentioned in Section 2.2.4, which are Kharga, Egypt, Chongjin, DPRK, and Singapore. The Heating and Cooling Thermostat Setpoints were fixed at 18.2°C and 22.9°C respectively according to MIL-STD-1472G [31].

The workflow goes from an empty seed OSM file to a complete model that is translated into an EnergyPlus model, which is run to obtain the simulation results and upload the results into the DEnCity Database, similar to the Morris Method Workflow. Differences between the Morris Method Workflow and the LHS Workflow reside in the parameters varied. The Thermostat Setpoints along with the Building Rotation were varied differently than in the Morris Method Workflow. The Thermostat Setpoints were fixed in this workflow, as previously mentioned, and the shelter rotation in 45 degree increments(0, 45, 90, 135, 180, 225, 270, or 315 degrees) instead of 90 degree increments as in the Morris Method Workflow. This workflow is displayed below in Figure 7.

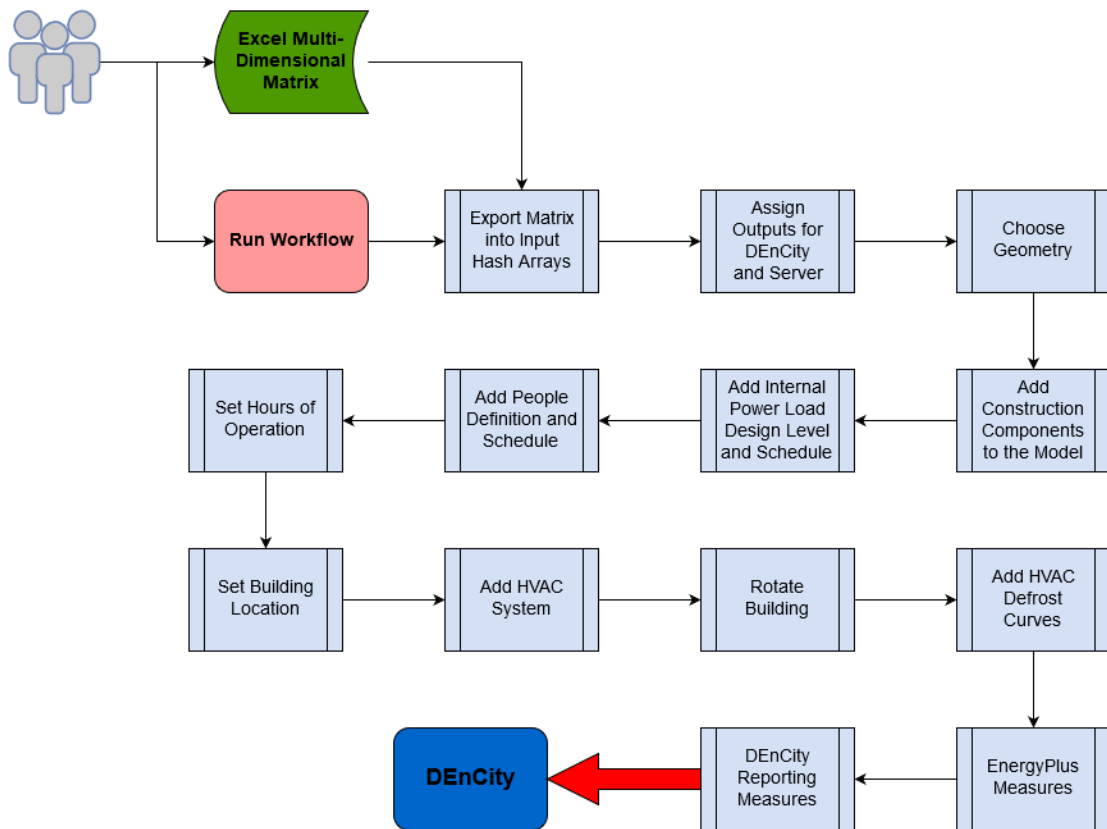


Figure 7 - Latin Hypercube Sampling Method Workflow

The analyses were run for every Shelter/Weather Location combination for a total of 36 analyses. With the LHS Method, the user can control how much the computational cost of the analysis will be, as explained in Section 3.3.1. For the purposes of the Sampling Study, the number of samples in the Latin Hypercube was chosen to be 12000 per analysis, which corresponds to 1000 data points per Shelter/Weather Location/ECU combination. The ‘randomLHS’ function in the ‘lhs’ R/CRAN package was used in the workflow to perform the LHS Sampling Study. [14]

CHAPTER 4. SENSITIVITY STUDY OF SHELTERS

In this chapter, the results of the full Sensitivity Study for all 12 shelters across all three weather locations are described. The chapter is divided into 15 sections: a section for an overview of the Sensitivity Study, 12 sections for the sensitivity analysis results corresponding to one section for each shelter, one section for the conclusions of the Morris Method Sensitivity Study, and one section for the Sensitivity Results using Sobol Method.

4.1 Sensitivity Study Overview

The Sensitivity Study was conducted on every Shelter/Location combination. For the 12 shelters, shown in Table 1, and the three weather locations, shown in Section 2.2.4, there were 36 Morris Method Sensitivity Analyses performed for the study. For each analysis, all nine parameters, listed in Table 4, were varied to determine their influence on the Total Electricity Intensity (TEI). The parameters are varied according to the Morris Method.

The nine parameters are varied according to each parameter's potential values. A uniform distribution was created based on the potential values that each parameter could have. The uniform distribution is defined by a static value, minimum value, maximum value, mean of the potential values, and the standard deviation of the potential values. The parameters, their static values, minimums, maximums, means, and standard deviations are shown in Table 6 below.

Table 6 - List of Parameter Uniform Distributions

Parameter Name	Variable Name	Static Value	Minimum Value	Maximum Value	Mean	Standard Deviation
Internal Load Level	standard_osc	3	0	4.33	2.165	1
ECU	hvacsystem	0	0	0.999	0.5	1.0
Number of People	peak_occupancy	12	0	32	17	14
Adjust Cooling Setpoint	cooling_thermostat	0	-2	2	2	2
Adjust Heating Setpoint	heating_thermostat	0	-2	2	2	2
Door Opening	doorOpening_pp	3	2	6	3	1
Pressure Gap Across Door	pressureAcrossDoor	23	15	30	23	1
Building Rotation	rotations	0	0	270	135	116
People Activity Level	occupancy_activity	130	100	160	130	1

The parameter uniform distribution for the Internal Load Level is based on the value set shown in Table 3, and due to the large variation and distribution in the values, the values

were changed to a logarithmic distribution to reduce the unnecessary impact of the variable's variation on the TEI. The distribution was changed based on the following equation

$$10^x = y \quad (19)$$

where y is the original parameter value in the distribution and x is the new logarithmic distribution parameter value. For instance, an Internal Load value of 3.162 kW will be a logarithmic value of 3.5.

The results of the Morris Method Sensitivity Study were used to determine the sensitivity and importance of the new parameters. The Sobol Sensitivity analyses were used to see if the Morris Method is the best method to use for the Sensitivity Study. For the Sensitivity Study, the absolute mean, μ^* , of the Morris Method is used to determine the sensitivity of the parameters [12]. After consultation with NREL, an absolute mean value of 75 has been used as the cut-off value to determine whether the parameter is sensitive or not. Parameters with an absolute mean value greater than 75 are sensitive to the TEI and were focused on in the Sampling Study. The following sections present the sensitive variables that were determined based on the Morris Method for each Shelter/Location combination. These sections present a table for each Shelter, showing the sensitive variables that were determined for each Weather Location. Due to the magnitude of the Sensitivity Study (36 analyses) the Morris Method Bar Plots and Morris Method Scatter Plots associated with the Sensitivity Study are displayed in Appendix A.

The Sobol Sensitivity analyses were conducted to see whether or not the Morris Method is the best method to be used for the sensitivity study. For this purpose only one

analysis was performed per shelter. The weather location used for this purpose was Kharga, Egypt, due to having both cold and hot weather conditions at this location. The metric used to determine whether or not the Sobol Sensitivity analysis worked better or not is based on the number of data points the analysis took to complete. Each Morris Method Analysis took 200 data points/simulation runs to complete. This number of data points was determined by setting the r value for each analysis to be 20 with the number of variables per analysis being nine, using Equation 5 in Section 3.2.1. For the Sobol Analysis, the LHS workflow was used to generate 200 data points for a specific Shelter/Weather Location combination and then those data points were used in a Sobol Sensitivity Analysis. If the Sobol Analysis converged with the given 200 data points, then the analysis was determined to be successful and a competitive method to the Morris Method. If the analysis did not converge with the given 200 data points, then the analysis was determined to be a failure in terms of being the better analysis method. This is due to the analyses being run through Amazon Web Services (AWS). Each simulation data point takes between 300 to 500 seconds to run, and along with Amazon Web Services instance pricing, any analysis that takes more data points than the Morris Method would cost more and therefore not be as cost effective. The 12 analyses were run and if the analyses were not completed when the 200th data point was completed, the analysis was stopped and considered a failure. The results presented in Section 4.3 describes whether or not the Sobol Analyses finished above or below 200 data points as well as the average time per data point for each analysis.

4.2 Morris Method Sensitivity Study Results

The following 12 sections present the results of the Sensitivity Study for the 12 shelters. The nine parameters and variables that are varied in the models are the same across all shelters and for the purposes of the Sensitivity Study and the documentation generation for the Sensitivity Study, an Xn nomenclature is used to represent the variables in the study. The Xn nomenclature is displayed in Table 7 below.

Table 7 - Sensitivity Study Xn Nomenclature

Xn	Variable Parameters
X1	Internal Load Level
X2	ECU/HVAC System
X3	Number of People
X4	Adjust Cooling Setpoint
X5	Adjust Heating Setpoint
X6	Door Opening Event Per Person
X7	Pressure Gap Across Door
X8	Building Rotation
X9	People Activity Level

The results of the Sensitivity Study are presented in the following 12 sections.

4.2.1 HDT Airbeam Shelter Sensitivity Study

This section presents the results of the HDT Airbeam shelter's sensitivity analyses. The HDT Airbeam shelter's OpenStudio Model is shown in Figure 8 below. Table 8 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

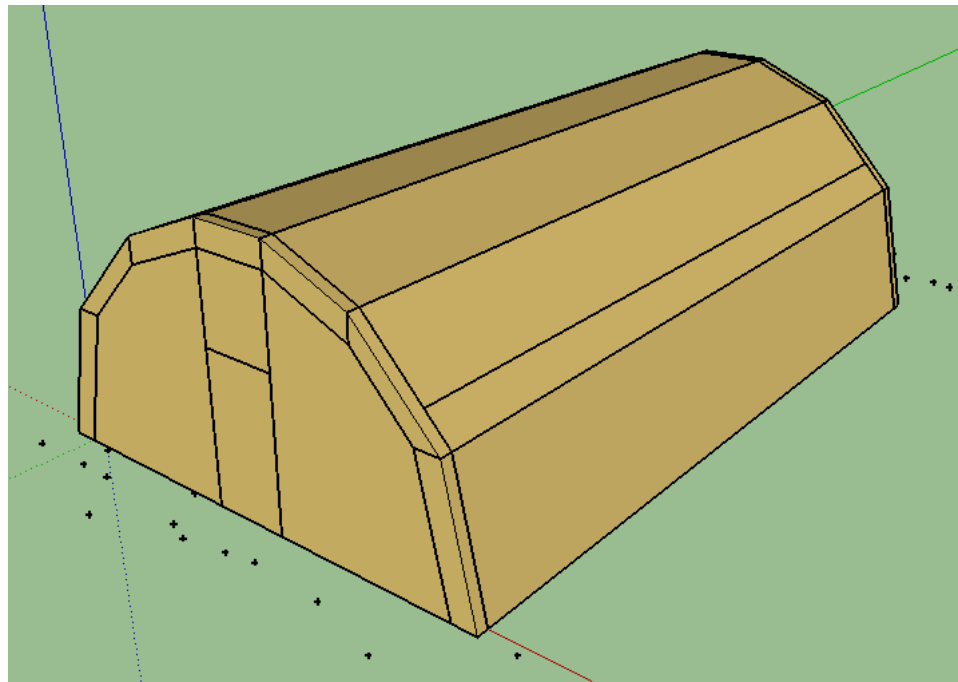


Figure 8 - HDT Airbeam Shelter OSM

Table 8 - HDT Airbeam Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X5	X3
4	X4	X6	X4
5	X5	X3	X6
6	X6	X4	X9
7	X9		
8			

The variables presented in Table 8 show all of the variables that have absolute mean, μ^* , values greater than 75. These values were compiled from the Morris Method Bar Plots for the Airbeam shelter's analyses in each Weather Location. Figure 9 shows the μ^* values for different parameters in a bar plot for Airbeam shelter. The data used in Figure 9 is derived from the Morris Method Analysis done on the Airbeam shelter in Kharga, the results of which are shown in Table 9 below.

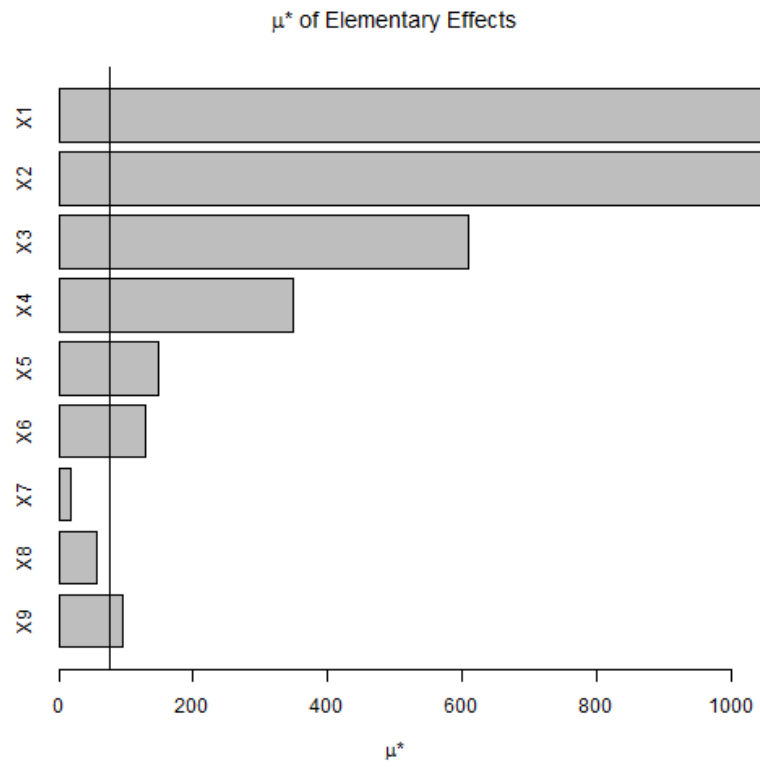


Figure 9 - Bar Plot of μ^* values for HDT Airbeam in Kharga, Egypt

Table 9 - Morris Sensitivity Results for HDT Airbeam in Kharga, Egypt

Variable	μ^*	μ	S
X1	9251.677	9251.677	17817.52
X2	4914.643	2184.722	6057.427
X3	608.929	608.929	278.649
X4	348.879	-348.879	141.806
X5	148.74	148.74	74.524
X6	129.534	129.534	171.978
X9	95.704	95.704	74.46
X8	57.51	-5.565	81.855
X7	18.988	18.988	16.056

This bar plot has a demarcation line drawn where the μ^* , the parameter's sensitivity value, equals 75, the minimum value this study uses to determine if a variable is sensitive. From these results, it is clear that the three most important, most sensitive, parameters for the Airbeam shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values close to or upward of 5000, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 24, 25, and 26 in Appendix A. The other variables that have absolute mean values

much greater than 75 are the changes in Cooling and Heating setpoint and the Door Opening Events per Person, X4, X5, and X6 respectively. These parameters consistently have μ^* values greater than 100 in the Airbeam shelter. Two of the parameters that do not fit this trend are the People Activity Level and the change in Heating Setpoint, X9 and X5 respectively, in Singapore, as seen in Table 26 in Appendix A. Due to Singapore being a hot-humid environment, the Heating Setpoint is rarely sensitive due to the ECUs mainly providing cooling in the shelter, which also causes the People Activity Level to be more sensitive.

The other metric used in a Morris Method analysis is the standard deviation of the EEs of a parameter, σ , which is used to measure the parameter's independence from other parameters. Low σ values indicate that the parameter is relatively independent from other parameters and high values indicate that the parameter is relatively dependent on other parameters. Figure 10 below shows the Morris Method Scatter Plot for the Airbeam shelter in Kharga and Figure 11 shows a detailed view of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

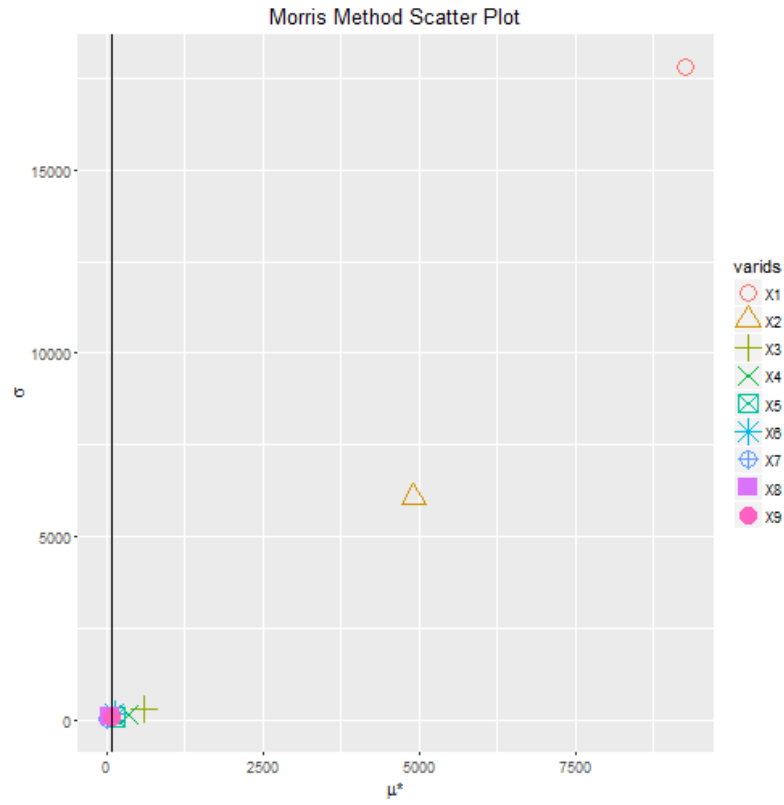


Figure 10 - HDT Airbeam in Kharga, Egypt Morris Method Scatter Plot

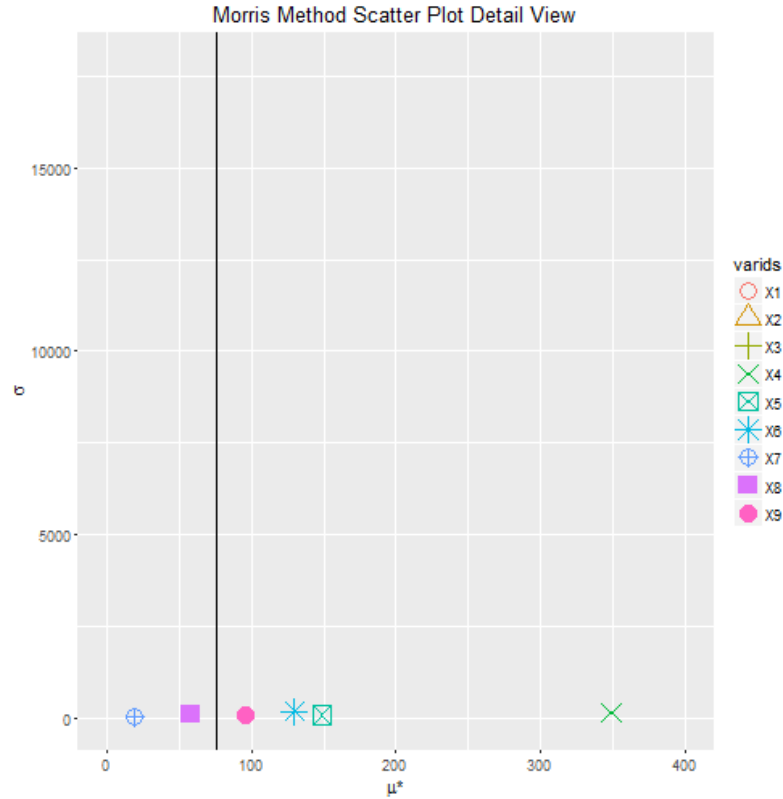


Figure 11 - HDT Airbeam in Kharga, Egypt Morris Method Scatter Plot Detail View

From these figures, as well as Table 9, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs whereas the other parameters have relatively low dependencies on other parameters. There are three parameters, the Number of People, the Cooling Setpoint, and the Door Opening per Person, which have dependency values on the order of 10^2 . All the other parameters have dependency values less than 100. Based on the other Airbeam analyses, whose figures and tables can be found in Appendix A, the Internal Load Level and the ECU are consistently the variables that are most dependent on other parameters. The Door Opening per Person, the Number of People, the Cooling Setpoint, and the Heating Setpoint in Chongjin also have dependencies consistently on the order of 10^2 .

4.2.2 HDT ArctiX Shelter Sensitivity Study

This section presents the results of the HDT ArctiX shelter's sensitivity analyses. Figure 12 shows the HDT ArctiX shelter OSM and Table 10 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

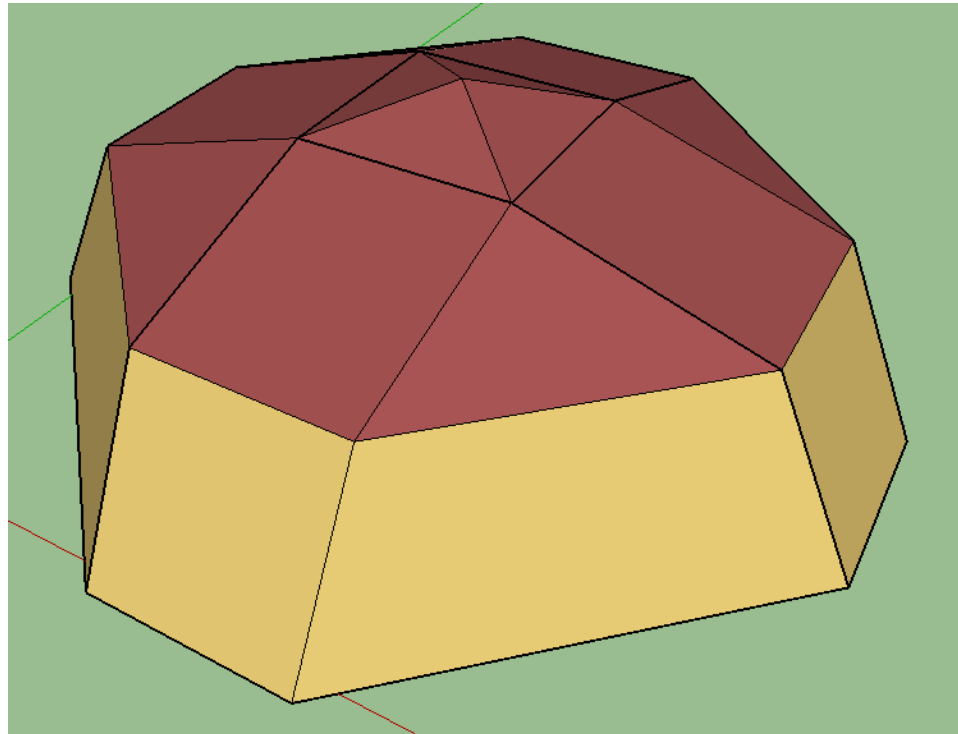


Figure 12 - HDT ArctiX Shelter OSM

Table 10 - HDT ArctiX Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X3	X3
4	X4	X6	X6
5	X9	X5	X4
6	X6	X4	X9
7		X9	X7
8		X7	

The variables presented in Table 10 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the ArctiX shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 4000, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 27, 28, and 29 in Appendix A. The Number of People also has μ^* values greater than 1000 in Kharga and Singapore. The other variables that have absolute mean values much greater than 75 are the changes in Cooling setpoint and the Door Opening Events

per Person, and the People Activity Level, X4, X6, and X9 respectively. These parameters consistently have μ^* values greater than 100 in the ArctiX shelter.

Low standard deviation of the EEs of a parameter, σ , indicates that the parameter is relatively independent from other parameters and high values indicate that the parameter is relatively dependent on other parameters. Figures 34, 37, and 40 in Appendix A show the Morris Method Scatter Plots for the ArctiX shelter in Kharga, Chongjin, and Singapore and Figures 35, 38, and 41 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 27, 28, and 29, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People, the Door Opening per Person, and the People Activity Level are also dependent on other parameters across all Weather Locations, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent on other parameters in warmer climates such as Kharga and Singapore.

4.2.3 B-Hut Shelter Sensitivity Study

This section presents the results of the B-Hut shelter's sensitivity analyses. Figure 13 shows the B-Hut shelter OSM and Table 11 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

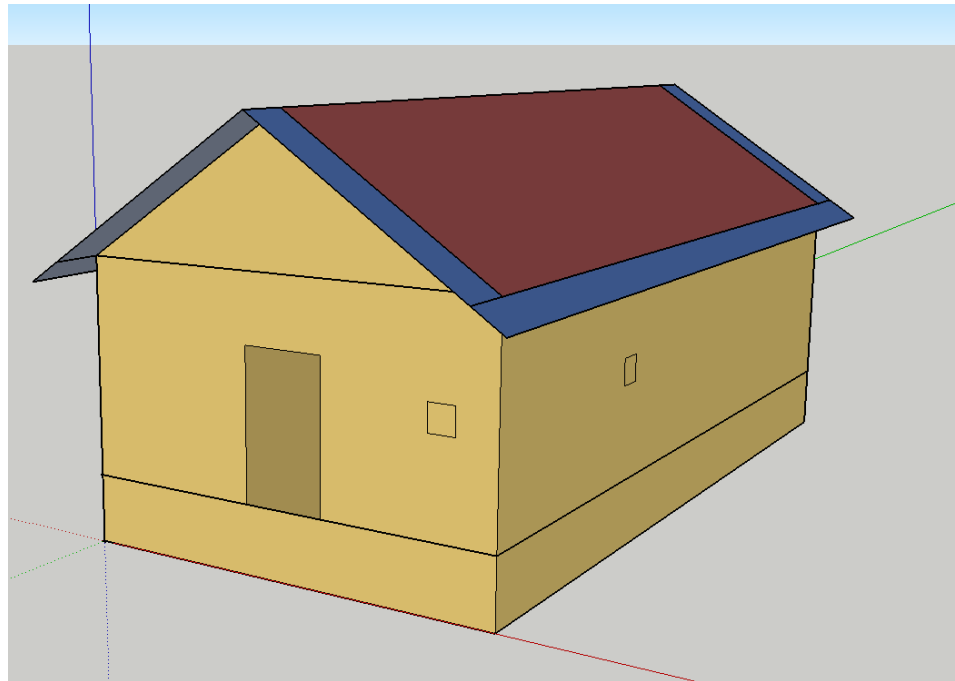


Figure 13 - B-Hut Shelter OSM

Table 11 - B-Hut Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X3	X3
4	X4	X6	X4
5	X6	X5	X6
6	X9	X4	X9
7	X5		
8			

The variables presented in Table 11 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the B-Hut shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 3500, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 30, 31, and 32 in Appendix A. The Number of People also has μ^* values greater than 500 in all three Weather Locations. The other variables that have absolute mean values much greater than 75 are the changes in Cooling and Heating setpoints, the Door Opening Events per Person, and the People Activity Level, X4, X5, X6, and X9 respectively. These parameters consistently have μ^* values greater than 100 in the B-Hut shelter, except in Chongjin, where X4 is just sensitive with a μ^* value of 77.58 and X9 which is not sensitive with a μ^* value of 68.2. Changes in Heating Setpoint is also not sensitive in Singapore and has a μ^* value of 0.578.

Figures 43, 46, and 49 in Appendix A show the Morris Method Scatter Plots for the B-Hut shelter in Kharga, Chongjin, and Singapore and Figures 44, 47, and 50 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 30, 31, and 32, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other

parameters. The Number of People and the Door Opening per Person are also dependent on other parameters across all Weather Locations, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent in warmer climates such as Kharga and Singapore and the Heating Setpoint is also dependent in the colder climate of Chongjin.

4.2.4 MILVAN Shelter Sensitivity Study

This section presents the results of the MILVAN shelter's sensitivity analyses. Figure 14 shows the MILVAN shelter OSM and Table 12 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

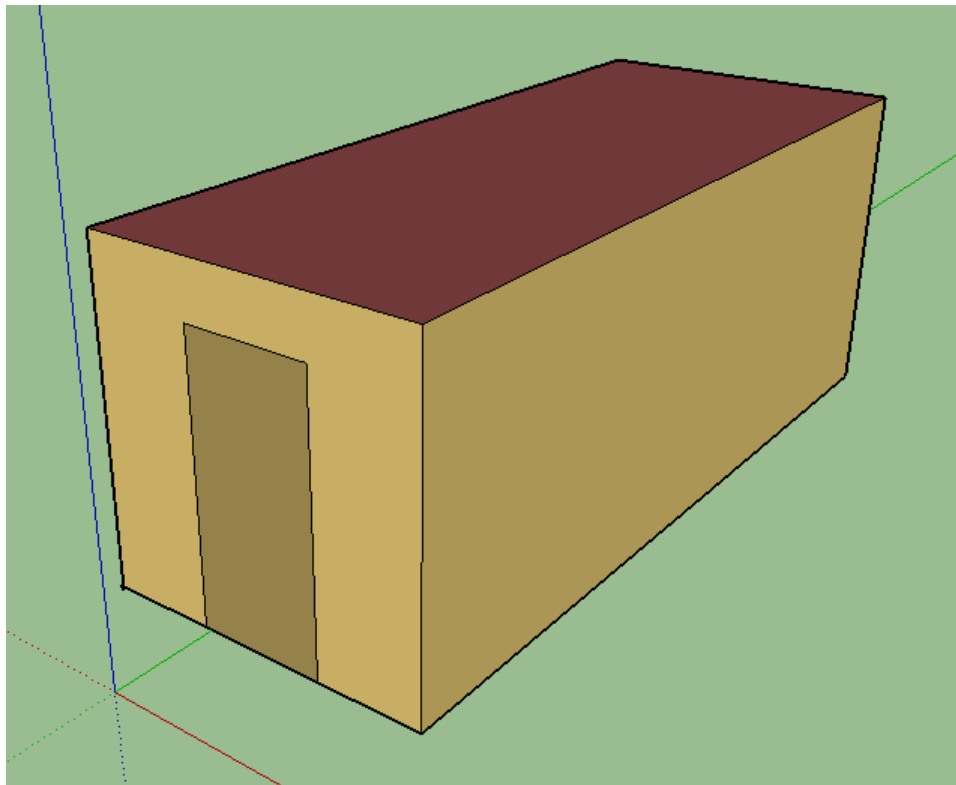


Figure 14 - MILVAN Shelter OSM

Table 12 - MILVAN Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X3	X4
5	X9	X5	X6
6	X6	X4	X9
7	X5	X7	X7
8		X9	

The variables presented in Table 12 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the MILVAN shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 8500, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 33, 34, and 35 in Appendix A. The Number of People also has μ^* values greater than 800 in all three Weather Locations. The other variables that have absolute mean values much greater than 75 are the changes in Cooling and Heating setpoints, the

Door Opening Events per Person, Pressure Gap Across the Door, and the People Activity Level, X4, X5, X6, X7, and X9 respectively. These parameters consistently have μ^* values greater than 100 in the MILVAN shelter, except for the Pressure Gap Across the Door in Kharga and the Heating Setpoint in Singapore.

Figures 52, 55, and 58 in Appendix A show the Morris Method Scatter Plots for the MILVAN shelter in Kharga, Chongjin, and Singapore and Figures 53, 56, and 59 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 33, 34, and 35, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more. The Number of People and the Door Opening per Person also consistently have dependency values on the order of 10^2 and higher. All other parameters have dependency values on the order of 10^2 except for the Building Rotation, the Door's Pressure Gap in Kharga, and the Heating Setpoint in Singapore.

4.2.5 Utilis TM60 Sensitivity Study

This section presents the results of the Utilis TM60 shelter's sensitivity analyses. Figure 15 displays the Utilis TM60 shelter OSM and Table 13 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

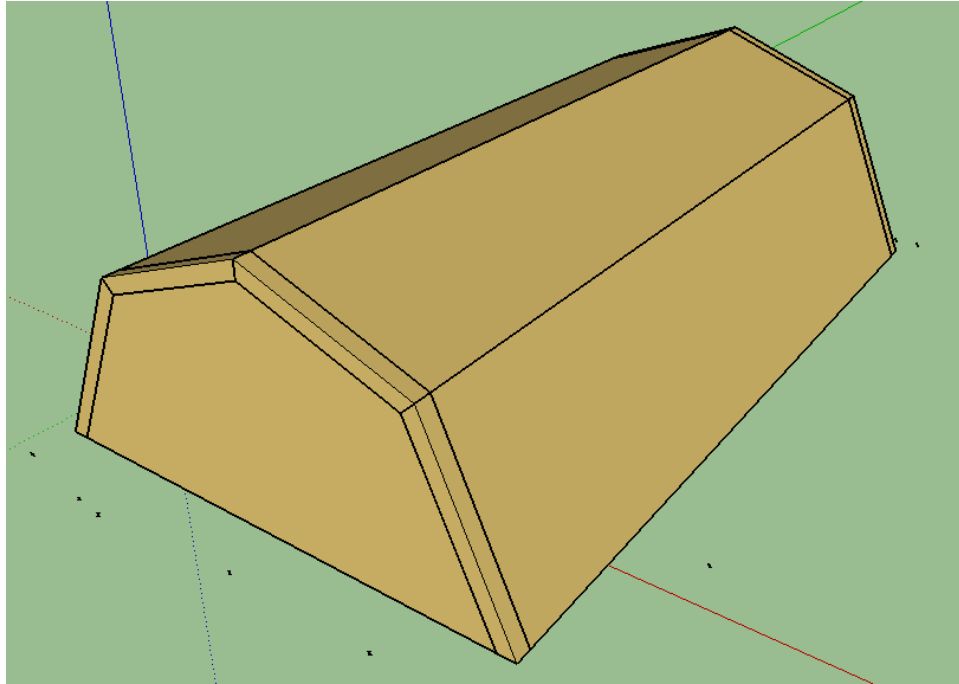


Figure 15 - Utilis TM60 Shelter OSM

Table 13 - Utilis TM60 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X5	X4
5	X9	X3	X6
6			X9
7			
8			

The variables presented in Table 13 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the TM60 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 4000, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 36, 37, and 38 in Appendix A. The Number of People also has μ^* values greater than 1000 in all Weather Locations except for Chongjin, which has an absolute mean of 312.2. The other variables that have absolute mean values much greater than 75 are the changes in Cooling and Heating setpoints, the Door Opening Events per Person, and the People Activity Level, X4, X5, X6, and X9 respectively. These parameters consistently have μ^* values greater than 100 in the TM60 shelter, except for the People Activity Level in Kharga and Chongjin and the Heating Setpoint in Singapore.

Figures 61, 64, and 67 in Appendix A show the Morris Method Scatter Plots for the TM60 shelter in Kharga, Chongjin, and Singapore and Figures 62, 65, and 68 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 36, 37, and 38, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, with the Number of People and the Building Rotation also on the order of 10^3 in Kharga. The Number of People and the Door Opening per Person are all also

consistently dependent on other parameters, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent in warmer climates such as Kharga and Singapore and the Heating Setpoint being dependent in Chongjin.

4.2.6 HDT Base X203 Sensitivity Study

This section presents the results of the HDT Base X203 shelter's sensitivity analyses. Figure 16 displays the HDT Base X203 shelter OSM and Table 14 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 7.

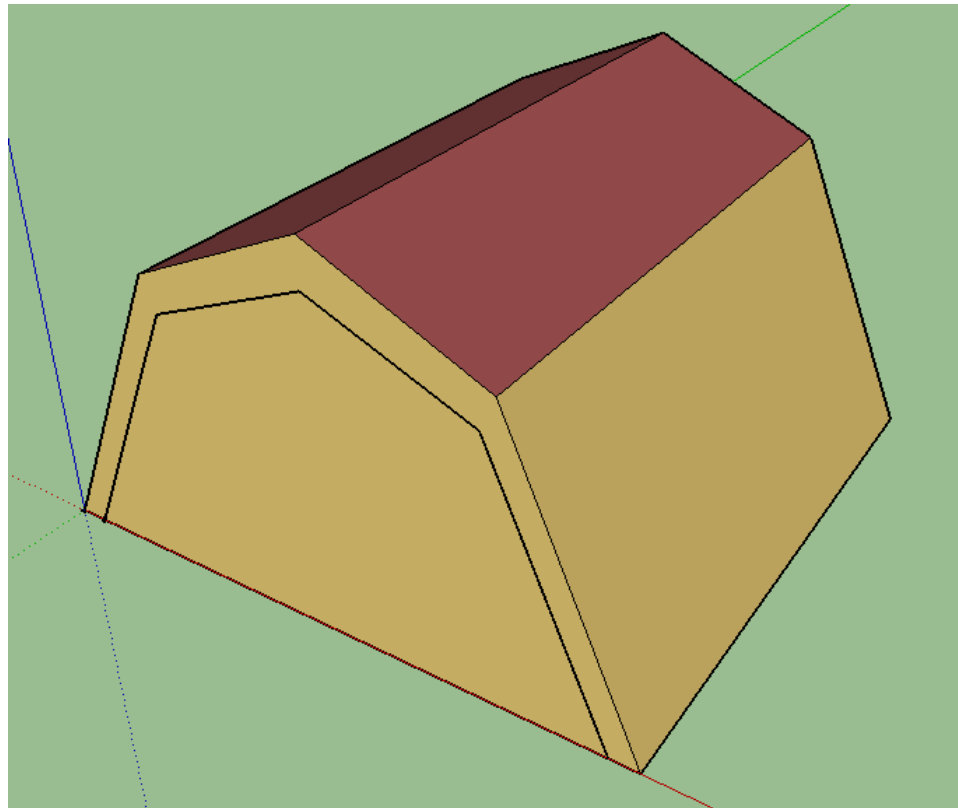


Figure 16 - HDT Base X203 Shelter OSM

Table 14 - HDT Base X203 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X7	X3	X3
4	X3	X6	X6
5	X6	X5	X4
6	X4	X4	X9
7	X9	X9	X7
8	X8	X7	

The variables presented in Table 14 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the Base X203 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 6100, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 39, 40, and 41 in Appendix A. The Number of People also has μ^* values greater than 2000 in all Weather Locations except for Chongjin, which has an absolute

mean of 664.7. Most other variables have absolute mean values greater than 75 except for the Heating Setpoint in Singapore and Kharga and the Building Rotation in Chongjin.

Figures 70, 73, and 76 in Appendix A show the Morris Method Scatter Plots for the X203 shelter in Kharga, Chongjin, and Singapore and Figures 71, 74, and 77 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 39, 40, and 41, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, with the Door Pressure Gap, the Door Opening per Person, the Number of People, and the Cooling Setpoint also being on that order in Singapore and Kharga. The only parameters that are not dependent are the Heating Setpoints in Kharga and Singapore, the Building Rotation in Chongjin and Singapore, and the Door Pressure Gap in Singapore. All of these parameters have dependencies less than 100.

4.2.7 HDT Base X305 Sensitivity Study

This section presents the results of the HDT Base X305 shelter's sensitivity analyses. Figure 17 shows the HDT Base X305 shelter OSM and Table 15 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

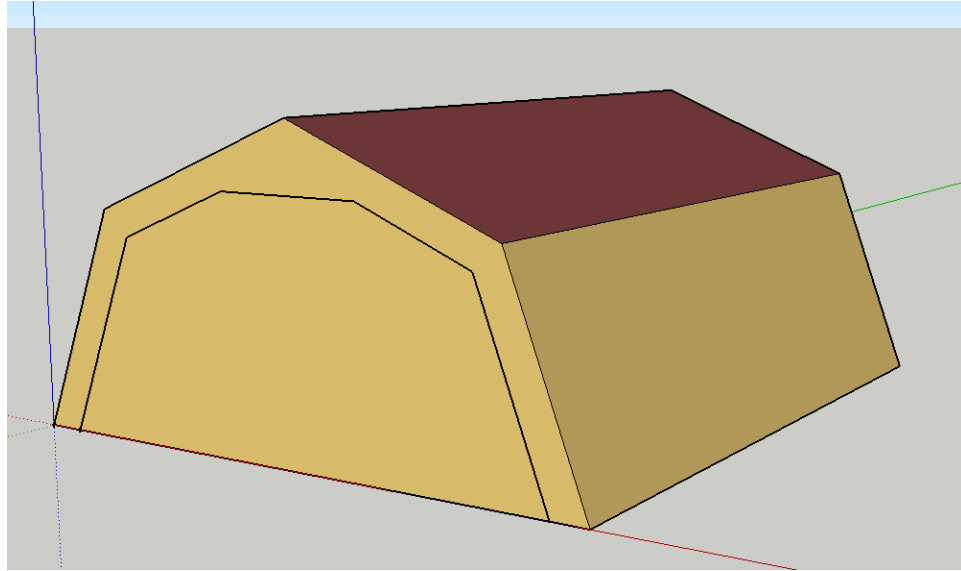


Figure 17 - HDT Base X305 Shelter OSM

Table 15 - HDT Base X305 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X3	X4
5	X9	X5	X6
6	X6	X4	X9
7	X8		
8			

The variables presented in Table 15 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the Base X305 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 3000, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 42, 43, and 44 in Appendix A. The Number of People also has μ^* values greater than 700 in all Weather Locations except for Chongjin, which has an absolute mean of 239.53. Most other variables have absolute mean values greater than 75 except for the Building Rotation in all Chongjin and Singapore, the Pressure Gap Across the Door in all Weather Location, and changes in Heating Setpoint in Singapore and Kharga.

Figures 79, 81, and 85 in Appendix A show the Morris Method Scatter Plots for the X305 shelter in Kharga, Chongjin, and Singapore and Figures 80, 83, and 86 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 42, 43, and 44, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People, the Door Opening per Person, and the People Activity Level are all also consistently dependent on other parameters, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent in warmer climates

such as Kharga and Singapore and the Heating Setpoint is dependent in Chongjin. The Building Rotation parameter is also dependent in Kharga.

4.2.8 HDT Base X307 Sensitivity Study

This section presents the results of the HDT Base X307 shelter's sensitivity analyses. Figure 18 shows the HDT Base X307 shelter OSM and Table 16 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

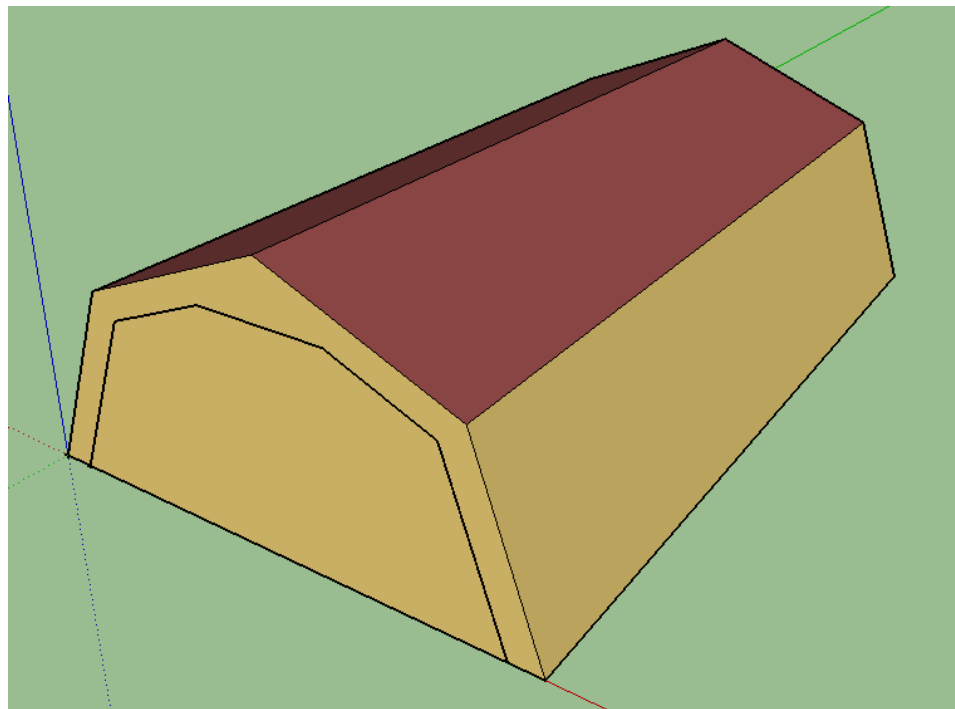


Figure 18 - HDT Base X307 Shelter OSM

Table 16 - HDT Base X307 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X3	X4
5	X9	X5	X6
6	X6	X4	X9
7	X8		
8			

The variables presented in Table 16 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the Base X307 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 2800, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 45, 46, and 47 in Appendix A. The Number of People also has μ^* values greater than 1000 in Singapore; in Kharga and Chongjin, the Number of People has a μ^* value of 742.45 and 239.53. Most other variables have absolute mean values greater than

75 except for the Building Rotation in all Weather Locations, the Pressure Gap Across the Door in all Weather Locations, the changes in Heating Setpoint in Singapore, and the People Activity Level in Chongjin.

Figures 88, 91, and 94 in Appendix A show the Morris Method Scatter Plots for the X307 shelter in Kharga, Chongjin, and Singapore and Figures 89, 92, and 95 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 45, 46, and 47, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People is consistently dependent on other parameters across all Weather Locations, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent in warmer climates such as Kharga and Singapore and the Heating Setpoint is dependent in Chongjin. The Door Opening per Person is dependent on the order of 10^2 in Chongjin and Singapore and the People Activity Level is dependent on that order in Singapore.

4.2.9 HDT Base X6D31 Sensitivity Study

This section presents the results of the HDT Base X6D31 shelter's sensitivity analyses. Figure 19 displays the HDT Base X6D31 shelter OSM and Table 17 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

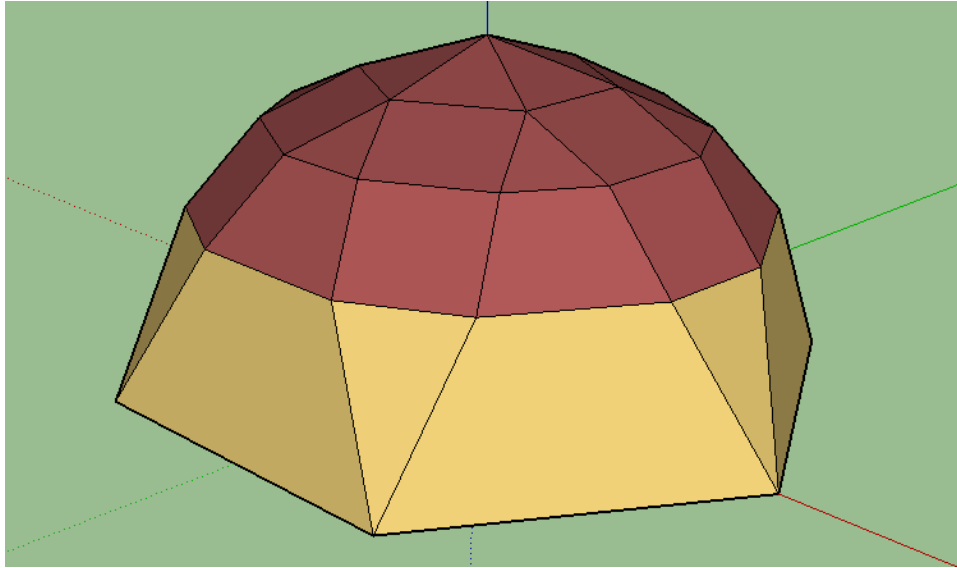


Figure 19 - HDT Base X6D31 Shelter OSM

Table 17 - HDT Base X6D31 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X3	X4
5	X5	X5	X6
6	X9	X4	X9
7			
8			

The variables presented in Table 17 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the Base X6D31 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 2200, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 48, 49, and 50 in Appendix A. The Number of People also has μ^* values greater than 1000 in Singapore; in Kharga and Chongjin, the Number of People has a μ^* value of 861.47 and 221.65 respectively. Most other variables have absolute mean values greater than 75 except for the Building Rotation in all Weather Locations, the Pressure Gap Across the Door in all Weather Locations, the changes in Heating Setpoint in Singapore, and the People Activity Level in all Weather Locations.

Figures 97, 100, and 103 in Appendix A show the Morris Method Scatter Plots for the X6D36 shelter in Kharga, Chongjin, and Singapore and Figures 98, 101, and 104 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 48, 49, and 50, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Cooling and the Heating Setpoints are also dependent on that magnitude in Kharga. The Number of People is also dependent on other parameters across all

Weather Locations, with dependency values on the order of 10^2 . The People Activity Level is also dependent in Kharga and Singapore, the Door Opening per Person is dependent in Chongjin and Singapore, and the Cooling Setpoint is also dependent in warmer climates such as Kharga and Singapore.

4.2.10 HDT Base X8D36 Sensitivity Study

This section presents the results of the HDT Base X8D36 shelter's sensitivity analyses. The HDT Base X8D36 shelter OSM is shown in Figure 20 and Table 18 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

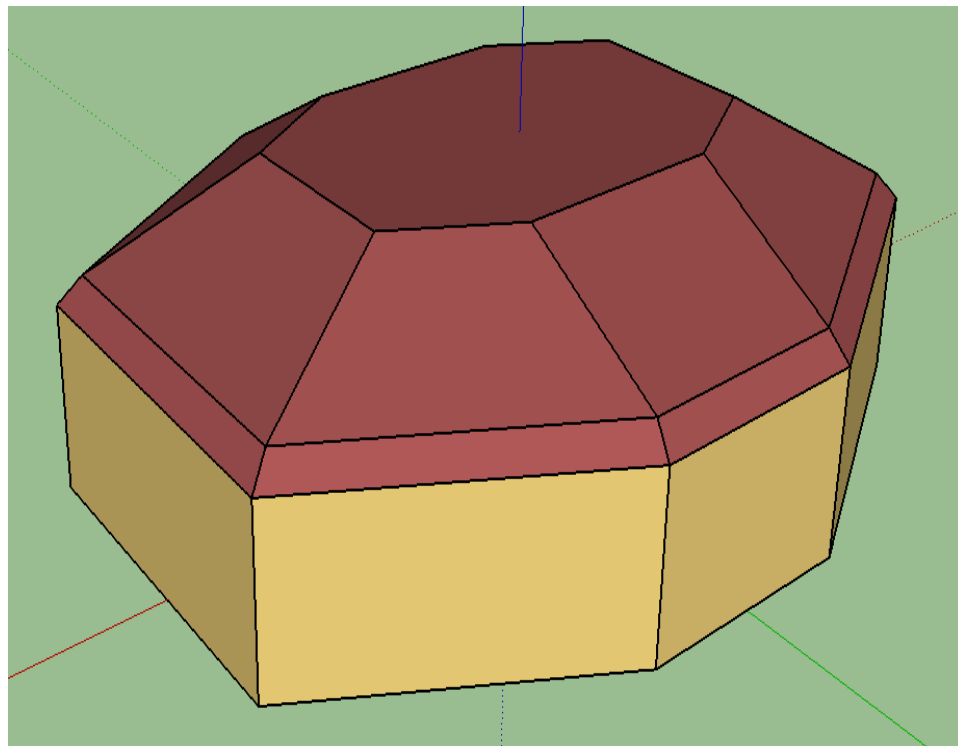


Figure 20 - HDT Base X8D36 Shelter OSM

Table 18 - HDT Base X8D36 Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X6	X3
4	X4	X5	X4
5		X3	X6
6			X9
7			
8			

The variables presented in Table 18 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the Base X8D36 shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 2200, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 51, 52, and 53 in Appendix A. Most other variables have absolute mean values greater than 75 except for the Building Rotation in all Weather Locations, the Pressure Gap Across the Door in all Weather Locations, the changes in Heating Setpoint in

Singapore, and the People Activity Level in all Weather Locations except for Singapore, and the Door Opening per Person for Kharga.

Figures 106, 109, and 112 in Appendix A show the Morris Method Scatter Plots for the X8D36 shelter in Kharga, Chongjin, and Singapore and Figures 107, 110, and 113 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 51, 52, and 53, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People is also dependent on other parameters across all Weather Locations, with dependency values on the order of 10^2 as well as the Door Opening per Person in Chongjin and Singapore.

4.2.11 Eureka MGPTS-M Sensitivity Study

This section presents the results of the Eureka MGPTS-L shelter's sensitivity analyses. The Eureka MGPTS-M shelter OSM is displayed in Figure 21 and Table 19 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

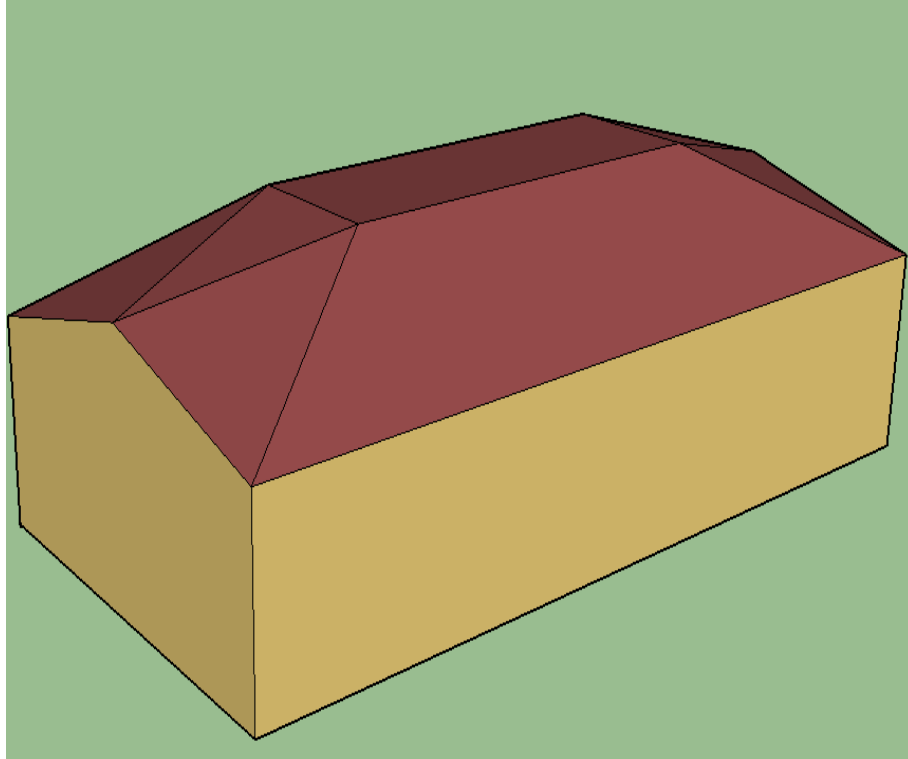


Figure 21 - Eureka MGPTS-M Shelter OSM

Table 19 - Eureka MGPTS-M Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X2
2	X2	X2	X1
3	X3	X5	X5
4	X4	X6	X3
5	X9	X3	X4
6	X6	X4	X6
7			X9
8			

The variables presented in Table 19 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the MGPTS-M shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 3200, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 54, 55, and 56 in Appendix A. This is also the only shelter where the Internal Load is not the most sensitive variable. The ECU is the most sensitive variable having an absolute mean of about 8400 while the Internal Load Level has an absolute value of about 8100. Most other variables have absolute mean values greater than 75 except for the Building Rotation in all Weather Locations and the Pressure Gap Across the Door in all Weather Locations.

Figures 115, 118, and 121 in Appendix A show the Morris Method Scatter Plots for the MGPTS-M shelter in Kharga, Chongjin, and Singapore and Figures 116, 119, and 122 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 54, 55, and 56, it can be seen that the Internal Load Level, the ECU, and the Heating Setpoint in Singapore have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People and the

Door Opening per Person are all also dependent on other parameters across all Weather Locations, with dependency values on the order of 10^2 . The Cooling Setpoint is also dependent in warmer climates such as Kharga and Singapore and the Heating Setpoint is dependent in Chongjin.

4.2.12 Eureka MGPTS-L Sensitivity Study

This section presents the results of the Eureka MGPTS-L shelter's sensitivity analyses. The Eureka MGPTS-L shelter OSM model is shown in Figure 22 and Table 20 presents the sensitivity results for all three Weather Locations using the Xn nomenclature shown in Table 8.

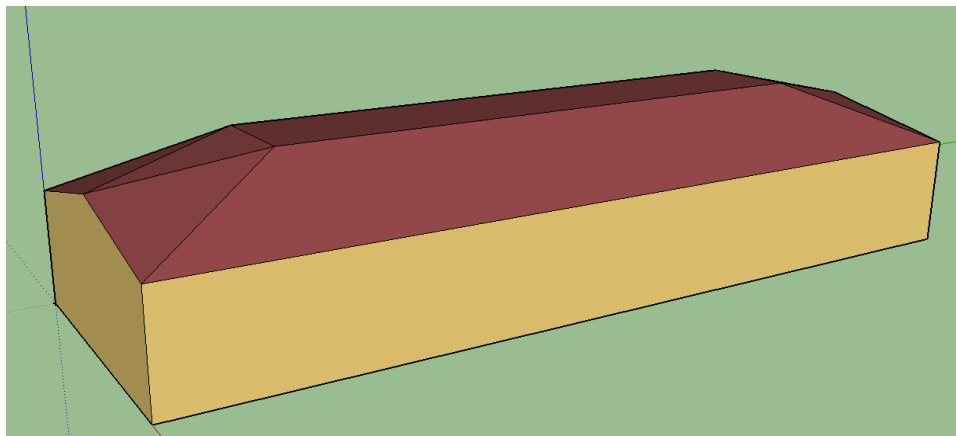


Figure 22 - Eureka MGPTS-L Shelter OSM

Table 20 - Eureka MGPTS-L Sensitive Parameters

Order of Importance	Kharga, Egypt	Chongjin, DPRK	Singapore
1	X1	X1	X1
2	X2	X2	X2
3	X3	X5	X3
4	X4	X6	X4
5	X5	X3	X6
6			X9
7			
8			

The variables presented in Table 20 show all of the variables that have absolute mean, μ^* , values greater than 75. From these results, the three most important, most sensitive, parameters for the MGPTS-L shelter are The Internal Load Level, the ECU/HVAC System, and the Number of People, X1, X2, and X3 respectively. Both the Internal Load Level and the ECU/HVAC System also have μ^* values that are an order of magnitude greater than the rest of the parameters, with values upward of 2700, compared to the values for the other variables which have values on the order of 10 to 10^2 , as seen in Tables 57, 58, and 59 in Appendix A. Most other variables have absolute mean values greater than 75 except for the Building Rotation in all Weather Locations, the Pressure Gap Across the Door in all Weather Locations, the People Activity Level in Kharga and

Chongjin, the Door Opening per Person in Kharga, the change in Heating Setpoint in Singapore, and the change in Cooling Setpoint in Chongjin.

Figures 124, 127, and 130 in Appendix A show the Morris Method Scatter Plots for the MGPTS-L shelter in Kharga, Chongjin, and Singapore and Figures 125, 128, and 131 in Appendix A show detailed views of the Morris Method Scatter Plot, focusing on the parameters that have a lower μ^* and lower σ values.

From these figures, as well as Tables 57, 58, and 59, it can be seen that the Internal Load Level and the ECU have high dependencies on other inputs, on the order of 10^3 or more, whereas the other parameters have relatively low dependencies on other parameters. The Number of People, the Door Opening per Person in Chongjin and Singapore, and the Cooling Setpoint in Singapore are all also dependent on other parameters, with dependency values on the order of 10^2 .

4.2.13 Morris Method Sensitivity Study Conclusions

From the results of the Morris Method studies it can be seen that the two most important variables that occurred consistently across all shelters are the Internal Load Level, the ECU/HVAC System, and the Number of People. In all or most cases, these parameters were at least an order of magnitude higher than the cut-off of 75 to determine if the parameter is sensitive or not. The next most sensitive variables are the Cooling Setpoint in Hot or Hot-Humid climates, Kharga and Singapore respectively, and the Heating Setpoint in Cold Climates, such as Chongjin. Other than those parameters, the Door Opening Events per Person, Building Rotation, and the People Activity Level are occasionally sensitive. The Pressure Gap Across the Door is also occasionally sensitive.

Due to these occurrences, it is important to vary the Internal Load Level, the ECU and the Number of People during the Sampling Study due to their high sensitivities. The People Activity Level, due to being closely related to the Number of People, should also be varied. Due to the sensitivity of the Cooling and Heating Setpoints it is also important to vary those parameters during a Sampling Study. Due to the occasional sensitivity of the Door Opening Events per Person, the Pressure Gap Across the Door, and the Building Rotation, these parameters are important to model correctly, but not necessarily important to vary during a Sampling Study. The Morris Method Study also shows that the Internal Load Level and the ECU are the two factors that have the most dependency on other variables. The study also shows that there is a correlation between shelter size and the dependency of parameters. The smaller shelters, such as the MILVAN and the Base X203 shelters, have more parameters with high dependency values as well as higher dependency values. This trend is also present in the sensitivity of the variables, where the smaller shelters have more sensitive parameters and higher sensitivities. This Sensitivity Study also demonstrates that the Morris Method Workflow was developed properly and is robust enough to handle a multiple analysis study along with a wide variety of Shelters, ECUs, and Internal Load Level types.

4.3 Sobol Sensitivity Study Results

This section presents the results of the Sobol Sensitivity study for the 12 shelters using the Kharga weather location. The 12 analyses used the same nine parameters being varied as in the Morris Method Sensitivity Study, shown in Table 7. The results of this study as described in Section 4.1 are shown in Table 21 below. The LHS Workflow was used to generate 200 data points to input into the Sobol Analysis. If the Sobol Analysis

converged using the 200 data points, then the analysis would be considered successful. Table 21 shows whether the analysis converged with the given 200 data points and what the average run time per data point, up until the 200th data point. The average run time is rounded to the nearest whole number.

Table 21 - Sobol Sensitivity Study Results

Shelter	Converged or Not within 200 Data Points	Average Run Time per Data Point [seconds]
HDT Airbeam	Did Not Converge	340
B-Hut	Did Not Converge	445
MILVAN	Did Not Converge	265
HDT ArctiX	Did Not Converge	308
Utilis TM60	Did Not Converge	339
HDT Base X203	Did Not Converge	302
HDT Base X305	Did Not Converge	312
HDT Base X307	Did Not Converge	331
HDT Base X6D31	Did Not Converge	333
HDT Base X8D36	Did Not Converge	465
Eureka MGPTS-M	Did Not Converge	427
Eureka MGPTS-L	Did Not Converge	470

Based on the results shown in Table 21, it can concluded that the Sobol Sensitivity analysis is not as cost effective as the Morris Method for running sensitivity analyses for military shelter modelling efforts, For each shelter model, the Sobol Analysis took more

than 200 data points to complete. Based on the structure of the Sobol Method, the Sobol Method will in most situations take more data points to run than the Morris Method, unless if the Sobol Method was bounded with more assumptions between the inputs and outputs of the model. The Average Run Time per Data Point is also comparable to that of the Morris Method analyses where the Average Run Time per Data Point was between 300 – 500 seconds. Based on those two metrics, the Sobol Method is not as cost effective as the Morris Method for military shelter analyses, and for the purposes of the ERPT, is not the desired method to use for outpost model generation.

To analyse the results of a Sobol Method analysis, a larger LHS analysis was run to input enough data for the Sobol Method to converge. The LHS Workflow was run with 20,000 data points, which provided the Sobol Method with a large enough data set for convergence. This analysis was run with the HDT Airbeam shelter in Kharga, Egypt. The LHS Workflow was run with all nine parameters being varied with the uniform distributions presented in Table 6. As described in Section 3.2.3, the sensitivity of parameters is measured by the Total Order and First Order Sobol Indices. The First and Total Sobol Indices are presented in Table 22. The values shown in Table 22 are rounded to the nearest hundredth.

Table 22 - HDT Airbeam Sobol Method Results

Parameter	First Order	Total Order
Internal Load Level	0.31	0.43
ECU	0.20	0.31
Number of People	0.06	0.07
Adjust Cooling Setpoint	0.05	0.06
Adjust Heating Setpoint	0.04	0.05
Door Opening Event Per Person	0.03	0.04
Pressure Gap Across Door	0.00	0.00
Building Rotation	0.01	0.01
People Activity Level	0.04	0.04

For this study, a Total Sobol Index value of 0.05 was used to determine if a parameter is sensitive, due to the complexity involved in a building energy simulation [33]. From this analysis, the Internal Load Level, the ECU, the Number of People, and the Cooling and Heating Setpoints were found to be sensitive. These parameters were also determined to be sensitive based on the Morris Method analysis presented in Section 4.2.1. The Morris Method analysis although found the People Activity Level and the Door Opening Event per Person to also be sensitive while the Sobol Method did not find them to be sensitive, based on the 0.05 metric. The sensitivities of the Internal Load Level and the ECU are also at least an order of magnitude greater than the sensitivities of the other parameters, similar to the Morris Method where the sensitivities were at least on

the order of 10^3 . The Sobol Method also yielded similar results as the Morris Method provided based on the order of importance of the parameters.

4.4 Summary

This thesis performed two different Sensitivity Studies, a study using the Morris Method and a study using the Sobol Method. The Morris Method study was performed on every Shelter in each of the three weather conditions. From the Morris Method study, the Internal Load Level and the ECU are the two most sensitive variables along with being the variables that have the highest dependencies on the other variables. These parameters had absolute means and standard deviations, for the EEs, on the order of 10^3 or greater. The other variables such as the Number of People, Cooling and Heating Setpoints, Door Opening Event per Person, Pressure Gap Across Door, Building Rotation, and People Activity Level, were occasionally sensitive and dependent on other variables in certain Shelter/Weather Location combinations, and usually having absolute mean and standard deviation values on the order of 10^2 . The study also revealed a correlation between shelter size and parameter sensitivity and dependency, where smaller shelters had more parameters being sensitive and dependent with higher absolute means and standard deviations. The Morris Method study also successfully informed which input parameters to use for the Sampling Study along with demonstrating the successful operation of the Morris Method Workflow.

The Sobol Method study was performed to evaluate the performance of the Morris Method, to see if the Morris Method was the best, most cost effective method to use to perform the sensitivity study. The Sobol Method study was performed on a smaller set of

conditions than the Morris Method study. The Sobol Method was only performed on each shelter using the Kharga, Egypt weather location, a set of 12 different conditions. In the study, it was shown that none of the 12 analyses converged using the Sobol Method using the same amount of computing power, measured by data points generated. The additional study performed on the HDT Airbeam shelter in Kharga, Egypt also yielded similar results as the comparable Morris Method analysis, although at 100 times the computing cost. This study shows that for performing sensitivity studies for military shelter energy modelling, the Morris Method is a more cost effective method to use.

CHAPTER 5. SAMPLING STUDY RESULTS

In this chapter, the results of the full Sampling Study, for all 12 shelters across all three weather locations are described. The chapter is divided into three sections, an overview and background section, a results section, a Quality Assurance/Quality Control (QA/QC) Documentation section, and a summary section. The overview section reiterates the premise and motivation for the Sampling Study. The results section describes the setup of the sampling study, the inputs to the analyses, and the results of the study. The QA/QC Documentation describes a QA/QC R/CRAN documentation script developed for this thesis. The final section summarizes the contents of this chapter.

5.1 Sampling Study Overview

The primary objective of the Sampling Study is the same as the primary objective of the project: to simulate enough military outpost shelter energy models to populate an Energy Resource Planning Tool (ERPT) currently being developed through the collaborative EEOMC effort. The Sensitivity Study, generating only 200 data points per simulation does not generate enough data for a full population of the ERPT. At only 200 data points per simulation, the Sensitivity Study only generated 7,200 outpost data points, which is not enough for a full population. For this reason, the Sensitivity Study was primarily used to identify the sensitive variables that need to be focused on during a Sampling Study. These variables were then used by the Latin Hypercube Sampling (LHS) Method to fully populate the DEnCity Database, and then have that data run through a Random Forest Regression analysis to extrapolate the characteristics of a full population of shelter characteristics, which will then be uploaded into the ERPT.

5.2 Sampling Study Results

The Sampling Study was conducted for the combinations of all 12 shelters, presented in Table 1, and the three Weather Locations, presented in Section 2.2.4. Similar to the Sensitivity Study, there were 36 LHS analyses run for the Sampling Study. Unlike the Sensitivity Study though, the Sampling Study varied less than nine parameters. These parameters were determined based on the sensitive parameters discovered in the Sensitivity Study along with consultation with NREL. The five parameters were varied following a uniform distribution that was created based on the potential values that each parameter could have. The uniform distribution is defined by a static value, minimum value, mean of the potential values, and the standard deviation of the potential values. The five parameters and their uniform distribution characteristics are displayed in Table 22 below.

Table 23 - Latin Hypercube Sampling Parameter Distributions

Parameter Name	Variable Name	Static Value	Minimum Value	Maximum Value	Mean	Standard Deviation
Internal Load Level	standard_osc	3	0	4.33	2.165	1
ECU	hvacsystem	0	0	0.999	0.5	1.0
Number of People	peak_occupancy	12	0	32	17	14
Building Rotation	rotations	0	0	315	157.5	110.227
People Activity Level	occupancy_activity	130	100	160	130	1

The Internal Load Level, the ECU, and the Number of People were left as variable in the Sampling Study due to their high sensitivities. The People Activity Level was also left as variable to get a larger range of people load levels. The Building Rotation was left as variable along with being modified to not just have rotation values at every 90 degrees, such as 0, 90, 180, and 270 degrees, but to have rotation values at every 45 degrees, such as 0, 45, 90, 135, 180, 225, 270, and 315 degrees. The parameter distribution for the Building Rotation was based on the new 45 degree consideration. The parameter distribution for the Internal Load Level is based on the value set shown in Table 4, and due to the large variation and distribution in these values, the values were changed to a logarithmic distribution, like in the Sensitivity Study, to reduce the

unnecessary impact of the variable's variation on the TEI. The distribution was changed based on Equation 19. Even though the Cooling Setpoint and Heating Setpoint were determined to be sensitive by the Sensitivity Study, these two parameters were not varied, as requested by NREL. They are kept at 22.9°C and 18.2°C, respectively, as dictated by military heating and ventilation requirements from MIL-STD1472G. The Door Opening Event per Person along with the Pressure Gap Across Door parameters were also kept constant due to their relative insensitivity to the Total Electricity Intensity.

Due to the nature of this study, specifically needing to be compatible with NREL's Random Forest Regression, some of the requirements were based on the needs of Regression analysis. Based on testing performed using the Random Forest Regression, NREL determined that the regression analysis needed 1000 sample data points, outpost models, for every Shelter/Weather Location/ECU combination in order to efficiently model the characteristics of the full population. Based on this requirement, a total of 432,000 outpost model data points were uploaded into the DEnCity Database, 1,000 data points for each combination of 12 Shelter Models, 3 Weather Locations, and 12 ECU models. To effectively upload the necessary data into the DEnCity Database, 36 analyses were performed, one for each Shelter/Weather Location combination. Each one of these analyses were defined to run 12,000 data points, which were evenly divided between the 12 ECU models displayed in Table 2.

The DEnCity Database is established using AWS server instances at <http://52.11.23.255:8080>. The information uploaded into DEnCity includes both time averaged and time-series data. Every data point generated by an analysis is uploaded into DEnCity separately with universally unique identifiers (UUIDs) detailing which analysis

the data point belongs to, as shown in an example image from the DEnCity Database, Figure 23.

DEnCity

Facet

Building Area (m²)
 • 0.0..1000.0 (230)

Buildings

Total Results: 230

Analysis Name	Added	Total Site EUI	Total Source EUI	Actions
Battalion TAC_Airbeam Command HDT	20 days ago	8374.85 MJ/m ²	26523.16 MJ/m ²	Destroy
Battalion TAC_Airbeam Command HDT	20 days ago	10383.88 MJ/m ²	32885.74 MJ/m ²	Destroy
Battalion TAC_Airbeam Command HDT	20 days ago	11289.01 MJ/m ²	35752.3 MJ/m ²	Destroy
Battalion TAC_Airbeam Command HDT	20 days ago	10884.05 MJ/m ²	34469.79 MJ/m ²	Destroy

Figure 23 - Example Population of the DEnCity Database

Each data point contains a unique outpost shelter model simulation, under a certain set of simulation parameters, and the results of the simulation. The simulation results include time averaged information such as the site’s Total Electricity Intensity (TEI), the number of Unmet Heating Hours, and the number of Unmet Cooling Hours. The simulation results also includes time-series data, including time-step electricity demand, ECU power demand, environmental conditions, and Main Occupied Zone Temperature. These metrics serve to populate the DEnCity Database, and through the Random Forrest Regression the ERPT, with information that military FOB designers can use to make engineering decisions based on military and ASHRAE comfort standards in context of what outposts to deploy. [31, 34]

A potential option for running the simulations is one analysis per Shelter model, and varying the 5 parameters along with the Weather Locations. Here, each of the 12 analyses, corresponding to 12 shelters, would have 36,000 data points, leading to 432,000 data points to be uploaded into DEnCity. This option also leads to less time on manual

labor and fewer analyses to run. Unfortunately the implementation of this method caused issues with uploading the data into the DEnCity Database. As the simulation progressed, the simulation time per data point increased, due to server space. Eventually the simulation time increased to the point where data point upload into DEnCity reached the timeout limit, increasing the data loss. With the 12 analysis method, data loss was observed in the 60% to 70% range. With the implementation of the 36 simulation method instead of the 12 simulation method, data loss was observed in the 0.008% to 0.1% range. Data loss on average was close to 0.05%, close to 6 data points, for each of the 36 analyses. In the future, modelling process could be modified to improve the data retention for data upload into DEnCity and to improve the efficiency of the simulation process. Even with this issue, this Sampling Study demonstrated that the LHS Workflow was developed properly and is robust enough to handle a multiple analysis study using a wide variety of Shelters, ECUs, and Internal Load Level types.

5.3 QA/QC Documentation

One of the deliverables for the project involves documenting the different processes, analyses, as well as results of the deliverables for the project, as explained in the Introduction section. One of the documentation deliverables is Quality Assurance/Quality Control (QA/QC) Documentation for the Sensitivity Study. This entailed creating documentation for the processes and components of the Sensitivity Study along with its results. This QA/QC Documentation would then be delivered to the EEOMC and reviewed by the consortium, as shown in the Flow Diagram, Figure 1. The consortium would then use this documentation for further detailed documentation. The structure of the Morris Method Sensitivity Study had a total of 36 sensitivity analyses

being performed, one for each Shelter/Weather Location combination. As dictated by the QA/QC Documentation requirements, each one of these analyses needs their own QA/QC document. This documentation would also have to be easily replicated in the event that more shelters, ECUs, weather locations, or other components are added to the model library residing on the GitHub repository.

Due to the requirements of the QA/QC Documentation and the magnitude of the Morris Method Sensitivity Study, a near-automated documentation process was needed to reduce man-hours spent on the documentation and to make the documentation process easily replicable. In order to automate the documentation process an R/CRAN script was created to generate a knitrBootstrap HTML document. R/CRAN was chosen as the script language due to OpenStudio using R/CRAN packages to perform data analytics. To perform sensitivity analyses, OpenStudio uses the R/CRAN package ‘sensitivity’ which contains a ‘morris’ method function. This allows for an R/CRAN script to easily access the information generated by OpenStudio and perform additional actions on that data. HTML documentation was chosen based on requests from NREL and due to its easily sharable format. knitrBootstrap is a type of documentation style and format within R/CRAN. knitrBootstrap was chosen based on requests from NREL.

This QA/QC Documentation script takes an R Data Frame created during a Morris Method Sensitivity Analysis and reads that data frame. A user has to download the data frame from the OS Server onto a local directory. The user then directs the script to that local directory, runs the script, and then the script reads the EEs calculated by the method and calculates each parameter’s mean, absolute mean, and standard deviation of the EEs. After calculating these values, the script generates the Morris Method Sensitivity Results

Table, shown in Table 10, the Morris Method Bar Plot, shown in Figure 8, the Morris Method Scatter Plot, shown in Figure 10, as well as the Morris Method Scatter Plot Detail View, shown in Figure 11. The script then generates a QA/QC document that details the Morris Method Workflow, the Morris Method, the inputs to the analysis, as well as the results of the Morris Method using the tables and figures generated by the script. The QA/QC Documentation Script can be found in the GitHub repository at the following location:

https://github.com/satishkumar33/Shelter_Corso/blob/master/shelter_modeling/documentation/sensitivity_analysis_reporting_final.Rmd

This QA/QC Documentation script was used to generate 36 sensitivity documents detailing the sensitivity study and its results. This documentation was then sent to NREL and to various EEOMC members for review, critiqued, and then updated based on the modifications requested by NREL and the other EEOMC members. The full documentation was then generated and sent to the EEOMC members, and accepted as fulfilling the documentation requirements, through uploading the documentation into the GitHub repository, as shown in the project flow diagram re-iterated in this section. The documentation can be found at the following location in the GitHub repository:

https://github.com/satishkumar33/Shelter_Corso/blob/master/shelter_modeling/documentation/sensitivity_qaqc_documentation.zip

5.4 Summary

This thesis performed a Sampling Study using the Latin Hypercube Sampling (LHS) Method. The Sampling Study was performed on all 12 shelters in each of the three weather conditions. The input parameters to the Sampling Study were informed by and determined through the results of the Morris Method Sensitivity Study and considering the input from NREL about the data points necessary to perform Regression Analysis. The Sampling Study varied the Internal Load Level, the ECUs, the Number of People, Building Rotation, and the People Activity Level in each of the LHS analyses. The Sampling Study used the LHS Workflow in a method that would generate 1,000 data points per Shelter/Weather Location/EKU combination. The Sampling Study generated 12,000 data points per analysis. With a total of 36 analyses, the Sampling Study generated a total of 432,000 data points, shelter load profiles, and uploaded those data points into the DEnCity Database. NREL has reviewed this data and has determined it has met their needs for serving as an input to their Random Forrest Regression and that the sampling requirement of the project has been fulfilled. The Sampling Study also demonstrated the successful operation and robustness of the LHS Workflow developed for this study.

CHAPTER 6. CONCLUSIONS AND FUTURE WORK

This thesis has refined multiple workflows developed by previous CORSO efforts that have successfully automated the military shelter modelling process using OpenStudio and Energy Plus. The workflows are composed of OpenStudio, EnergyPlus, and Reporting measures that build shelter energy models from an empty seed file to a complete model, run EnergyPlus analyses on those models, use those results for statistical analyses, and upload the data into a database for further analyses. The workflows have also been refined to be able to run on Amazon Web Services servers to improve on analysis run time and improving the connection between the workflows and the DEnCity Database. Twelve Shelter models, twelve Environmental Control Unit models, along with many other energy modelling parameters have successfully been integrated into those workflows.

With the wide variety of inputs, a complete Sensitivity Study has been performed with the results being reviewed and accepted by NREL. This Sensitivity Study determined that the main parameters that affect a shelter's energy consumption are Internal Load Level (electric equipment loads and lighting loads), Environmental Control Units (ECUs), and the Number of People in the shelter. The Cooling and Heating Thermostat Setpoints can also be sensitive depending on the environmental conditions the shelter is exposed to.

Documentation has also been generated for the complete Sensitivity Study and has been reviewed and accepted by NREL. This documentation is currently being reviewed by NSWC Philadelphia. An easy-use, near-automated documentation generation script

was also created for the mass documentation generation the Sensitivity Study required. This documentation script not only assisted in the work in this thesis, but it has also been made available for others to use if the database needs to be expanded in the future. Another available Sensitivity Analysis Method was also used to determine whether the Morris Method was indeed the correct method to use. According to that study, the Morris Method is indeed the most efficient and cost effective method to use. The integration of the inputs has also enabled a full Sampling Study to be performed, uploading 432,000 outpost data points into the DEnCity database. This data has been reviewed and accepted by NREL and is in a proper format for NREL to do the Random Forest Regression and the upload the data into the Energy Resource Planning Tool.

This thesis has also developed a mass-modeling approach that can be mimicked in other types of analyses than just shelter or building energy modeling using OpenStudio and EnergyPlus. For any object oriented modeling program, programmatic workflows can be created using Ruby in order to build a model and run mass analyses with the program, and even run parametric analyses on the models and their inputs. Even if a modeling program is not object oriented, a workflow can still be created to interact with the program with the language that the program is built upon. Instructions can be created to build the model and run analyses on the model. This method can help users run mass simulations varying different model parameters to study the effect of parameters on the model outputs with relatively little manual labor. For example, mass simulations could be run on the thermal dissipation of a heat sink where the length, width, fin height, number of fins, fin material, base material, and other parameters could be varied through a workflow in order to study their effects on the heat dissipation of the heat sink.

6.1 Future Work

Even though the project is in the closing stages, there are plenty of modifications and analyses need to be done in future. The key objective of the Sensitivity Study is to fully identify the sensitivity of all of the potential parameters in the model. Due to the nature of the Constructions measure as well as the nature of soft shelters, the impact of the change in materials and constructions could not be quantified. Future work could be done to refine the shelter models and the measure to be able to quantify the effect of changing shelter constructions. The workflows, in their current state, can also only handle one conditioned space with one environmental control unit, limiting the types of shelters the workflow can model properly. Future work could be done to allow the workflow to consider multiple conditioned spaces with multiple environmental control units.

Future work can also be done to improve the Energy Resource Planning Tool's capabilities by integrating more shelter models, ECU models, weather locations, and internal loads. This could improve the range of data that NREL can provide by modelling the characteristics of the full population of shelters available to the military, improving the ERPT's capabilities. Not only could more components be integrated into the workflows, more data can be collected and statistical analyses can be performed on the input parameters. With further analysis, the parameters themselves can be modeled more accurately instead of using the uniform distribution modeling method. To better model and understand the ECU parameter, modeling efforts can be undertaken to perform sensitivity analyses including the variation of ECU curves. This would allow for the ERPT and the military to model what would happen if an ECU varied from its standard

performance. In case of malfunctions, extreme environmental conditions, or extreme loads inside of the conditioned space, the ERPT could model the energy consumption of the varied ECU performance.

There are also improvements that can be made into running the analyses. Automating the workflows has been discussed with NREL to provide more capabilities for the analyses such as improved data analysis methods and plotting tools. Automating the analyses would also decrease the manual labor involved in running many simulations. There could also be improvements made with the connection between the workflows and DEnCity to decrease data loss in larger simulations in order to increase the amount of data one analysis can provide.

APPENDIX A. SENSITIVITY STUDY DOCUMENTATION

This appendix contains all of the figures and tables referenced by Chapter 4. These figures and tables were generated by the automated documentation script explained in Section 4.4.

Table 24 - Airbeam/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	9251.677	9251.677	17817.52
X2	4914.643	2184.722	6057.427
X3	608.929	608.929	278.649
X4	348.879	-348.879	141.806
X5	148.74	148.74	74.524
X6	129.534	129.534	171.978
X9	95.704	95.704	74.46
X8	57.51	-5.565	81.855
X7	18.988	18.988	16.056

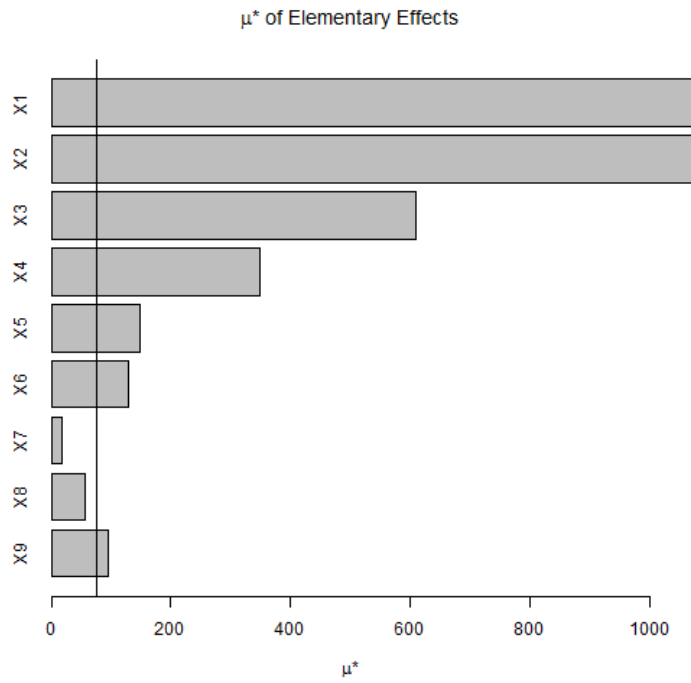


Figure 24 - Airbeam/Kharga Sensitivity Bar Plot

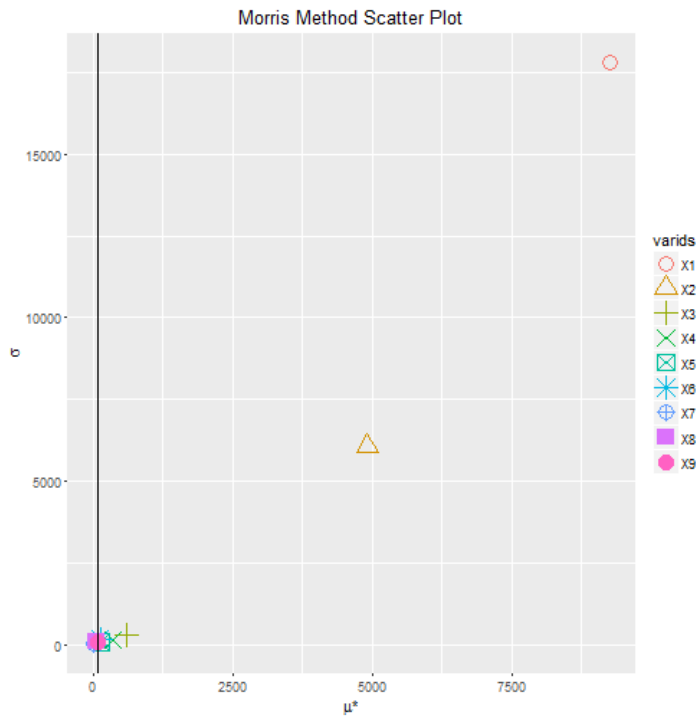


Figure 25 - Airbeam/Kharga Morris Scatter Plot

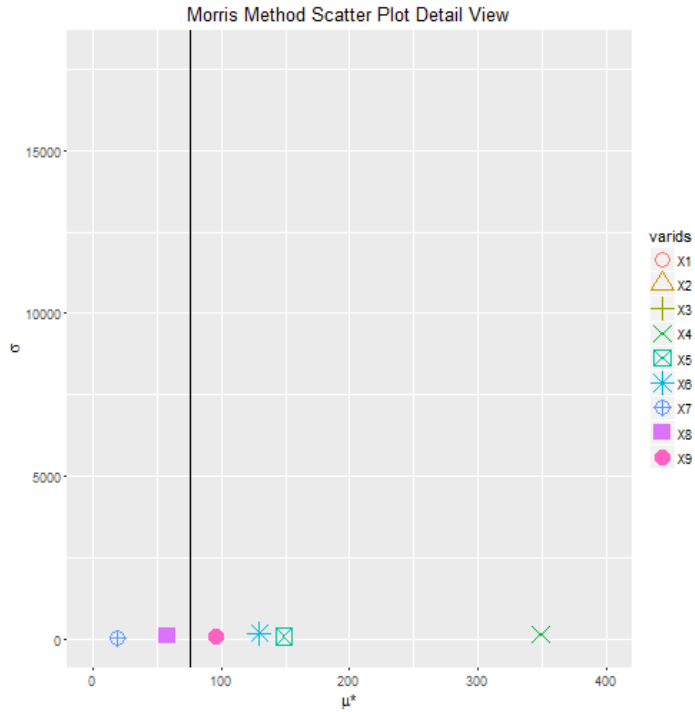


Figure 26 - Airbeam/Kharga Morris Scatter Plot Detail

Table 25 - Airbeam Shelter/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	5826.617	5826.617	12073.42
X2	5069.385	3690.893	7007.944
X5	474.048	474.048	169.532
X6	402.569	402.569	480.002
X3	384.673	-339.494	328.594
X4	106.508	-106.508	57.765
X7	56.528	56.528	50.365
X9	46.597	-30.883	48.064
X8	41.796	-23.681	42.465

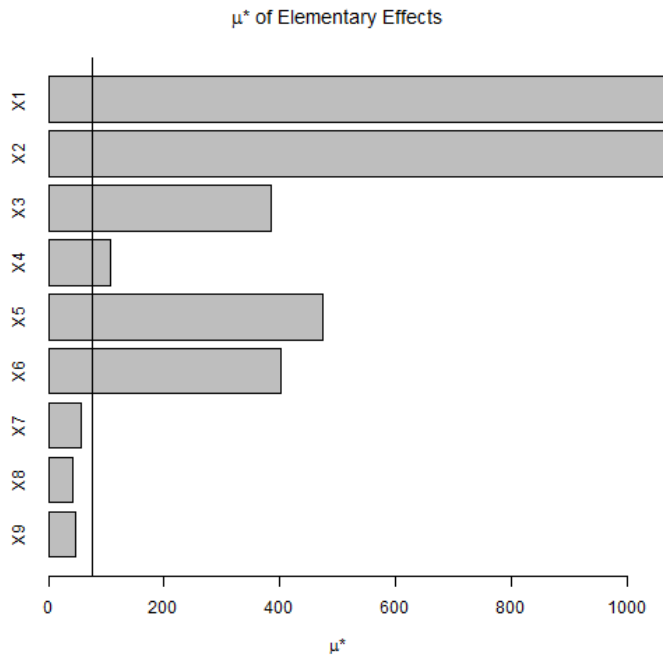


Figure 27 - Airbeam/Chongjin Sensitivity Bar Plot

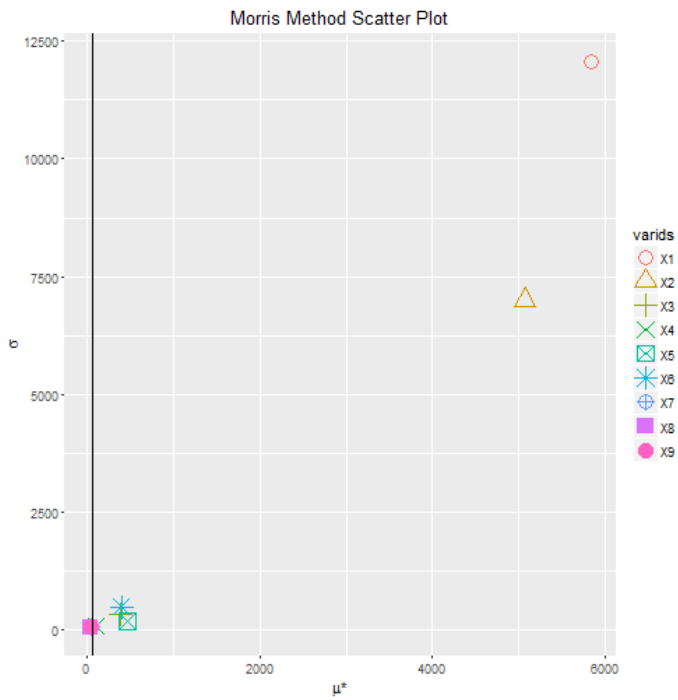


Figure 28 - Airbeam/Chongjin Morris Scatter Plot

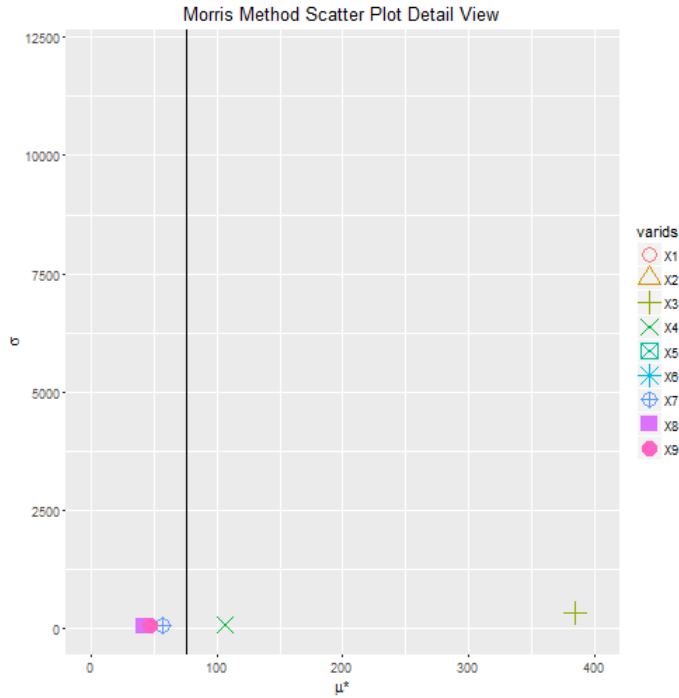


Figure 29 - Airbeam/Chongjin Morris Scatter Plot Detail

Table 26 - Airbeam/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	9865.734	9865.734	18207.666
X2	5363.264	2005.645	7446.33
X3	1410.248	1410.248	504.653
X4	480.704	-480.704	209.296
X6	286.786	286.786	415.849
X9	169.802	169.802	113.204
X7	43.978	43.978	34.006
X8	33.284	-10.804	37.812
X5	0	0	0

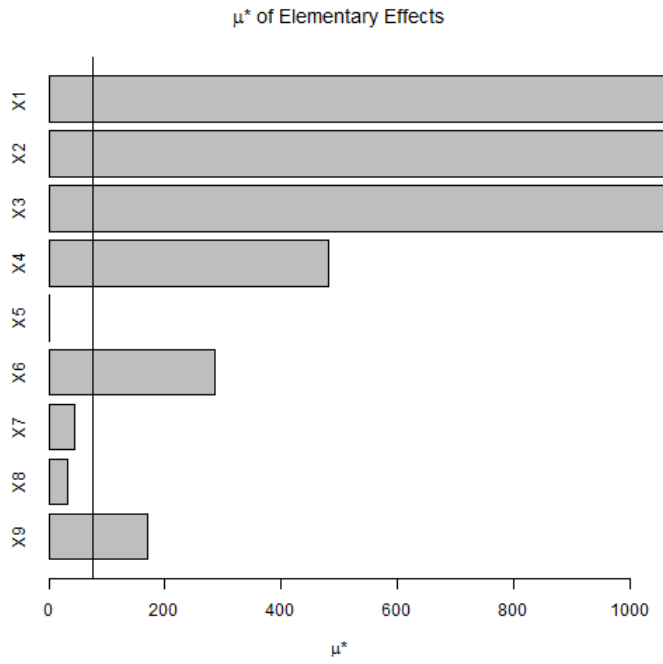


Figure 30 - Airbeam/Singapore Sensitivity Bar Plot

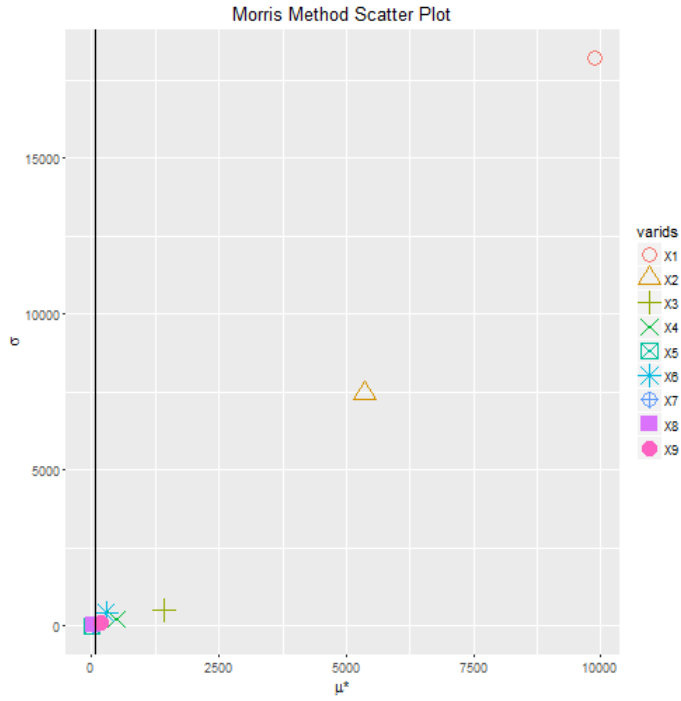


Figure 31 - Airbeam/Singapore Morris Scatter Plot

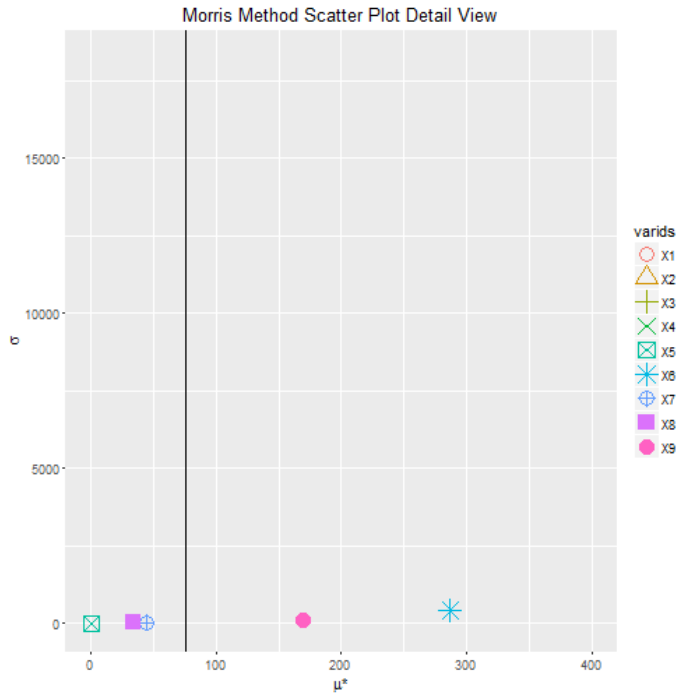


Figure 32- Airbeam/Singapore Morris Scatter Plot Detail

Table 27 - ArctiX/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	17504.396	17504.396	31944.817
X2	6021.17	1338.451	9104.248
X3	1727.19	1727.19	475.238
X4	746.973	-746.973	1712.877
X9	281.603	281.603	195.782
X6	93.372	40.176	121.705
X7	22.692	12.648	27.32
X8	19.53	7.254	20.676
X5	13.392	13.392	18.907

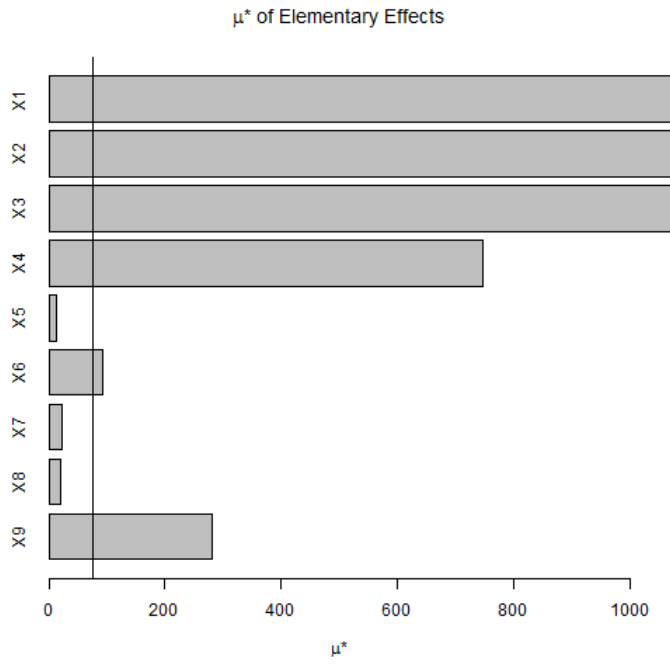


Figure 33 - ArctiX/Kharga Sensitivity Bar Plot

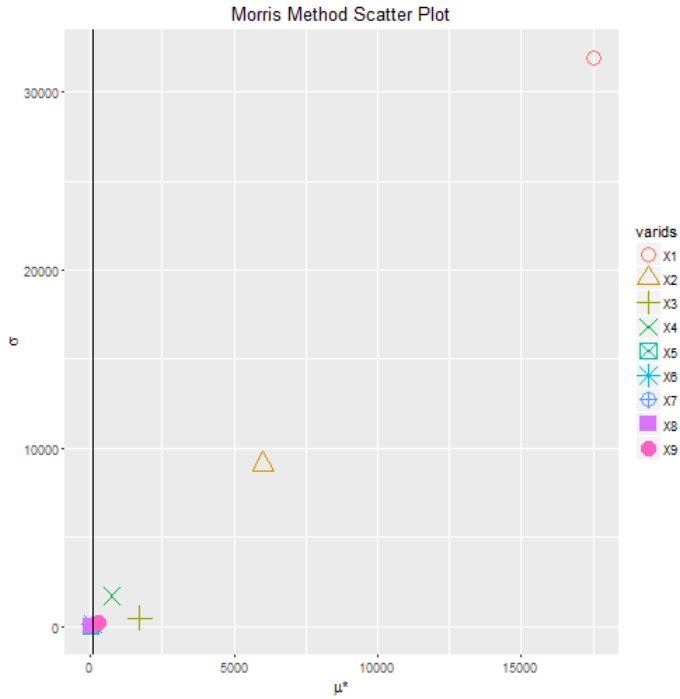


Figure 34 - ArctiX/Kharga Morris Scatter Plot

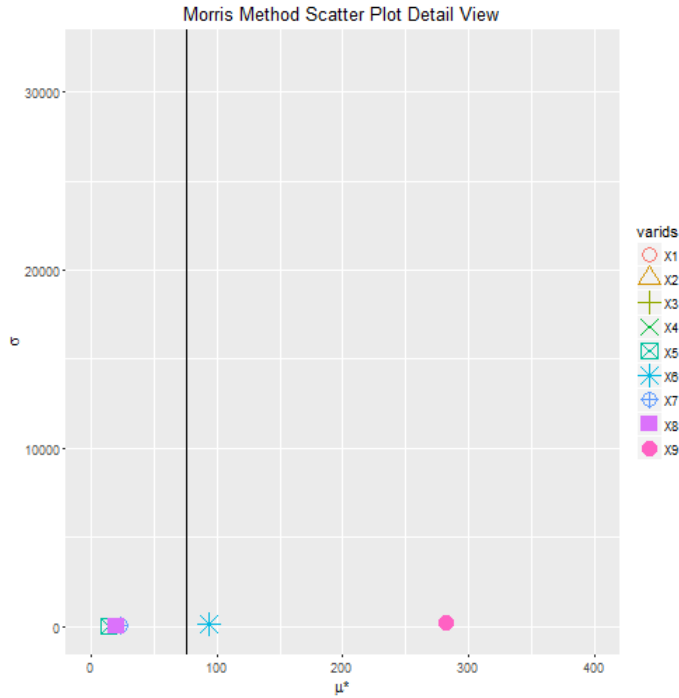


Figure 35 - ArctiX/Kharga Morris Scatter Plot Detail

Table 28 - ArctiX/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	16543.338	16543.338	33004.843
X2	4007.913	248.867	6284.085
X3	448.072	325.685	479.076
X6	348.191	138.383	421.364
X5	173.351	173.351	98.476
X4	163.493	-163.493	92.591
X9	102.672	92.256	152.634
X7	82.584	41.664	99.661
X8	9.3	0.372	10.922

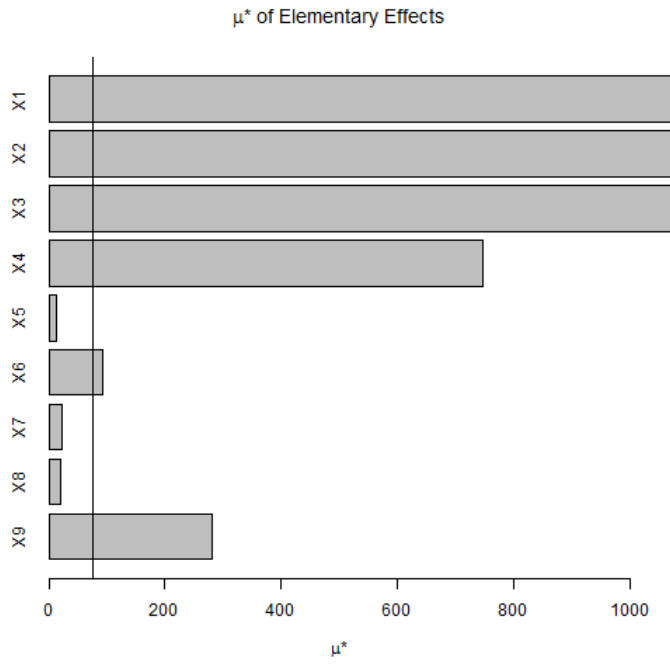


Figure 36 - ArctiX/Chongjin Sensitivity Bar Plot

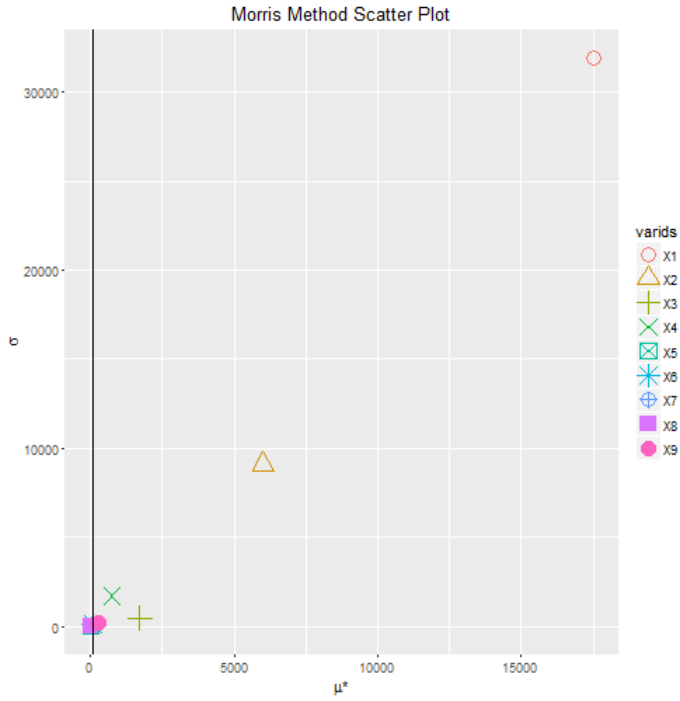


Figure 37 - ArctiX/Chongjin Morris Scatter Plot

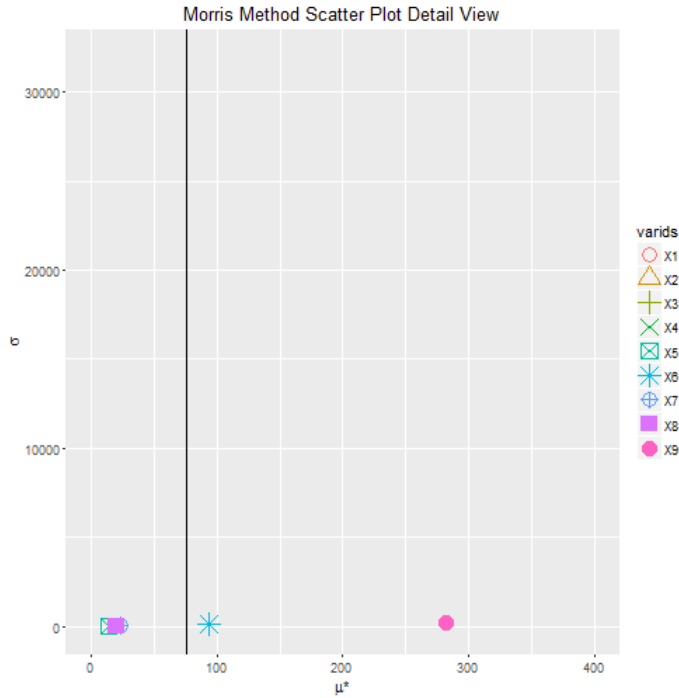


Figure 38 - ArctiX/Chongjin Morris Scatter Plot Detail

Table 29 - ArctiX/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	16837.775	16837.775	31224.584
X2	7148.512	1906.679	10821.198
X3	2453.703	2453.703	779.134
X6	553.906	553.906	772.892
X4	433.378	-433.378	183.494
X9	321.965	321.965	223.634
X7	80.538	80.538	56.819
X8	8.184	-0.744	9.996
X5	0	0	0

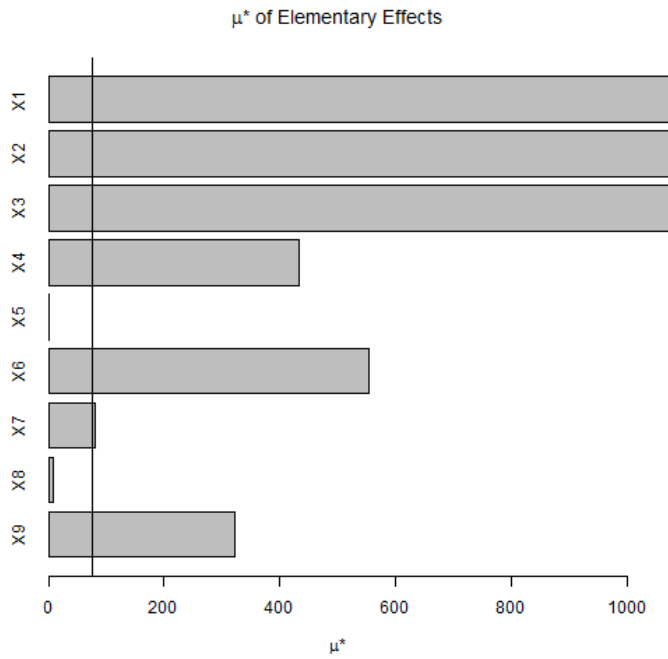


Figure 39 - ArctiX/Singapore Sensitivity Bar Plot

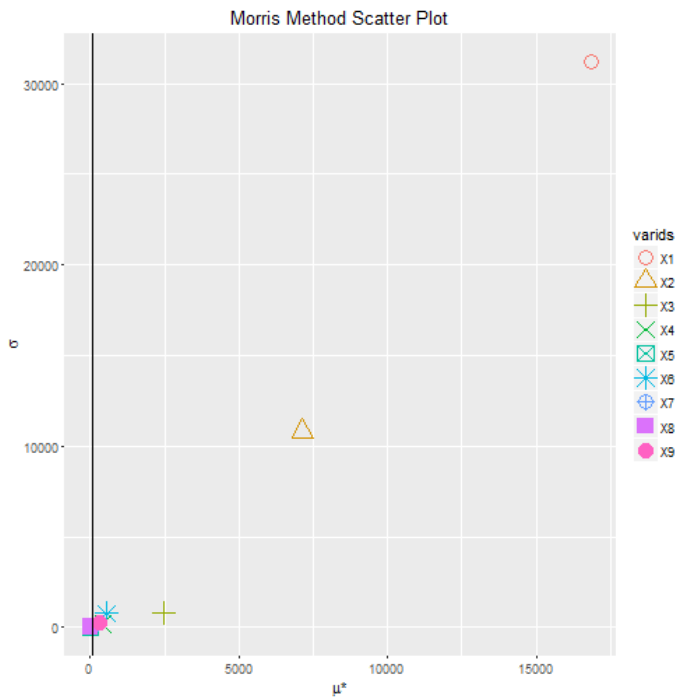


Figure 40 - ArctiX/Singapore Morris Scatter Plot

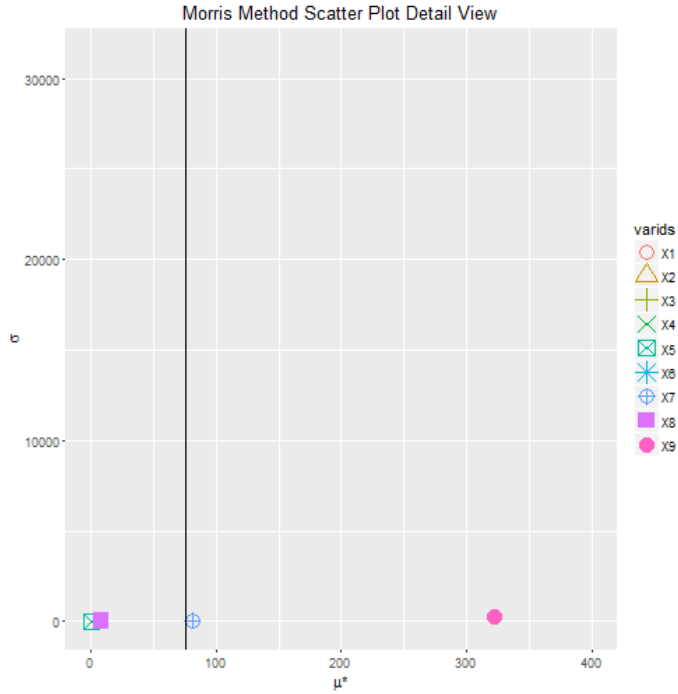


Figure 41 - ArctiX/Singapore Morris Scatter Plot Detail

Table 30 - B-Hut/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	10582.384	10582.384	20439.458
X2	3588.354	1153.185	5101.517
X3	721.926	721.926	349.663
X4	334.024	-334.024	122.987
X6	134.465	132.153	166.343
X9	114.232	114.232	96.102
X5	103.017	103.017	64.199
X8	41.623	-15.262	48.525
X7	22.199	20.349	20.65

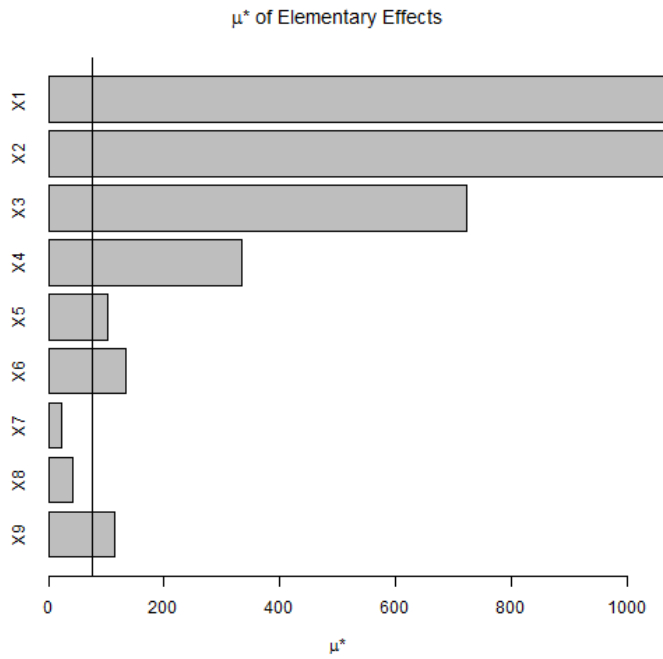


Figure 42 - B-Hut/Kharga Sensitivity Bar Plot

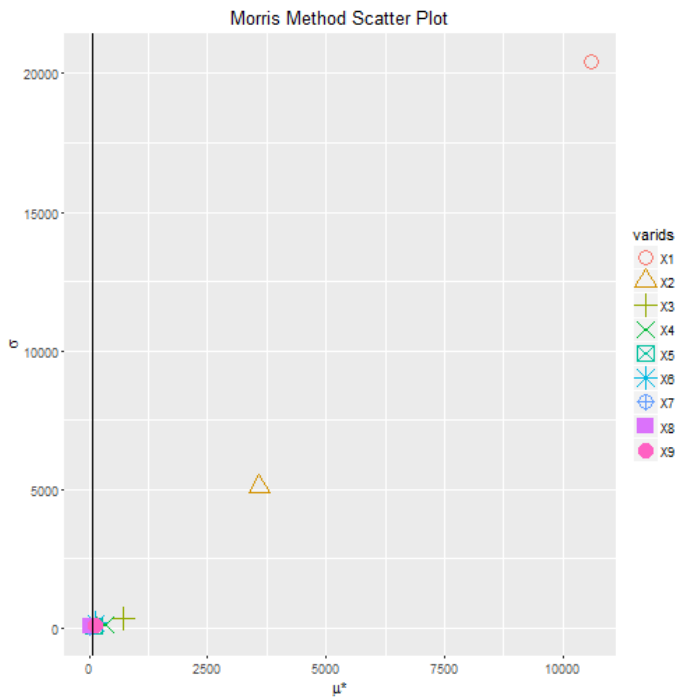


Figure 43 - B-Hut/Kharga Morris Scatter Plot

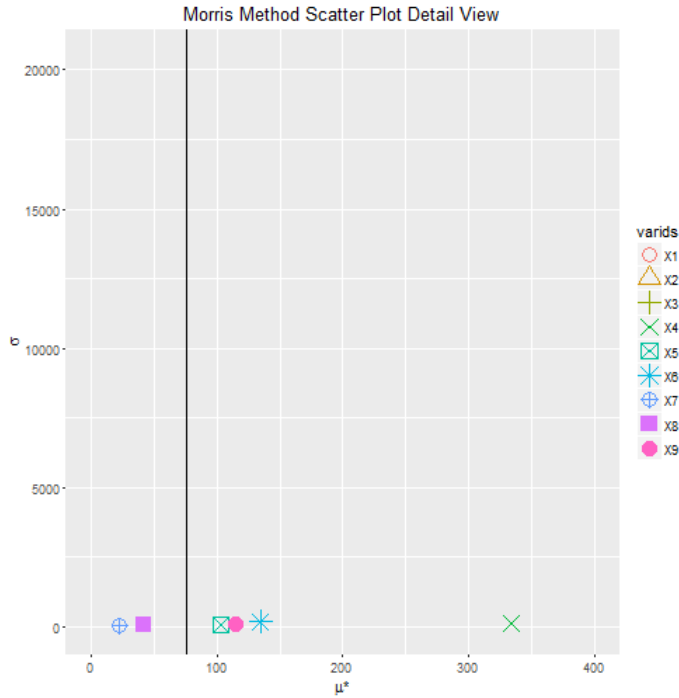


Figure 44 - B-Hut/Kharga Morris Scatter Plot Detail

Table 31 - B-Hut/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	7506.338	7506.338	15974.545
X2	3959.491	2629.872	5664.007
X3	519.477	-410.101	492.042
X6	448.718	448.718	549.101
X5	417.038	417.038	172.82
X4	77.58	-77.58	66.975
X9	68.215	-26.13	86.206
X7	62.666	58.503	61.245
X8	16.302	-8.671	22.393

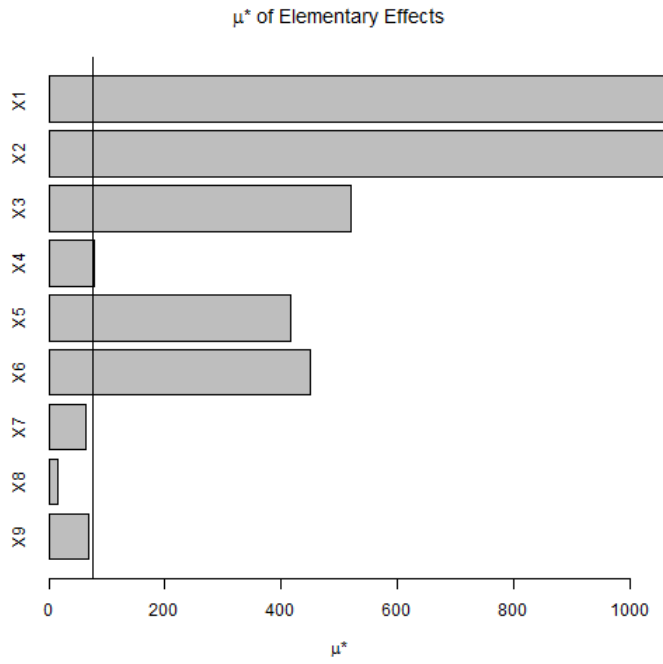


Figure 45 - B-Hut/Chongjin Sensitivity Bar Plot

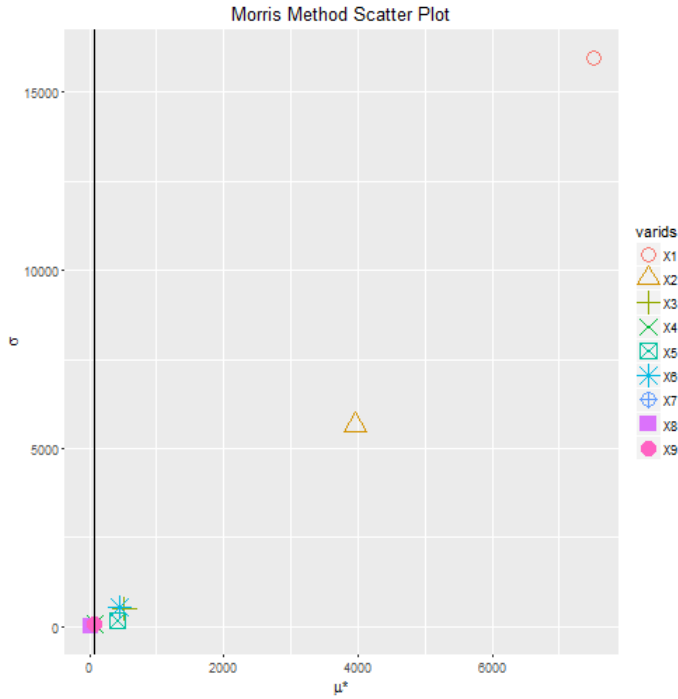


Figure 46 - B-Hut/Chongjin Morris Scatter Plot

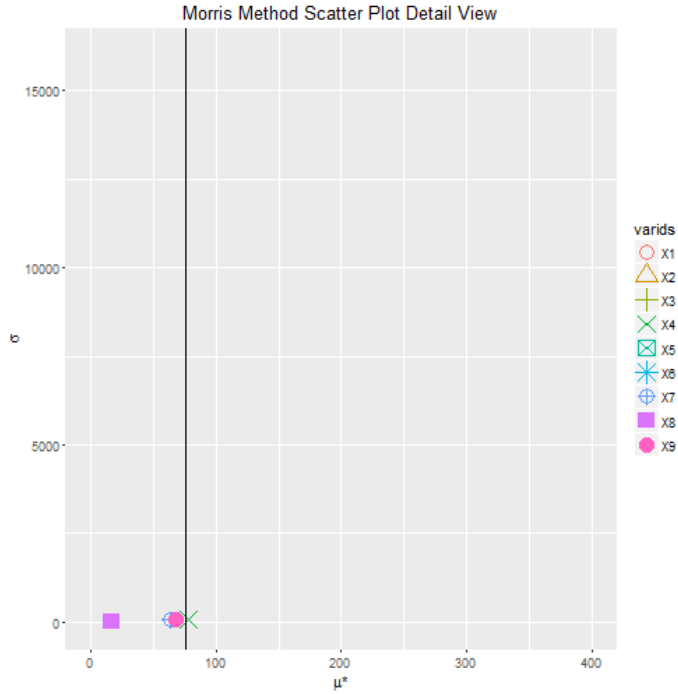


Figure 47 - B-Hut/Chongjin Morris Scatter Plot Detail

Table 32 - B-Hut/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	10949.359	10949.359	20127.46
X2	4089.447	838.238	6411.311
X3	1540.971	1540.971	606.666
X4	484.328	-484.328	172.615
X6	265.115	265.115	358.792
X9	181.984	181.984	143.656
X7	40.467	40.467	32.499
X8	17.458	-4.047	20.393
X5	0.578	0.578	2.585

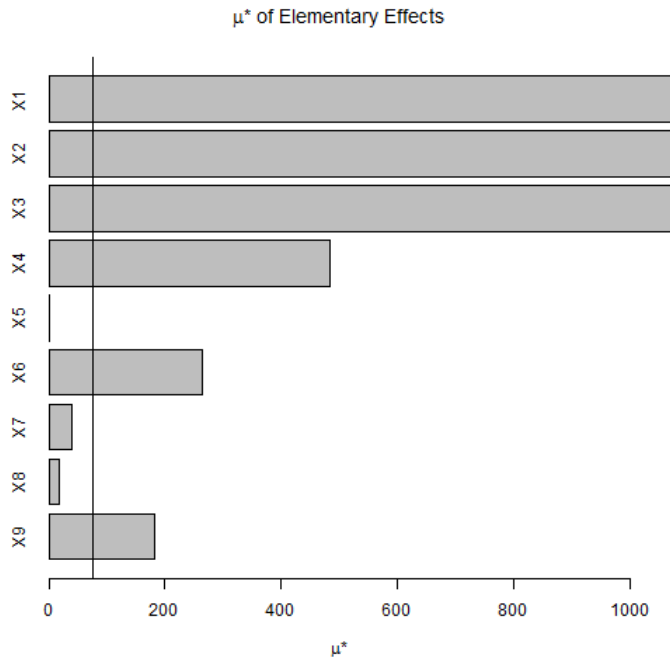


Figure 48 - B-Hut/Singapore Sensitivity Bar Plot

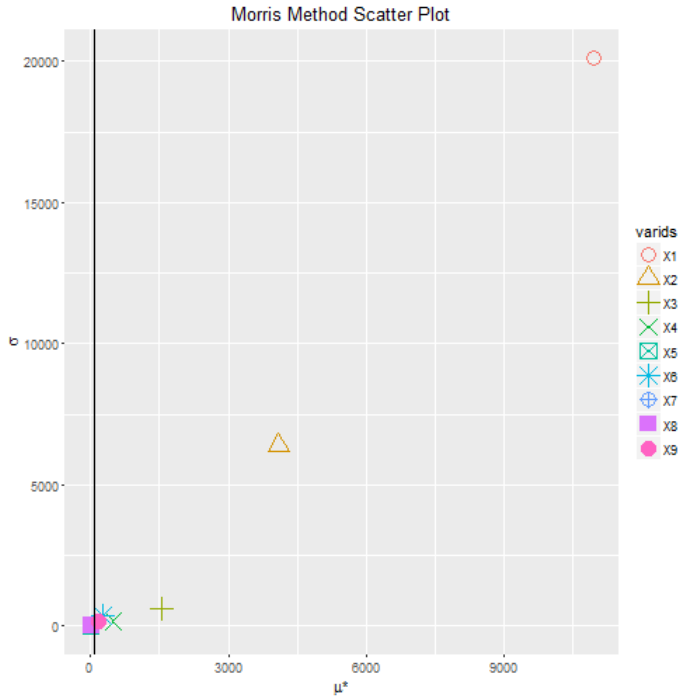


Figure 49 - B-Hut/Singapore Morris Scatter Plot

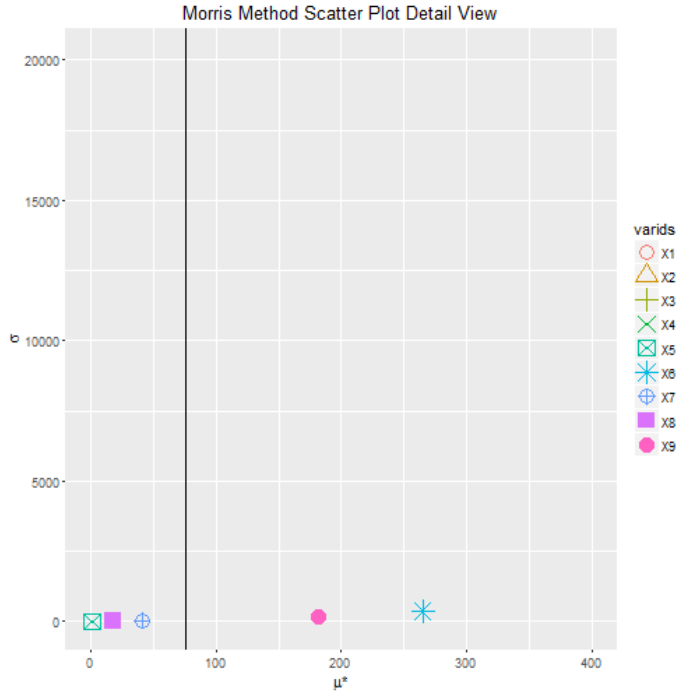


Figure 50 - B-Hut/Singapore Morris Scatter Plot Detail

Table 33 - MILVAN/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	35328.802	35328.802	66877.703
X2	10379.307	2382.47	15421.545
X3	3017.598	3017.598	930.821
X4	943.439	-943.439	407.218
X9	331.258	323.856	287.226
X6	272.409	270.188	284.387
X5	96.972	96.972	102.258
X7	54.408	52.187	50.348
X8	43.674	2.961	49.126

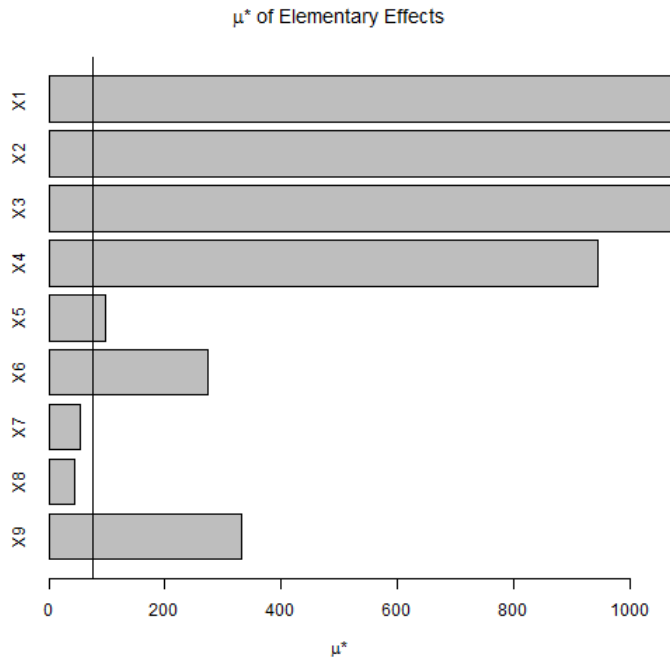


Figure 51 - MILVAN/Kharga Sensitivity Bar Plot

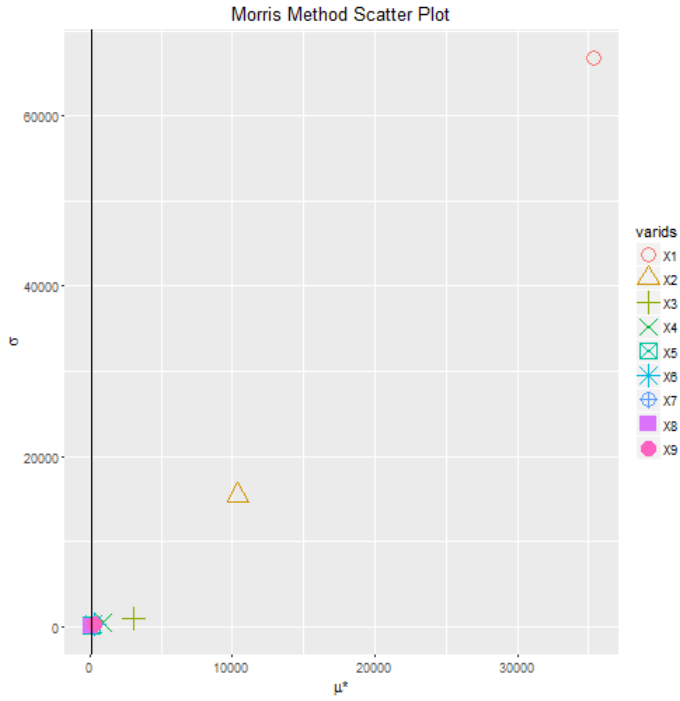


Figure 52 - MILVAN/Kharga Morris Scatter Plot

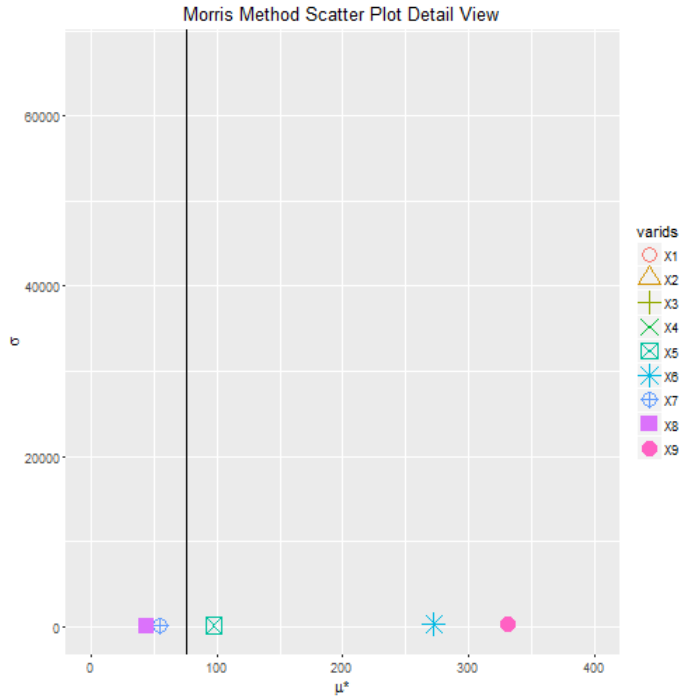


Figure 53 - MILVAN/Kharga Morris Scatter Plot Detail

Table 34 - MILVAN/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	30547.948	30547.948	62536.296
X2	8560.532	3388.459	11260.052
X6	940.478	930.114	1170.224
X3	814.266	-64.401	1194.163
X5	720.996	720.996	333.203
X4	346.803	-346.803	245.302
X7	159.892	125.101	176.598
X9	107.705	7.032	164.097
X8	19.246	-7.402	20.799

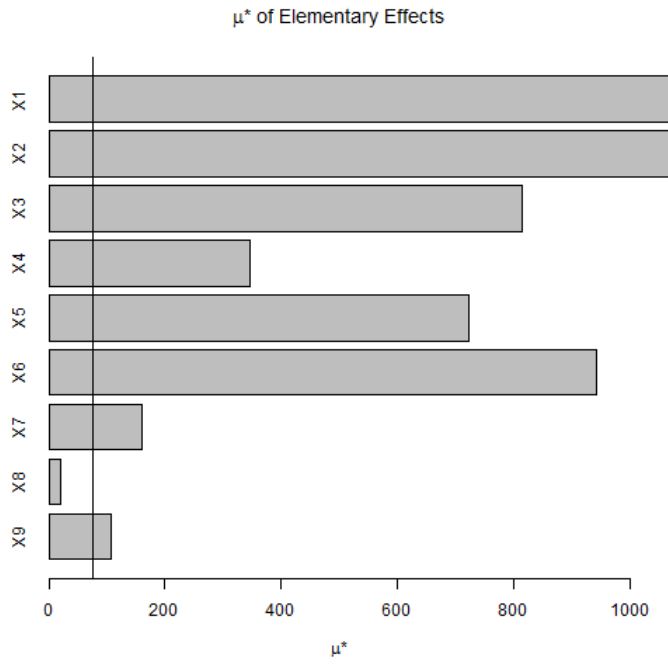


Figure 54 - MILVAN/Chongjin Sensitivity Bar Plot

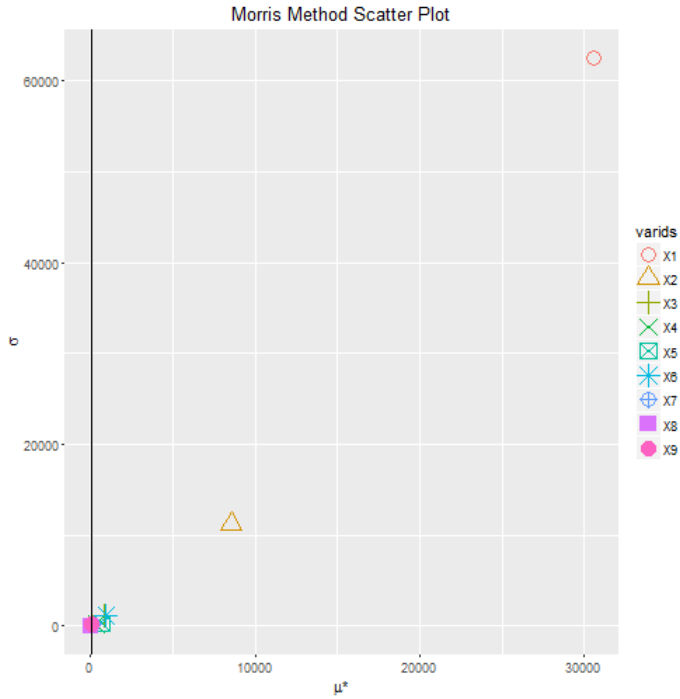


Figure 55 - MILVAN/Chongjin Morris Scatter Plot

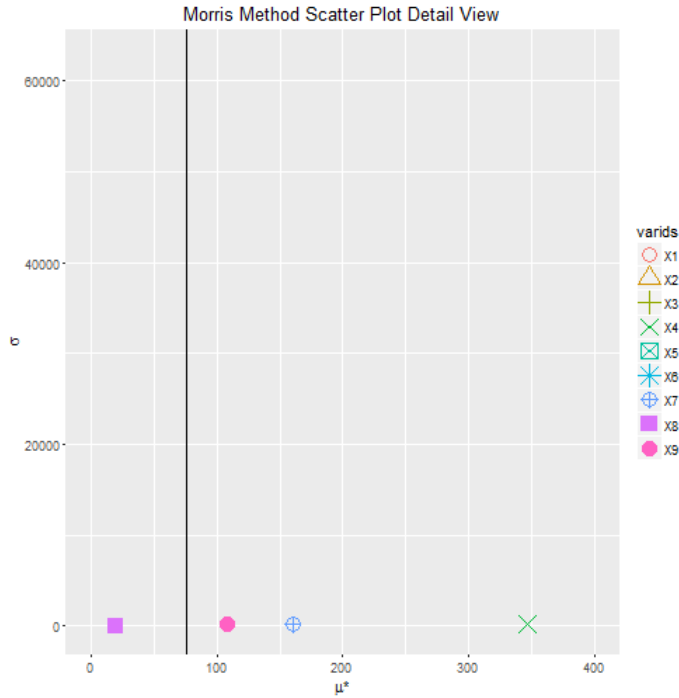


Figure 56 - MILVAN/Chongjin Morris Scatter Plot Detail

Table 35 - MILVAN/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	34851.346	34851.346	64210.415
X2	16087.315	4477.355	22561.193
X3	5086.575	5086.575	1650.89
X4	1182.907	-1182.907	415.409
X6	740.612	740.612	929.566
X9	575.168	575.168	403.094
X7	123.25	123.25	102.747
X8	8.883	3.701	11.888
X5	0	0	0

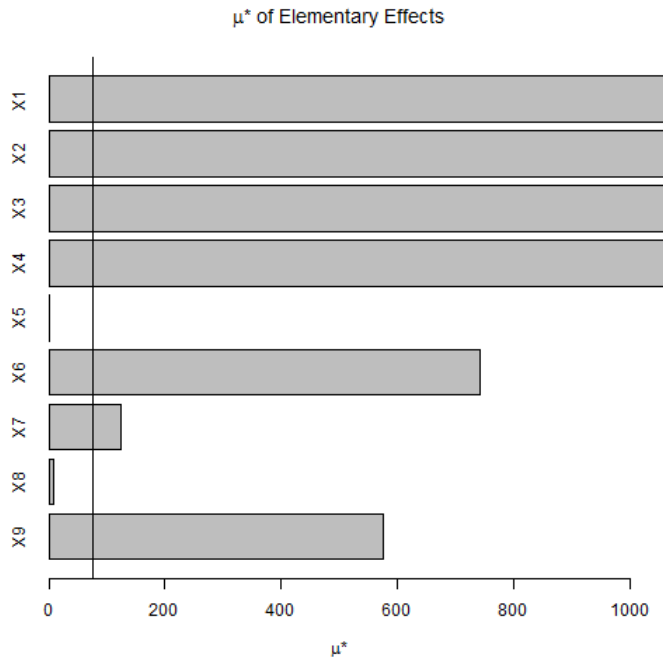


Figure 57 - MILVAN/Singapore Sensitivity Bar Plot

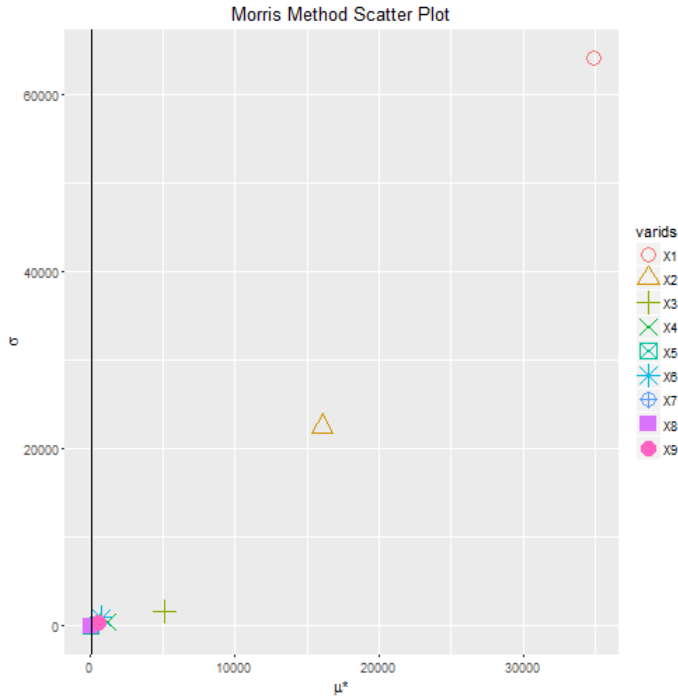


Figure 58 - MILVAN/Singapore Morris Scatter Plot

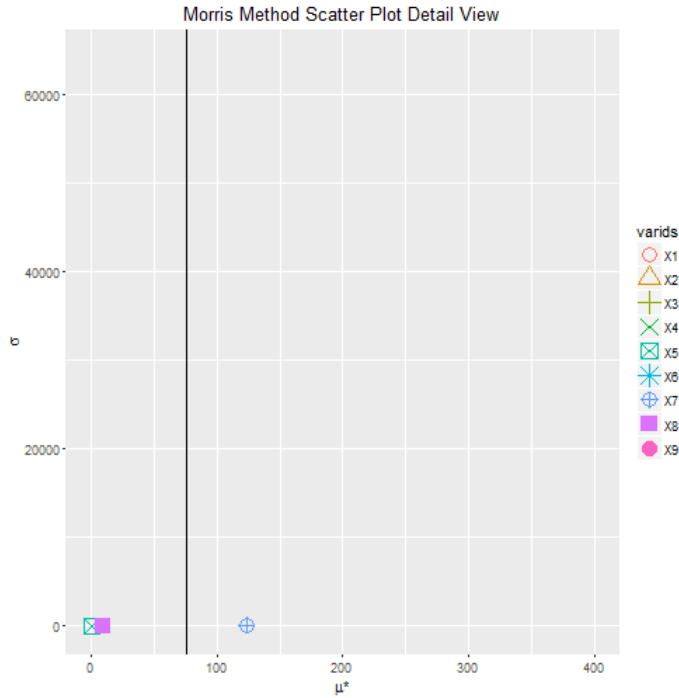


Figure 59 - MILVAN/Singapore Morris Scatter Plot Detail

Table 36 - TM60/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	7660.322	7660.322	14752.84
X2	4570.535	2083.53	5494.787
X3	1414.953	-506.473	4409.523
X8	1037.596	-1013.77	4377.673
X4	278.391	-278.391	118.003
X5	128.291	128.291	64.542
X6	104.465	104.465	142.66
X9	77.891	77.891	60.401
X7	15.212	15.212	13.521

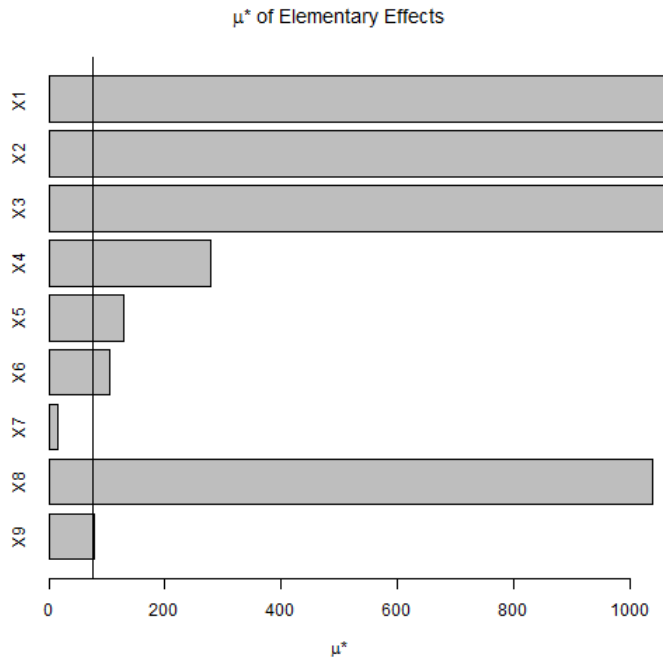


Figure 60 - TM60/Kharga Sensitivity Bar Plot

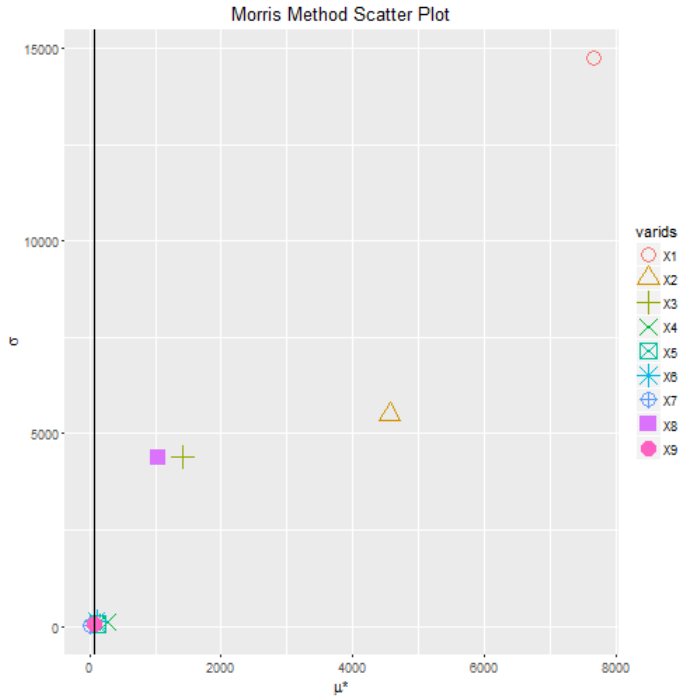


Figure 61 - TM60/Kharga Morris Scatter Plot

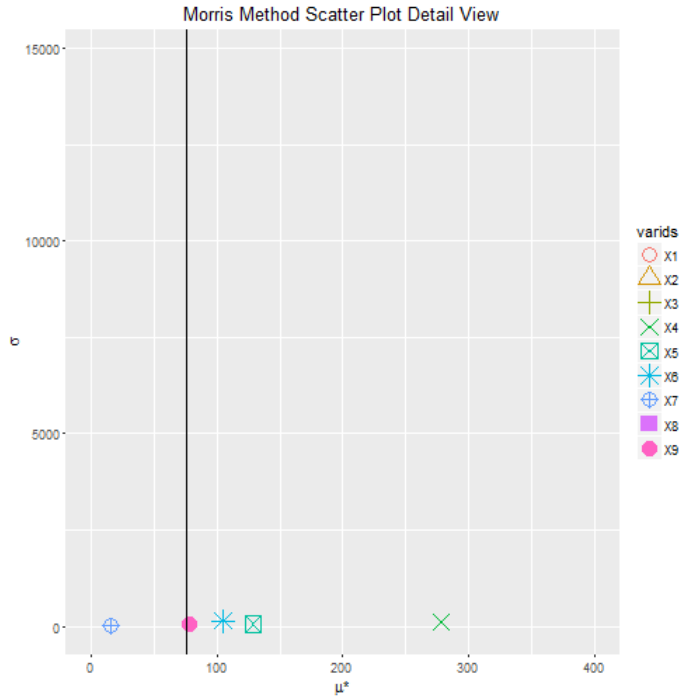


Figure 62 - TM60/Kharga Morris Scatter Plot Detail

Table 37 - TM60/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	5021.568	5021.568	10396.726
X2	4273.451	3069.169	5774.739
X5	383.314	383.314	138.581
X6	325.95	325.95	385.879
X3	312.204	-274.45	271.488
X4	99.059	-99.059	52.331
X7	46.093	46.093	41.658
X9	38.762	-24.467	40.487
X8	23.184	-18.052	24.038

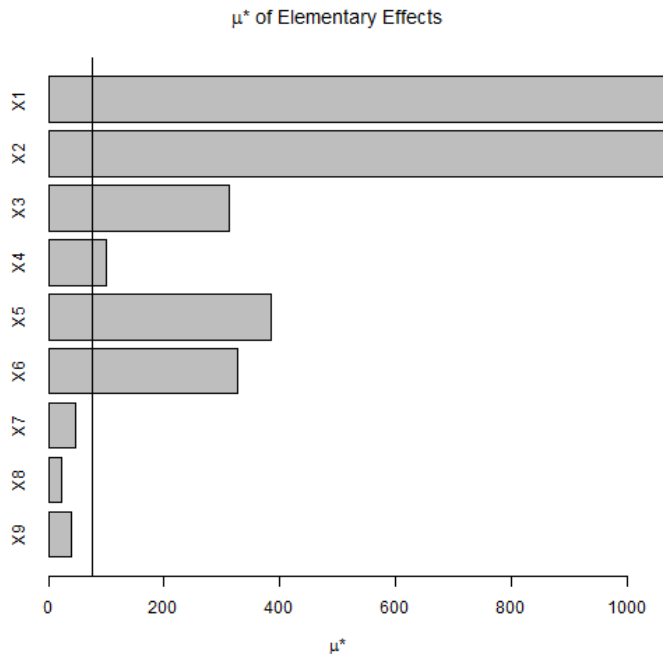


Figure 63 - TM60/Chongjin Sensitivity Bar Plot

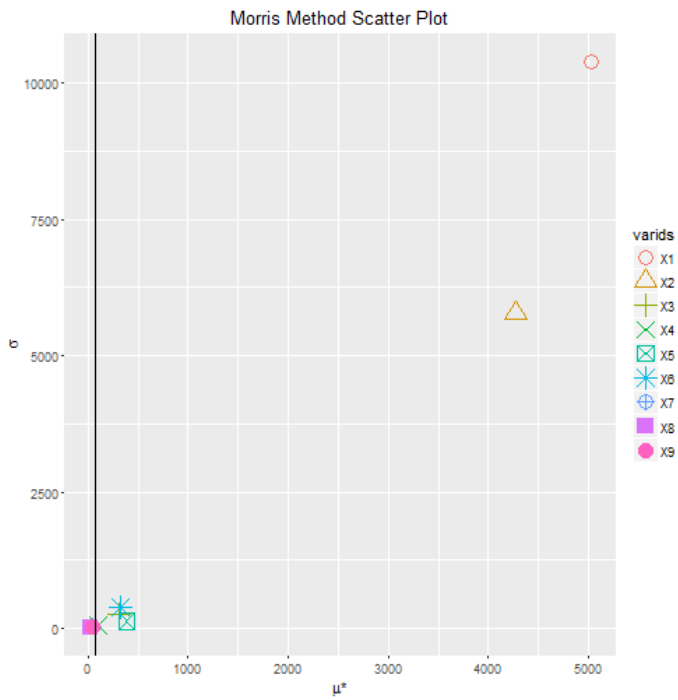


Figure 64 - TM60/Chongjin Morris Scatter Plot

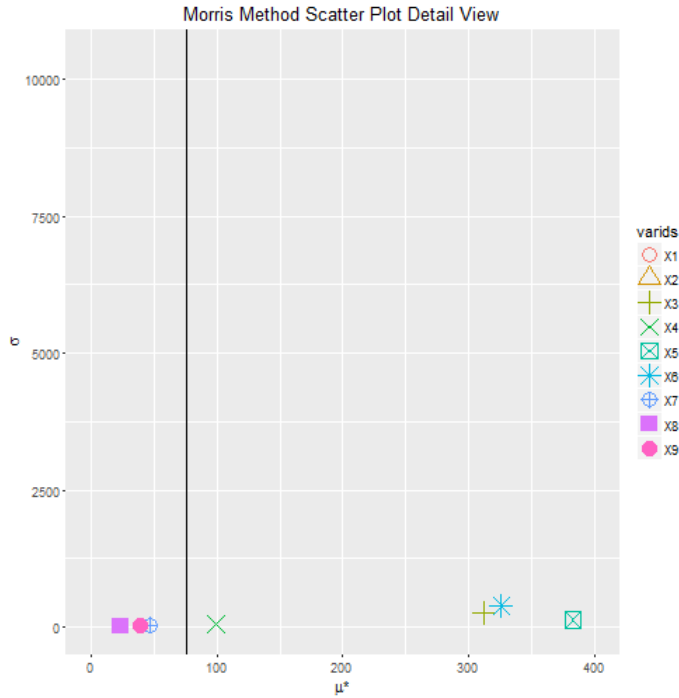


Figure 65 - TM60/Chongjin Morris Scatter Plot Detail

Table 38 - TM60/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	8199.6	8199.6	15126.179
X2	4711.654	1802.757	6536.665
X3	1164.42	1164.42	425.832
X4	374.059	-374.059	169.185
X6	246.868	246.868	356.735
X9	143.869	143.869	100.64
X8	39.862	-16.22	42.631
X7	37.204	37.204	28.293
X5	0	0	0

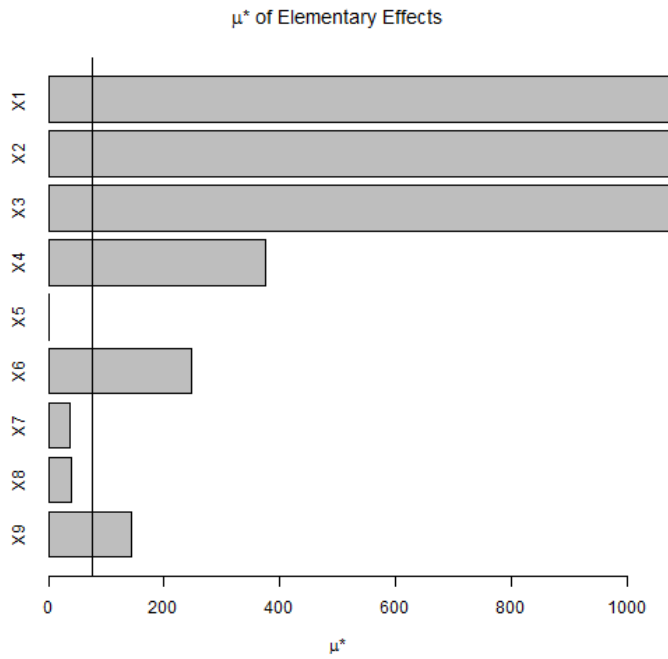


Figure 66 - TM60/Singapore Sensitivity Bar Plot

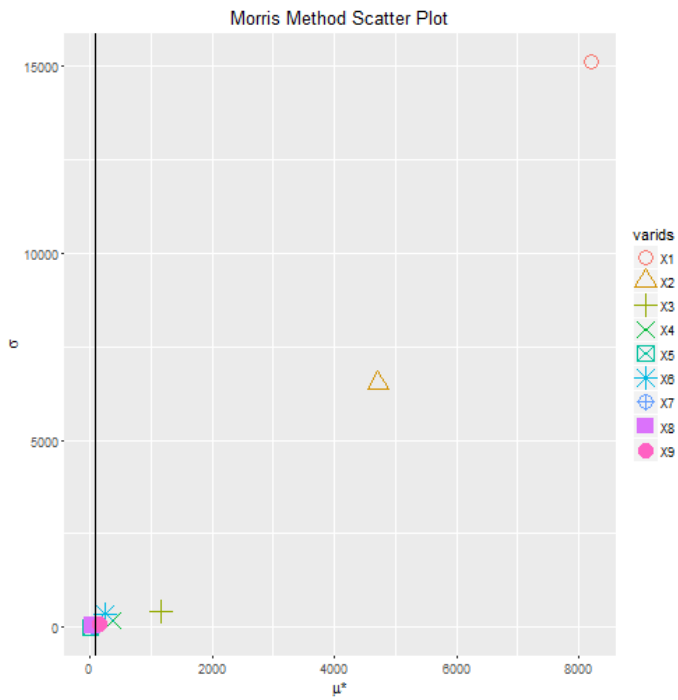


Figure 67 - TM60/Singapore Morris Scatter Plot

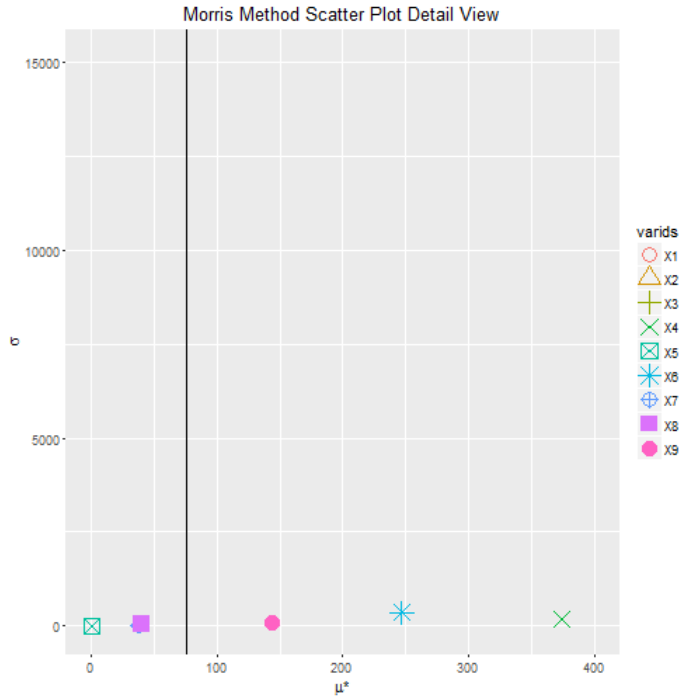


Figure 68 - TM60/Singapore Morris Scatter Plot Detail

Table 39 - X203/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	25885.238	25885.238	48725.892
X2	8709.226	1751.205	13365.098
X7	2961.712	-2903.075	9773.018
X3	2495.156	2495.156	707.002
X6	2217.76	-1955.587	9237.644
X4	1398.257	-1398.257	3926.095
X9	413.839	413.839	296.973
X8	127.704	29.036	167.976
X5	36.648	36.648	50.677

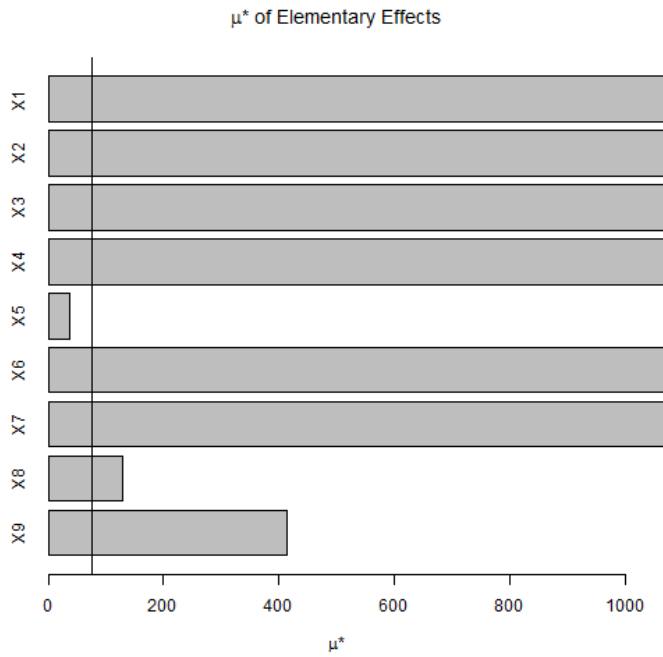


Figure 69 - X203/Kharga Sensitivity Bar Plot

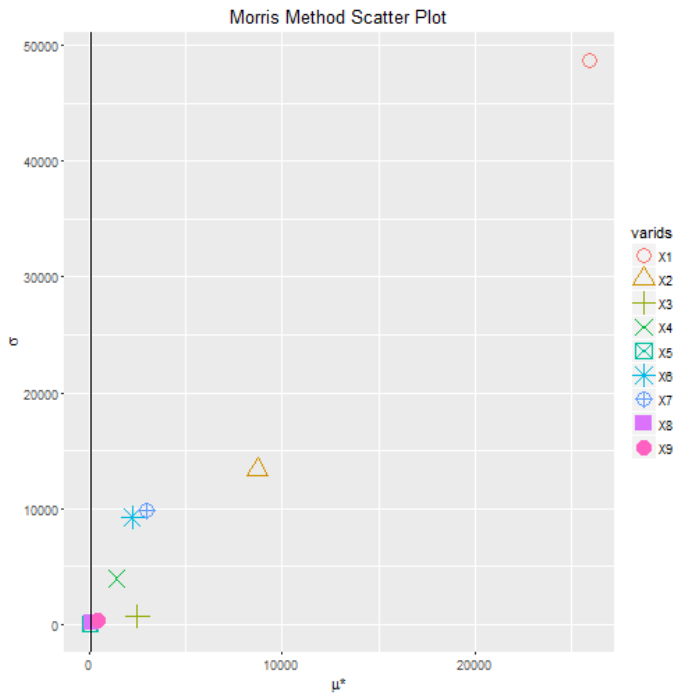


Figure 70 - X203/Kharga Morris Scatter Plot

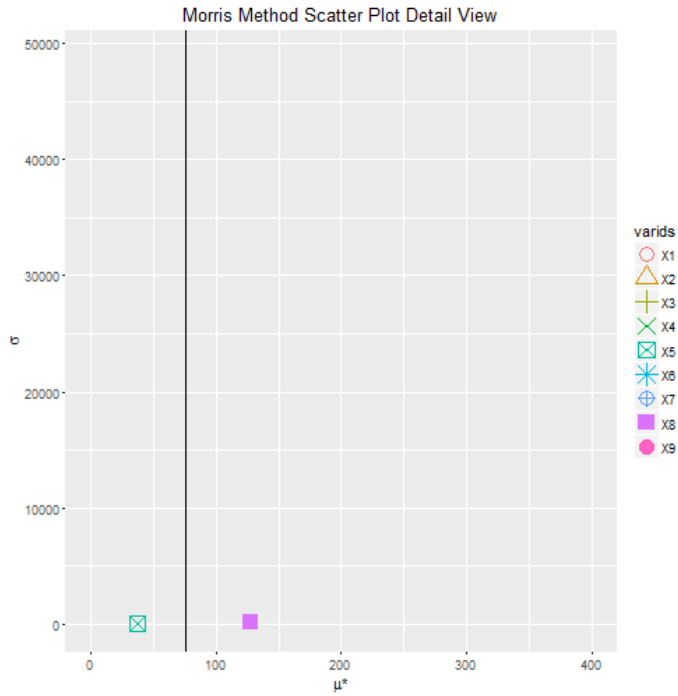


Figure 71 - X203/Kharga Morris Scatter Plot Detail

Table 40 - X203/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	24826.679	24826.679	49682.276
X2	6131.471	391.85	9537.79
X3	664.736	443.721	753.539
X6	550.564	268.657	635.157
X5	281.061	281.061	154.247
X4	231.164	-231.164	133.648
X9	150.538	128.549	226.226
X7	122.066	65.684	146.286
X8	52.717	9.303	69.011

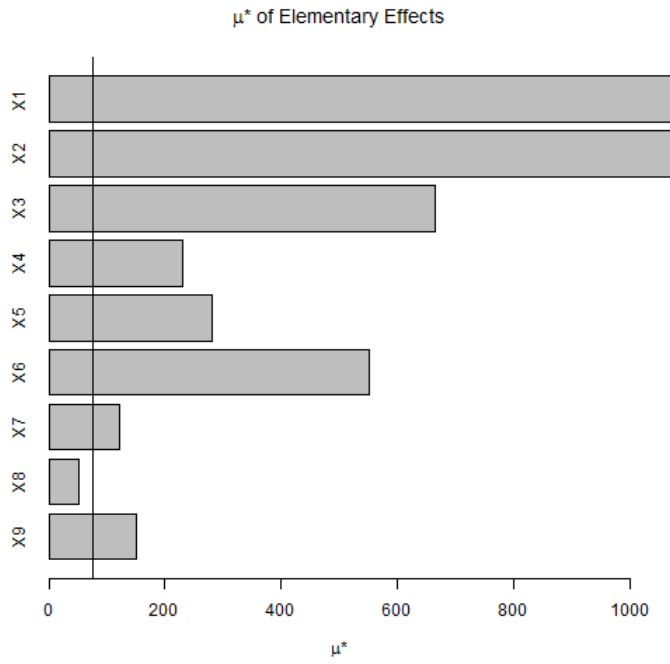


Figure 72 - X203/Chongjin Sensitivity Bar Plot

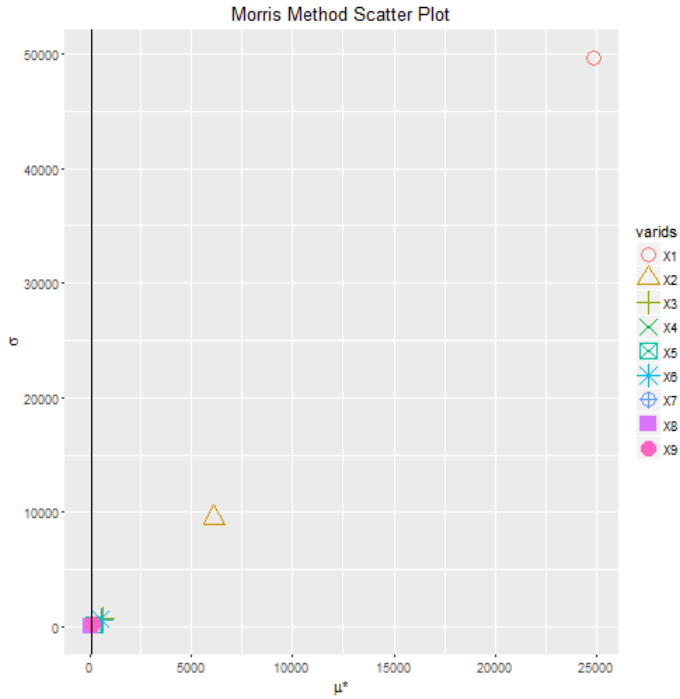


Figure 73 - X203/Chongjin Morris Scatter Plot

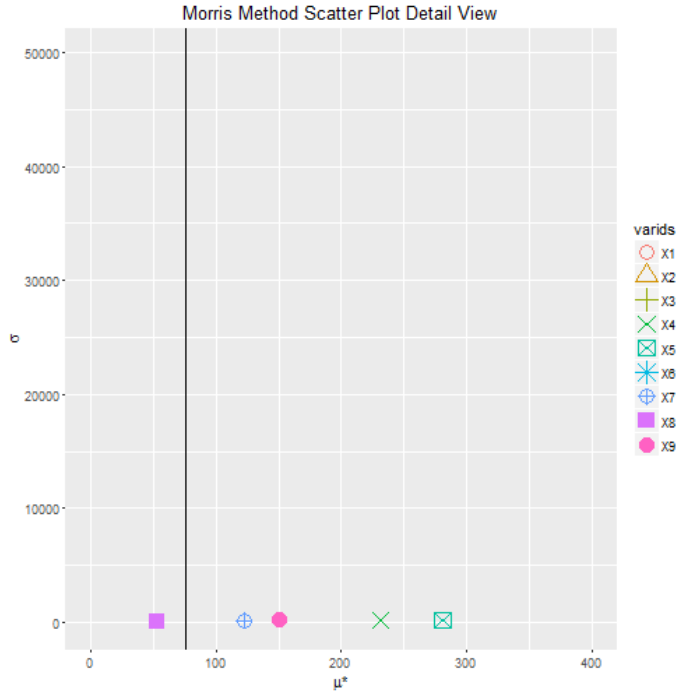


Figure 74 - X203/Chongjin Morris Scatter Plot Detail

Table 41 - X203/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	25540.466	25540.466	47388.179
X2	10404.049	2612.148	16025.968
X3	3665.633	3665.633	1159.098
X6	811.891	811.891	1125.482
X4	616.248	-616.248	262.171
X9	487.699	487.699	333.117
X7	118.683	118.683	84.354
X8	53.562	15.223	66.914
X5	0	0	0

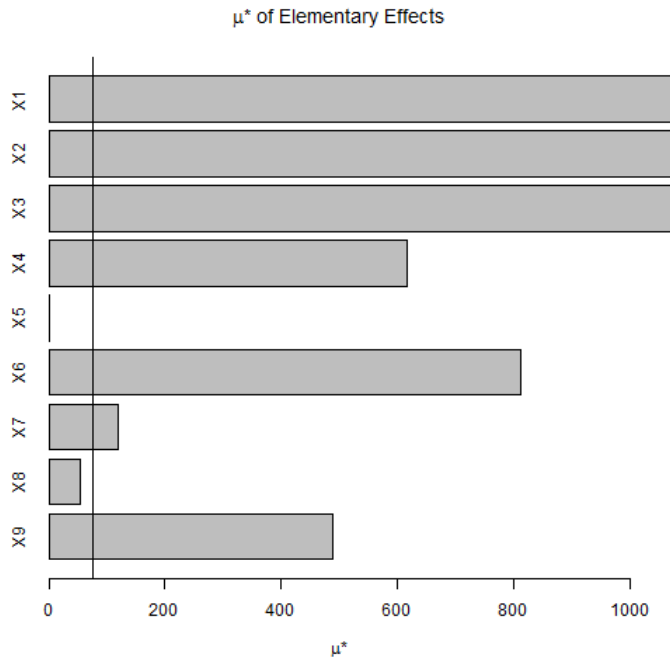


Figure 75 - X203/Singapore Sensitivity Bar Plot

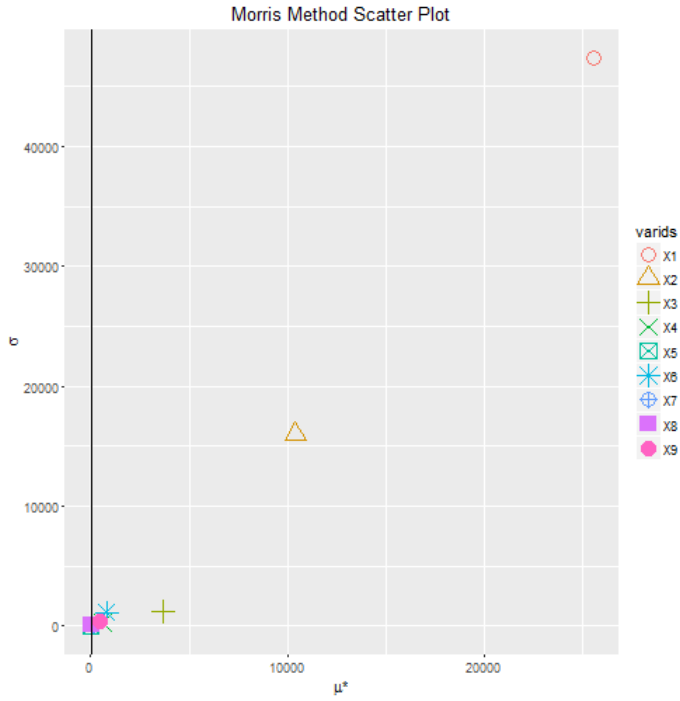


Figure 76 - X203/Singapore Morris Scatter Plot

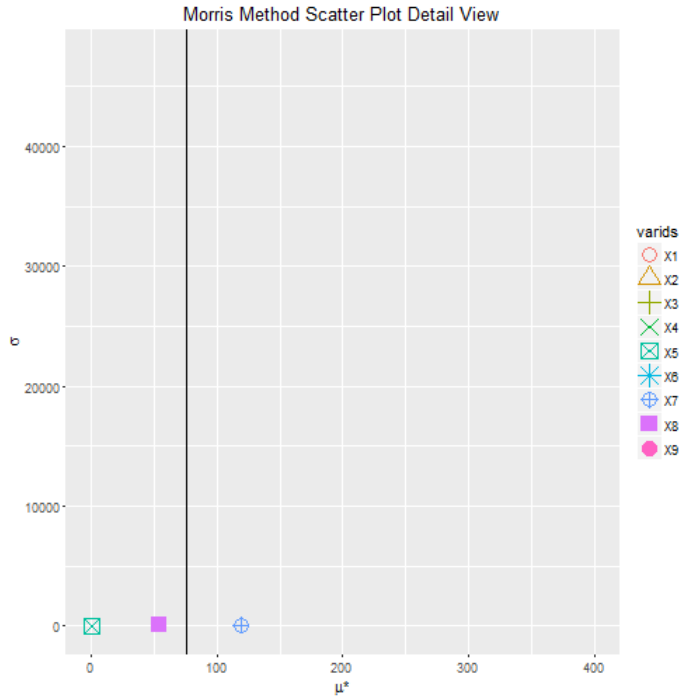


Figure 77 - X203/Singapore Morris Scatter Plot Detail

Table 42 - X305/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	11870.581	11870.581	22485.12
X2	4764.781	1286.14	6774.752
X3	1037.778	1037.778	337.51
X4	326.238	-326.238	126.066
X9	172.064	172.064	128.304
X6	87.216	80.376	92.498
X8	81.691	14.339	109.461
X5	39.333	39.333	29.723
X7	17.233	13.549	18.589

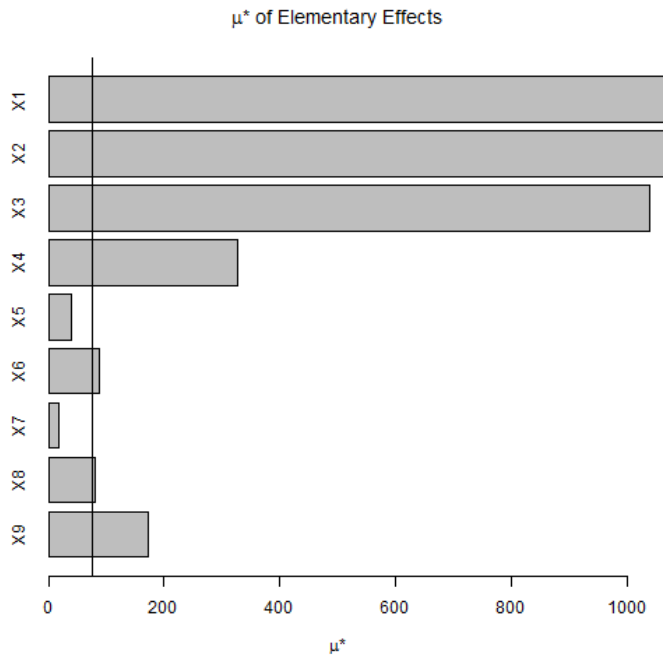


Figure 78 - X305/Kharga Sensitivity Bar Plot

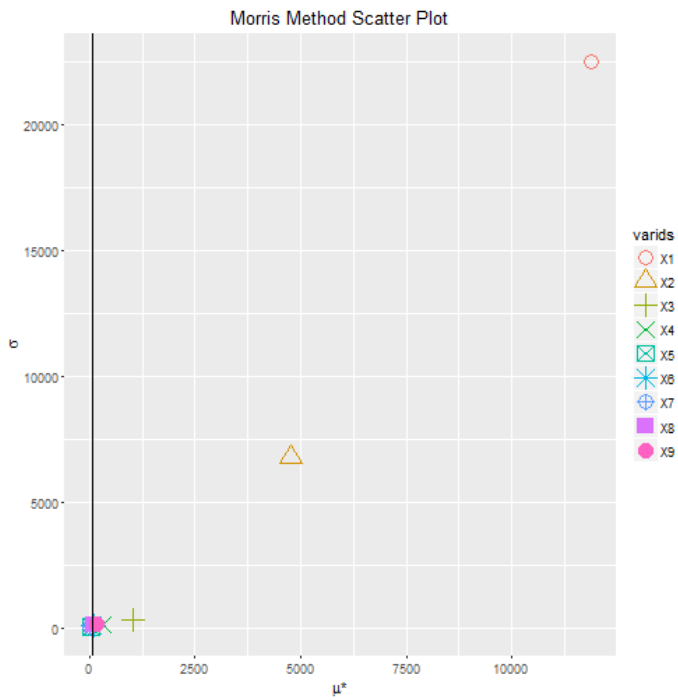


Figure 79 - X305/Kharga Morris Scatter Plot

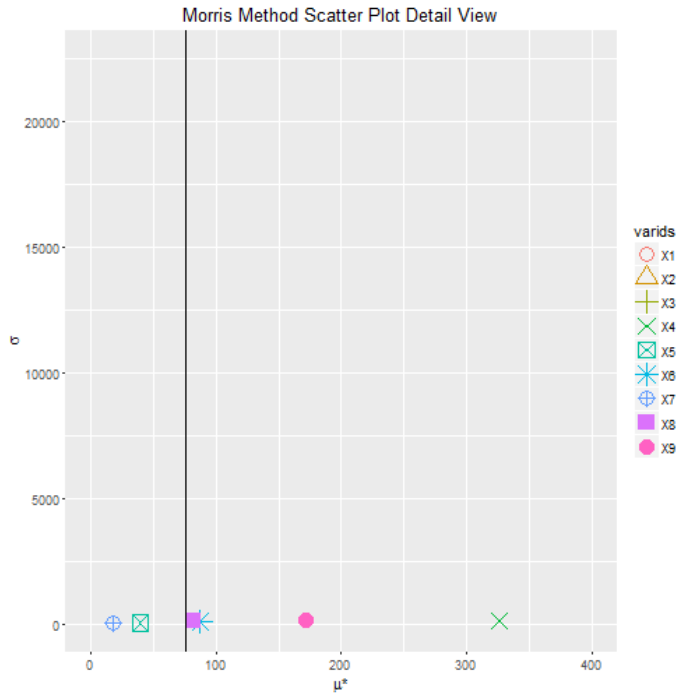


Figure 80 - X305/Kharga Morris Scatter Plot Detail

Table 43 - X305/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	10273.332	10273.332	20960.807
X2	3102.153	1335.733	4232.865
X6	324.528	321.897	387.268
X3	253.097	29.993	357.604
X5	246.388	246.388	107.709
X4	121.024	-121.024	67.428
X7	55.908	44.595	61.426
X9	51.304	28.94	87.903
X8	41.964	1.184	47.873

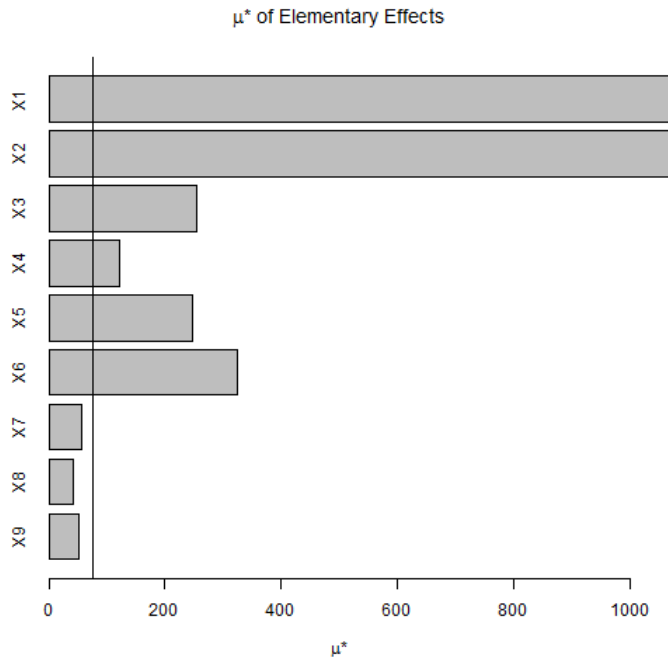


Figure 81 - X305/Chongjin Sensitivity Bar Plot

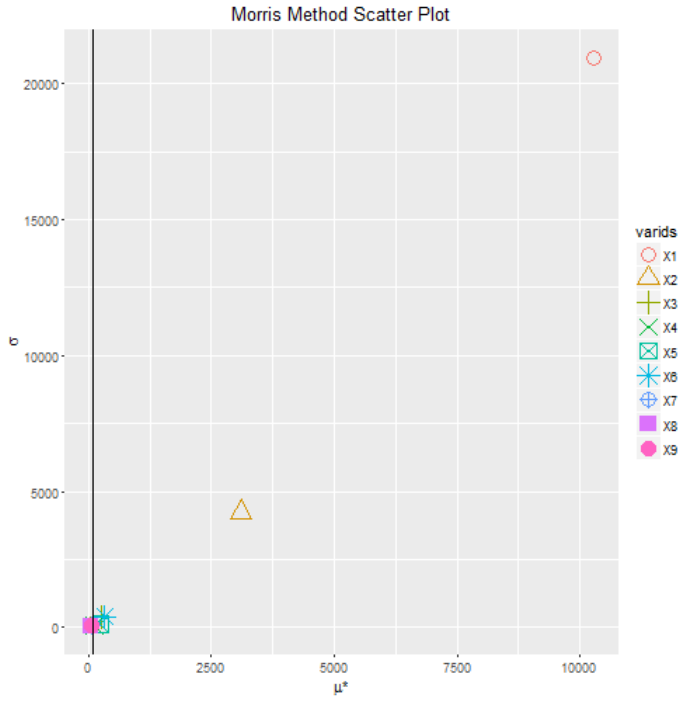


Figure 82 - X305/Chongjin Morris Scatter Plot

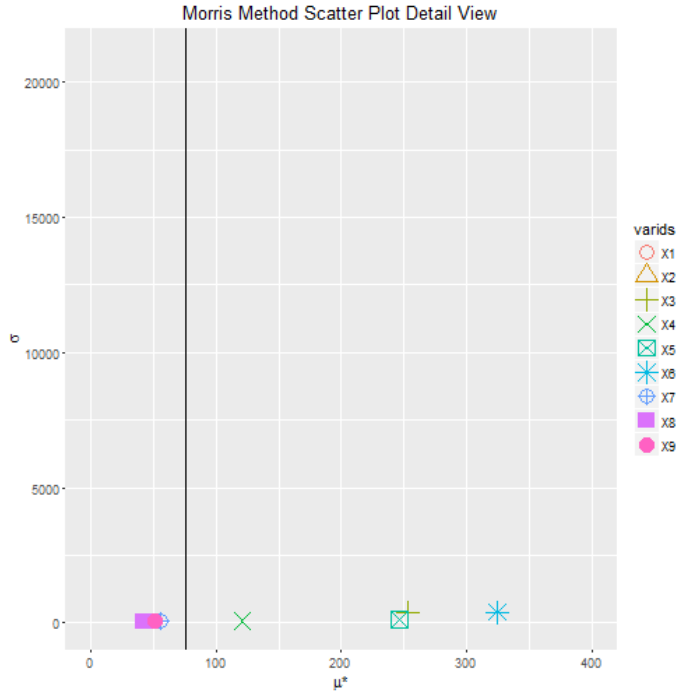


Figure 83 - X305/Chongjin Morris Scatter Plot Detail

Table 44 - X305/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	11829.012	11829.012	21944.613
X2	5647.465	1746.556	8062.242
X3	1666.838	1666.838	557.338
X4	399.904	-399.904	149.169
X6	371.227	371.227	518.238
X9	219.947	219.947	150.587
X7	55.513	55.513	39.854
X8	31.571	8.419	41.788
X5	0	0	0

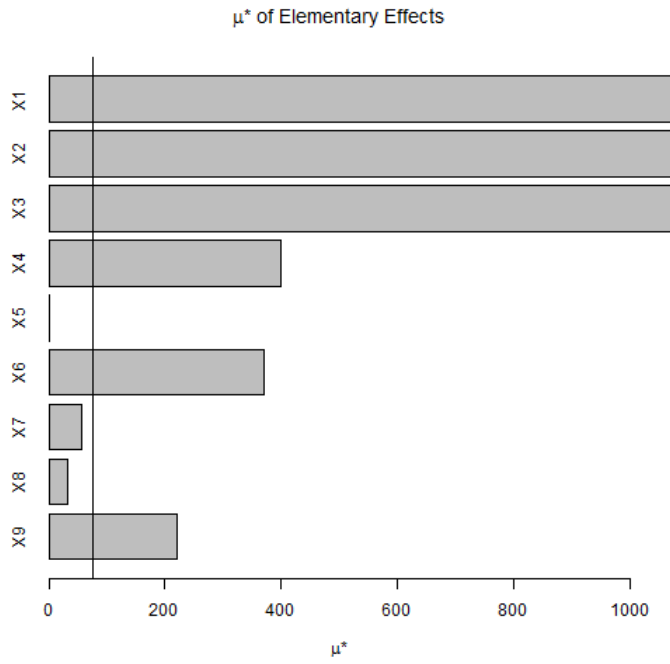


Figure 84 - X305/Singapore Sensitivity Bar Plot

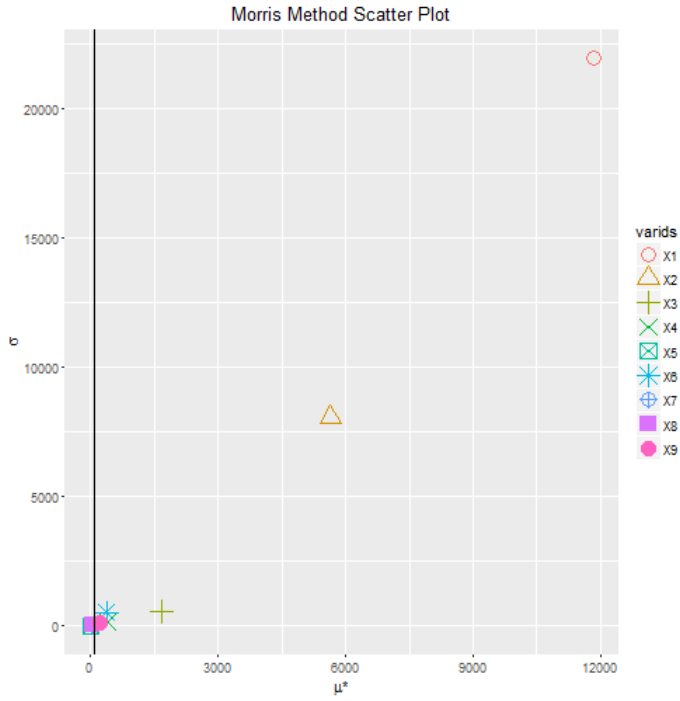


Figure 85 - X305/Singapore Morris Scatter Plot

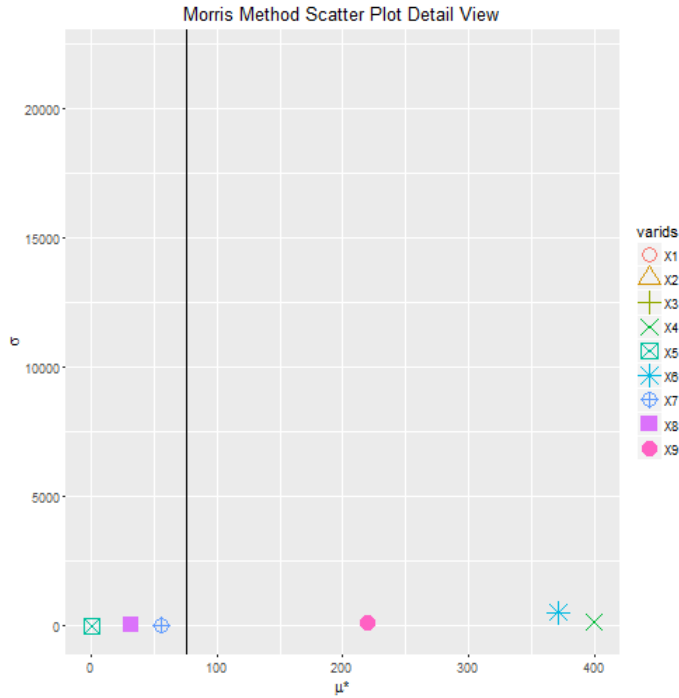


Figure 86 - X305/Singapore Morris Scatter Plot Detail

Table 45 - X307/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	8354.493	8354.493	15910.487
X2	3894.165	1185.606	5453.663
X3	742.448	742.448	263.533
X4	274.013	-274.013	105.484
X9	133.718	133.718	94.636
X6	76.021	68.315	97.206
X8	59.764	0	73.775
X5	54.502	54.502	32.983
X7	13.532	9.961	15.427

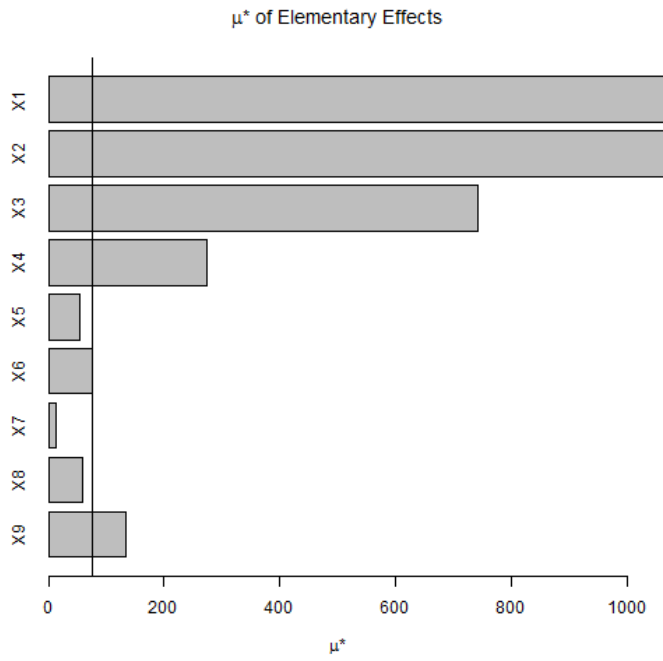


Figure 87 - X307/Kharga Sensitivity Bar Plot

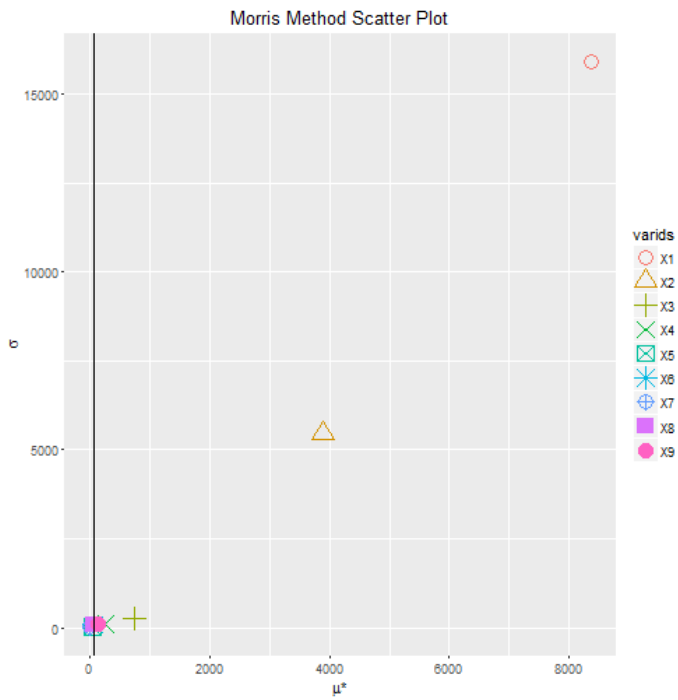


Figure 88 - X307/Kharga Morris Scatter Plot

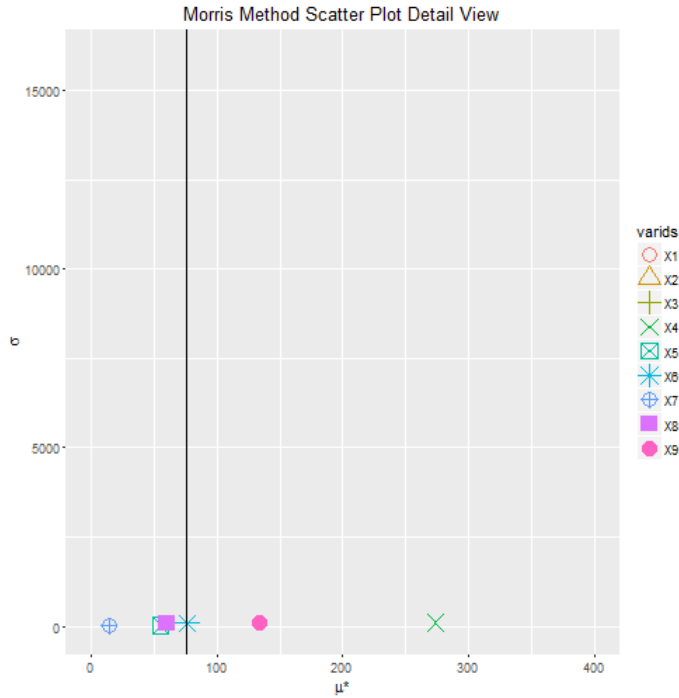


Figure 89 - X307/Kharga Morris Scatter Plot Detail

Table 46 - X307/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	6310.482	6310.482	12982.227
X2	2812.677	1724.141	4020
X6	293.935	293.935	348.378
X5	267.529	267.529	107.076
X3	239.527	-118.871	304.451
X4	91.244	-91.244	45.904
X9	43.977	15.975	89.144
X7	43.32	38.057	45.249
X8	34.956	-2.067	41.134

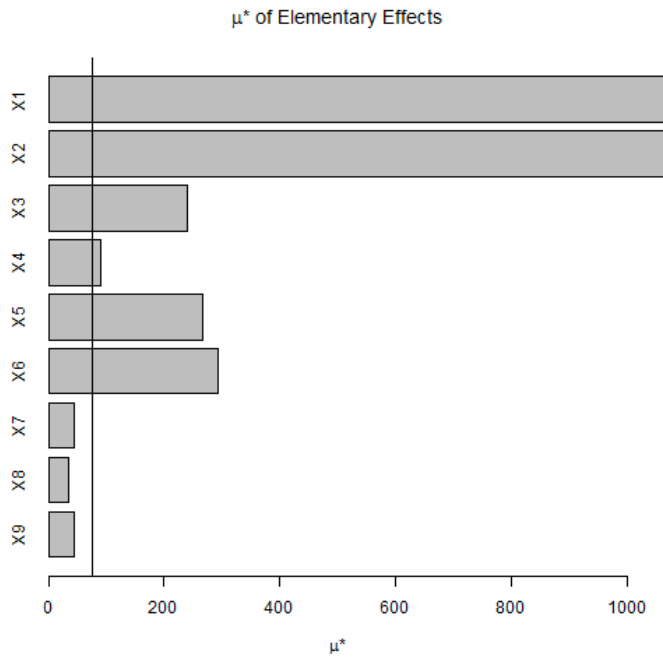


Figure 90 - X307/Chongjin Sensitivity Bar Plot

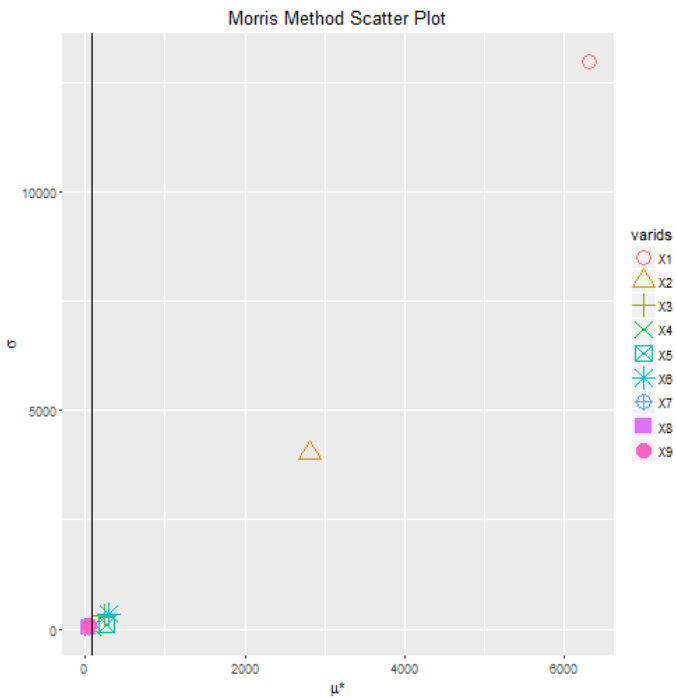


Figure 91 - X307/Chongjin Morris Scatter Plot

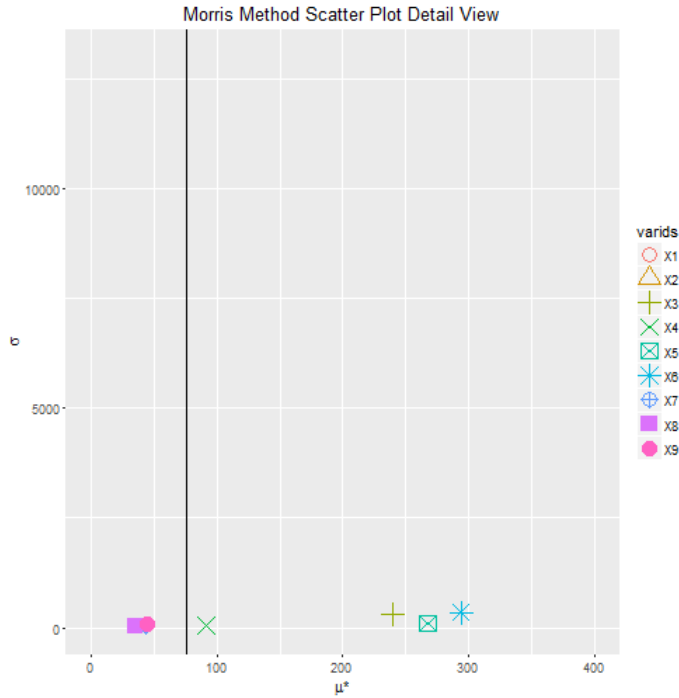


Figure 92 - X307/Chongjin Morris Scatter Plot Detail

Table 47 - X307/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	8424.218	8424.218	15648.11
X2	4232.735	1410.661	6058.358
X3	1274.688	1274.688	446.806
X4	361.029	-361.029	157.337
X6	306.433	306.433	452.012
X9	160.217	160.217	104.44
X7	44.917	44.917	32.773
X8	18.7	1.597	24.323
X5	0	0	0

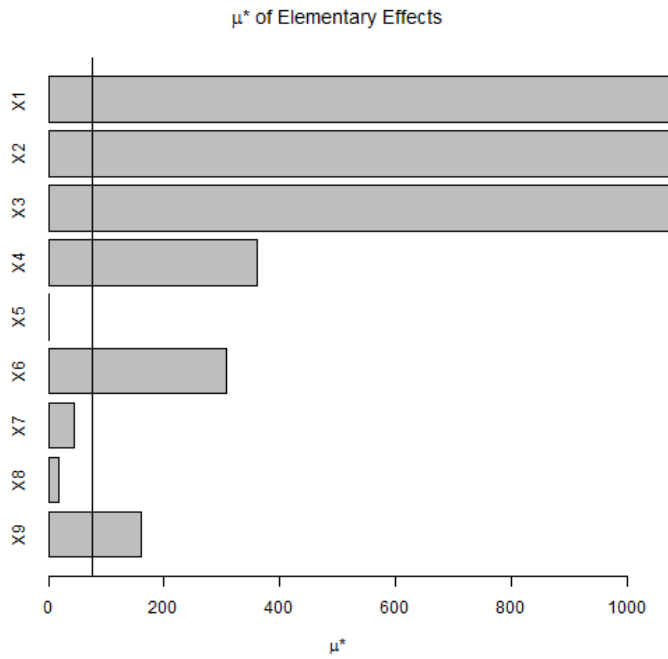


Figure 93 - X307/Singapore Sensitivity Bar Plot

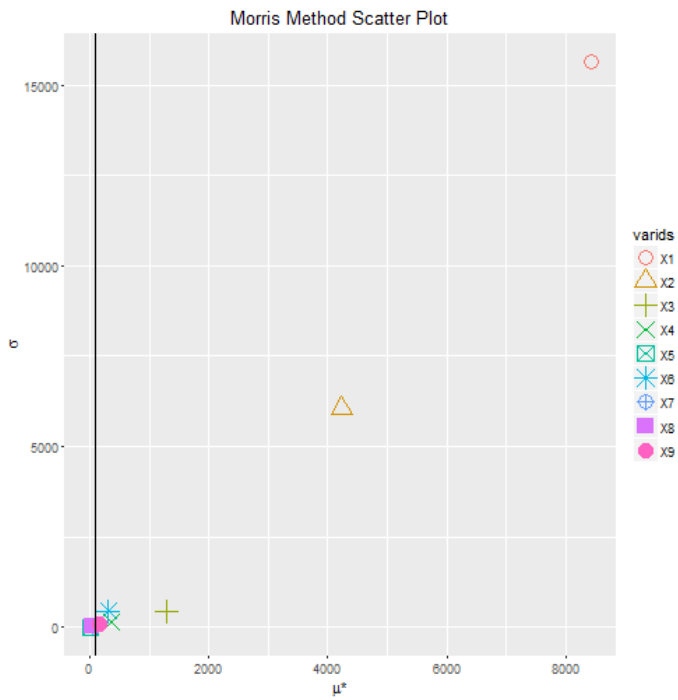


Figure 94 - X307/Singapore Morris Scatter Plot

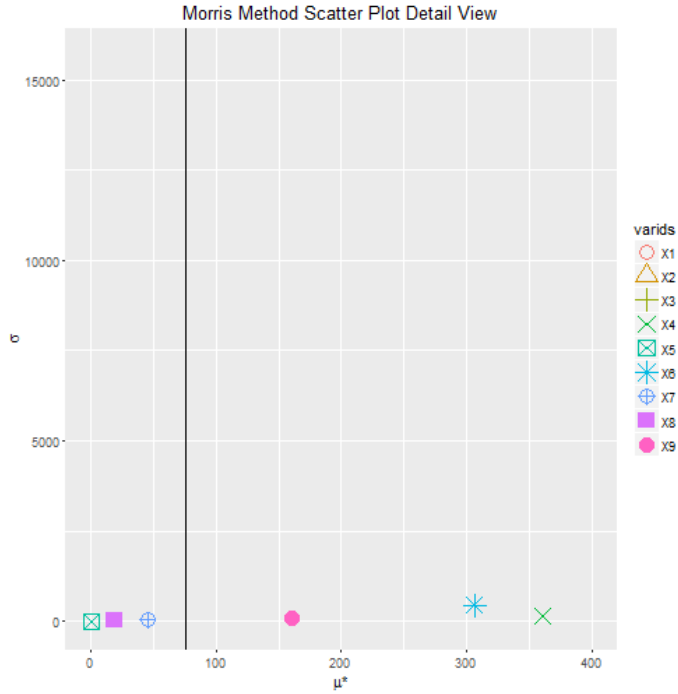


Figure 95 - X307/Singapore Morris Scatter Plot Detail

Table 48 - X6D31/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	9239.478	9239.478	17436.166
X2	3281.513	781.494	4851.569
X3	861.472	861.472	256.535
X4	702.019	-702.019	2063.238
X5	478.763	-443.396	2066.259
X9	138.856	138.856	100.844
X6	55.161	46.319	62.801
X7	13.765	10.148	15.213
X8	2.411	-1.809	2.834

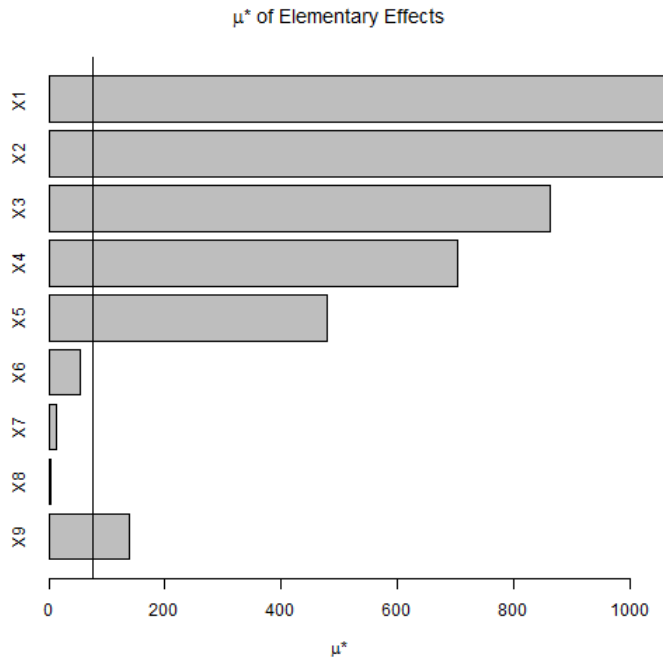


Figure 96 - X6D31/Kharga Sensitivity Bar Plot

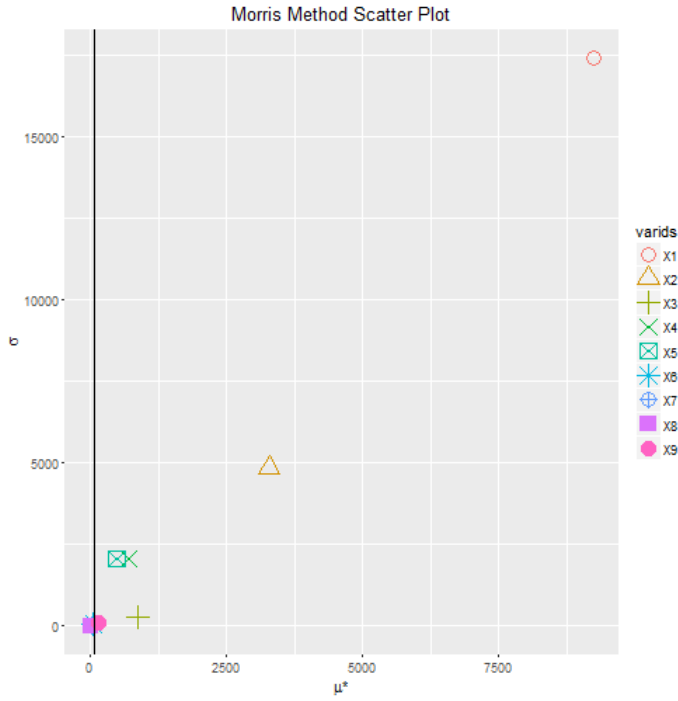


Figure 97 - X6D31/Kharga Morris Scatter Plot

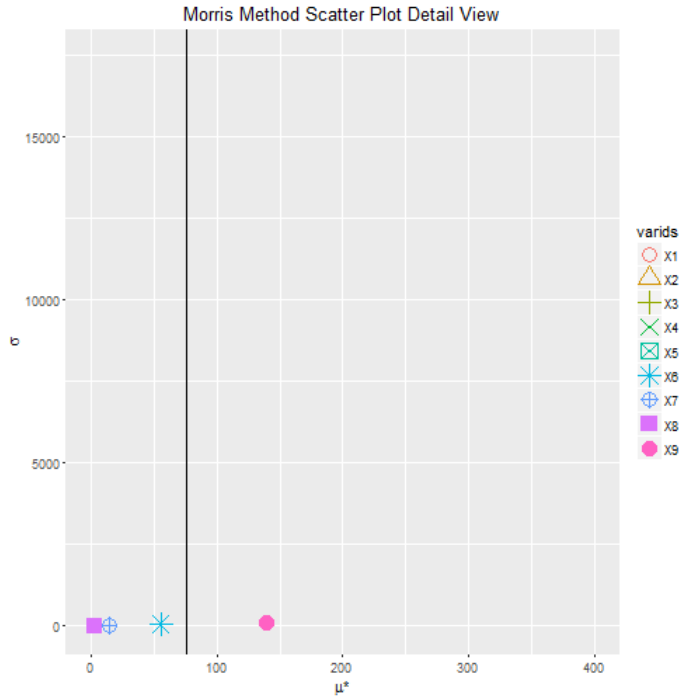


Figure 98 - X6D31/Kharga Morris Scatter Plot Detail

Table 49 - X6D31/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	8185.596	8185.596	16823.327
X2	2213.263	882.371	3076.116
X6	256.412	246.164	316.735
X3	221.648	-15.071	324.566
X5	185.577	185.577	86.604
X4	83.997	-83.997	51.002
X7	47.424	33.559	52.227
X9	44.41	19.291	73.332
X8	0.703	-0.301	1.18

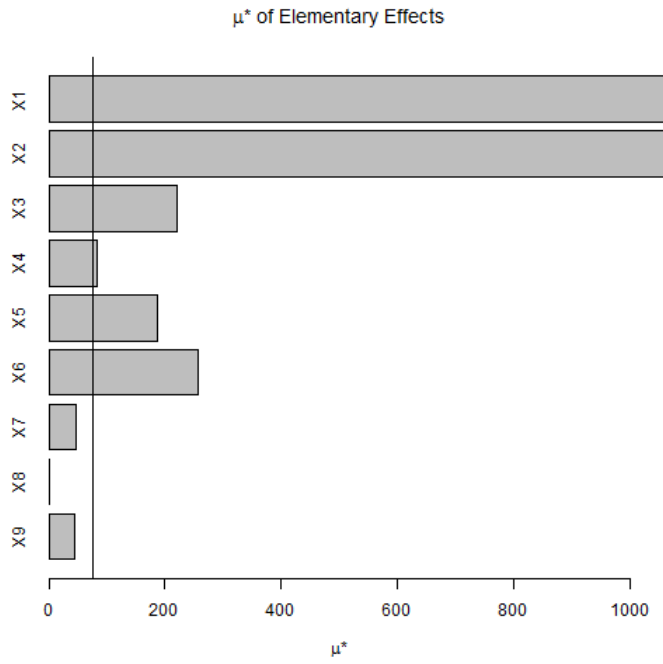


Figure 99 - X6D31/Chongjin Sensitivity Bar Plot

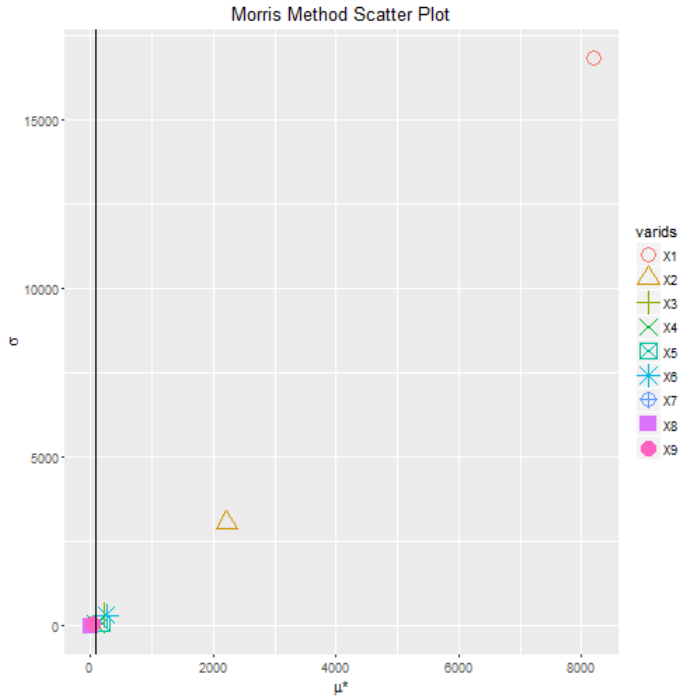


Figure 100 - X6D31/Chongjin Morris Scatter Plot

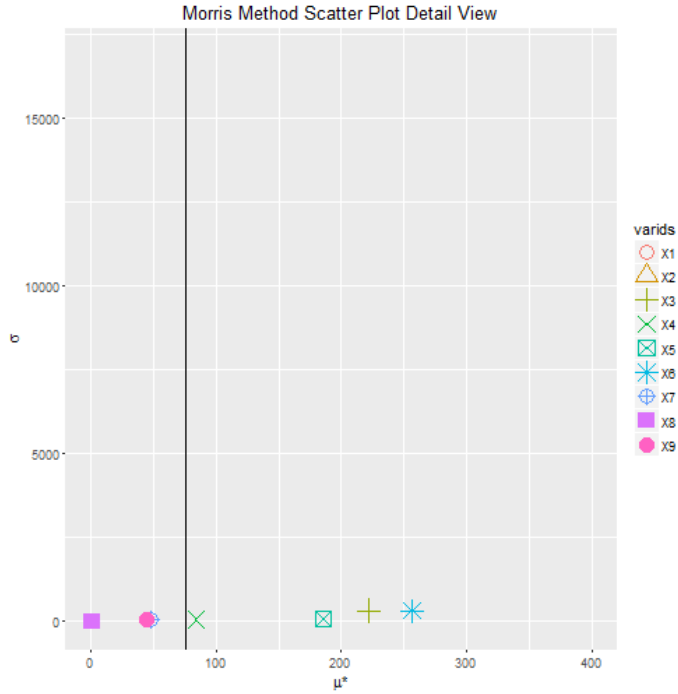


Figure 101 - X6D31/Chongjin Morris Scatter Plot Detail

Table 50 - X6D31/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	9101.023	9101.023	16863.869
X2	4040.902	1130.343	5982.364
X3	1311.299	1311.299	421.228
X4	298.411	-298.411	114.627
X6	290.373	290.373	405.283
X9	170.104	170.104	119.471
X7	42.601	42.601	29.796
X8	1.909	0.1	2.565
X5	0	0	0

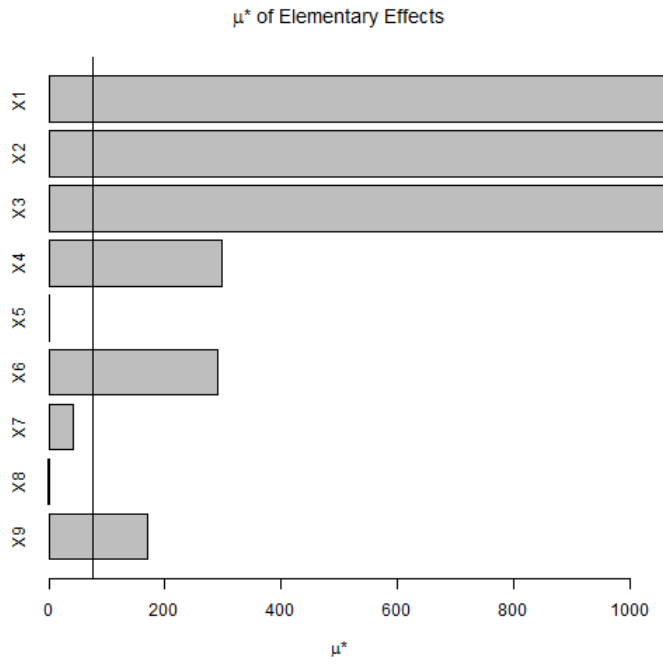


Figure 102 - X6D31/Singapore Sensitivity Bar Plot

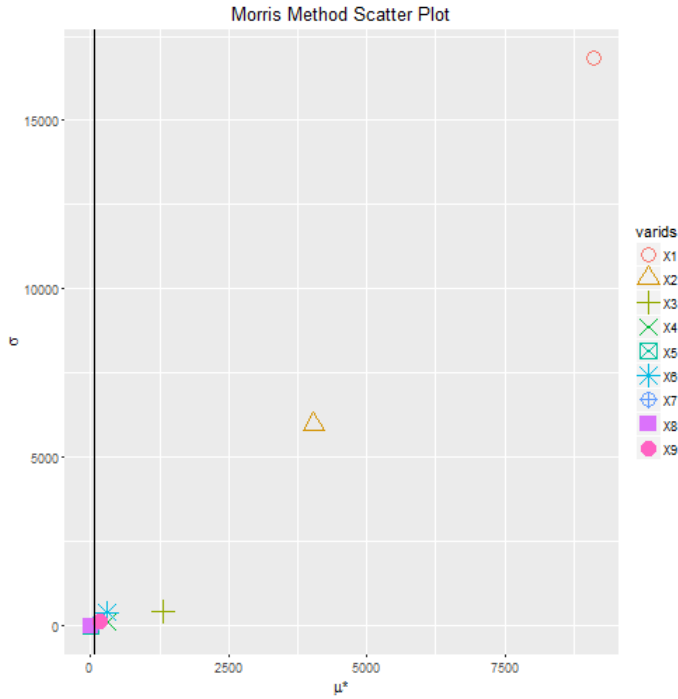


Figure 103 - X6D31/Singapore Morris Scatter Plot

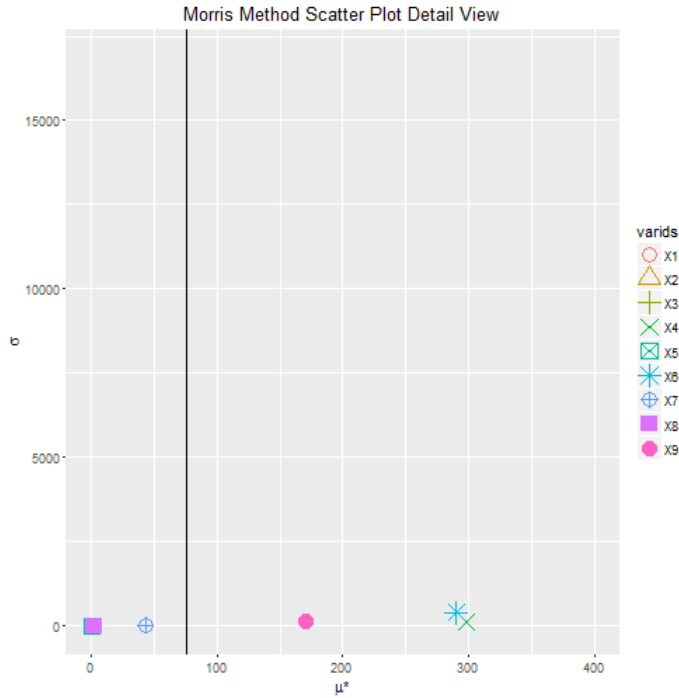


Figure 104 - X6D31/Singapore Morris Scatter Plot Detail

Table 51 - X8D36/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	6372.213	6372.213	12280.815
X2	2230.694	704.676	3206.094
X3	437.812	437.812	190.028
X4	180.468	-180.468	67.901
X9	74.105	74.105	60.775
X6	71.974	70.269	87.321
X5	50.233	50.233	29.072
X7	11.865	10.586	11.391
X8	10.658	5.116	14.07

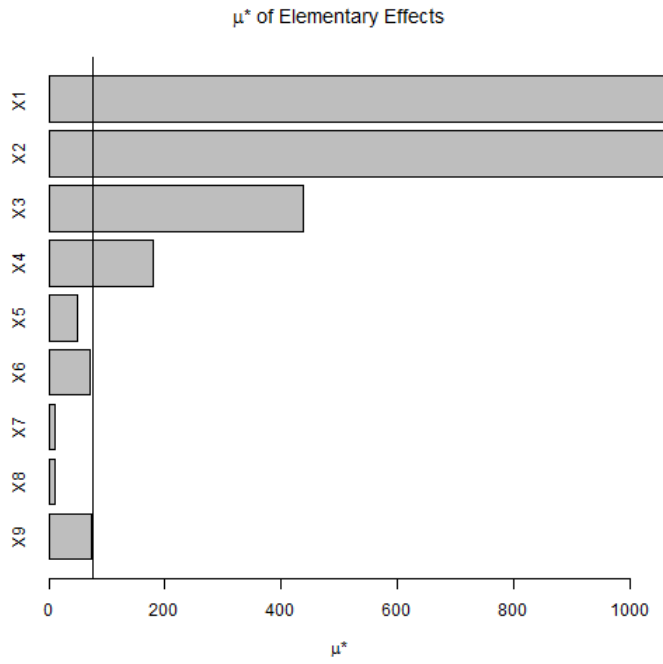


Figure 105 - X8D36/Kharga Sensitivity Bar Plot

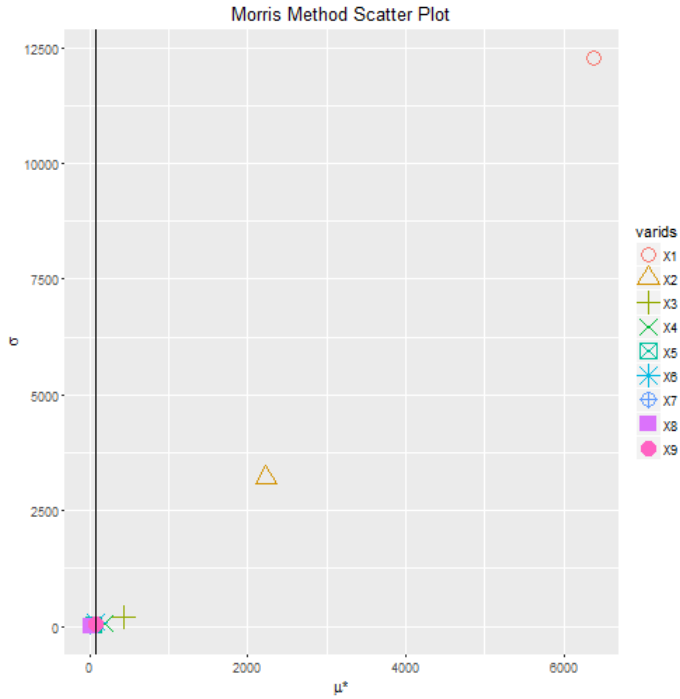


Figure 106 - X8D36/Kharga Morris Scatter Plot

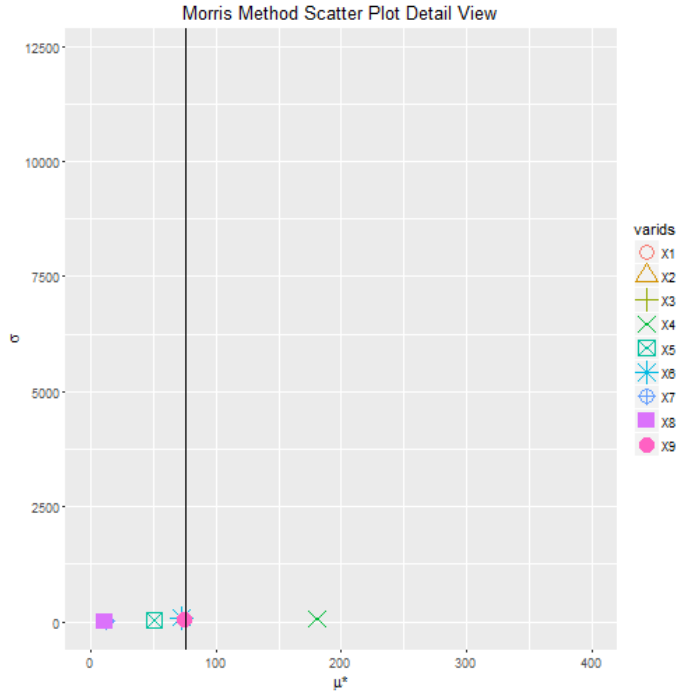


Figure 107 - X8D36/Kharga Morris Scatter Plot Detail

Table 52 - X8D36/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	4751.557	4751.557	9801.934
X2	2046.531	1324.661	2947.044
X6	233.968	233.968	275.581
X5	191.907	191.907	76.684
X3	180.397	-95.847	220.219
X4	54.638	-54.638	34.4
X7	33.82	31.404	33.303
X9	28.917	0.924	47.173
X8	4.121	2.416	4.925

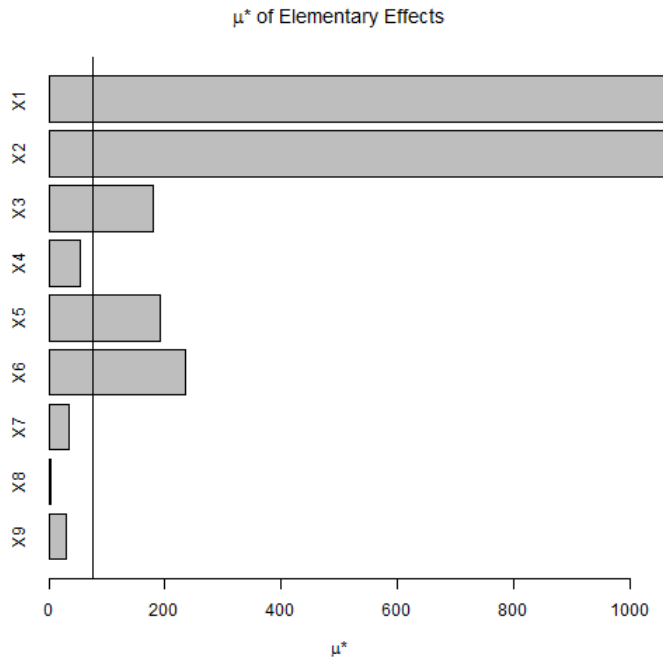


Figure 108 - X8D36/Chongjin Sensitivity Bar Plot

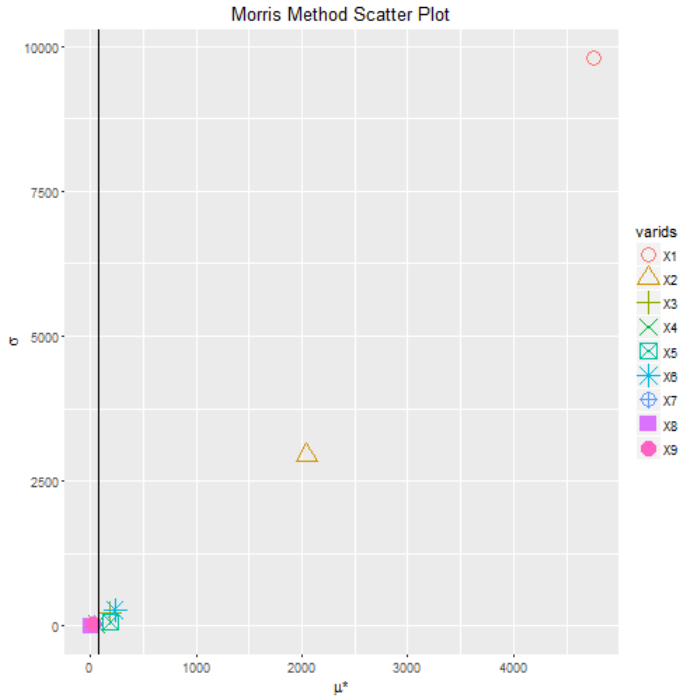


Figure 109 - X8D36/Chongjin Morris Scatter Plot

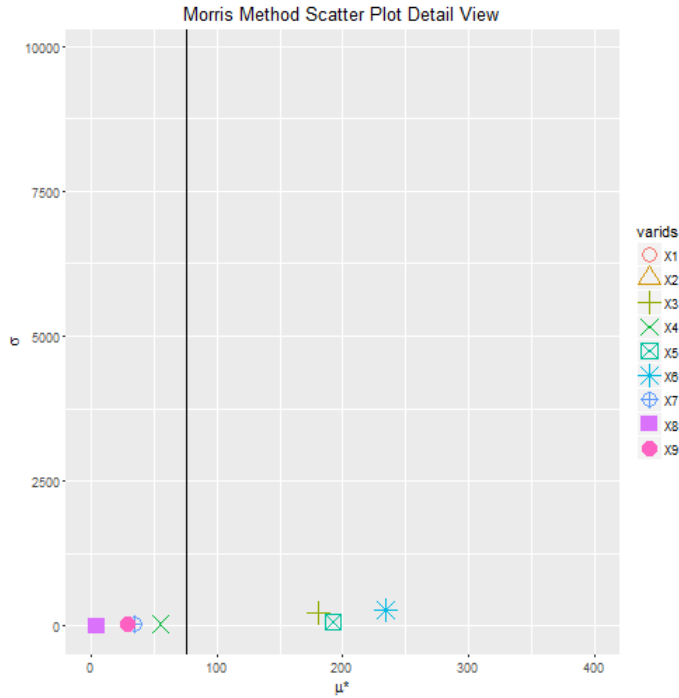


Figure 110 - X8D36/Chongjin Morris Scatter Plot Detail

Table 53 - X8D36/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	6518.505	6518.505	12042.995
X2	2677.245	665.812	4005.35
X3	888.91	888.91	316.574
X4	241.358	-241.358	85.395
X6	170.805	170.805	230.235
X9	114.391	114.391	84.702
X7	26.004	26.004	19.728
X8	8.739	3.055	9.541
X5	0	0	0

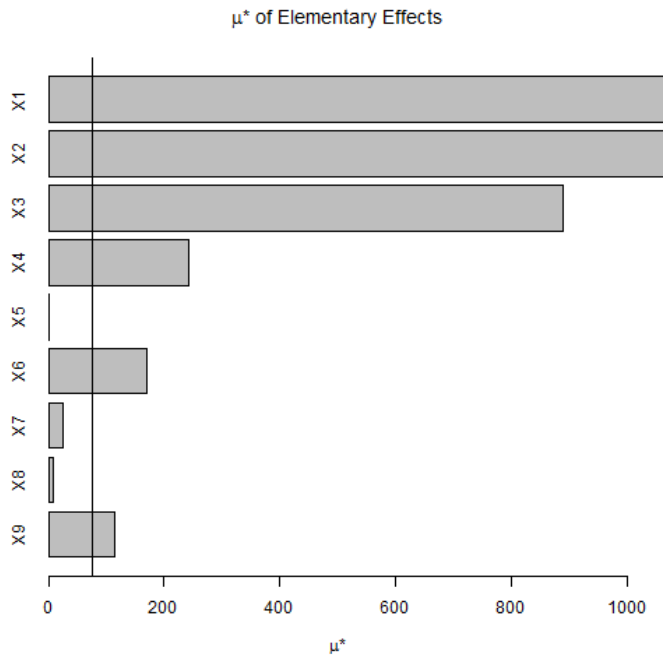


Figure 111 - X8D36/Singapore Sensitivity Bar Plot

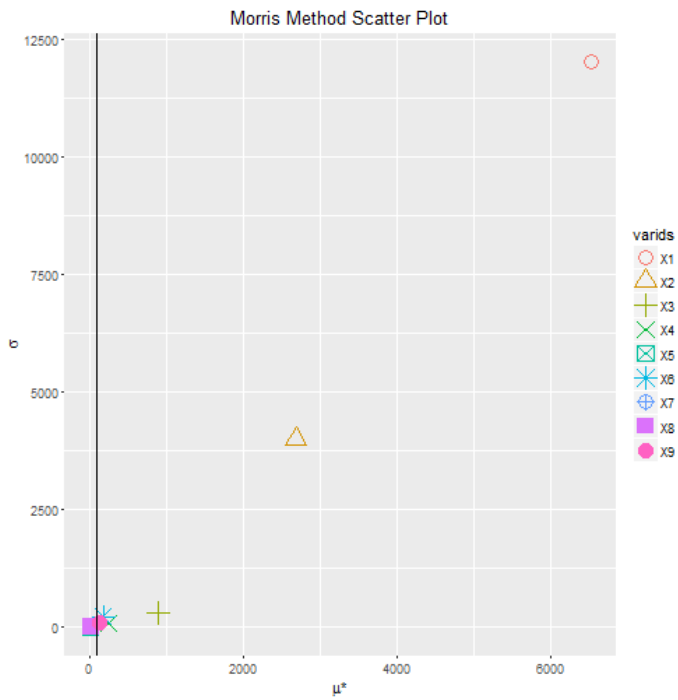


Figure 112 - X8D36/Singapore Morris Scatter Plot

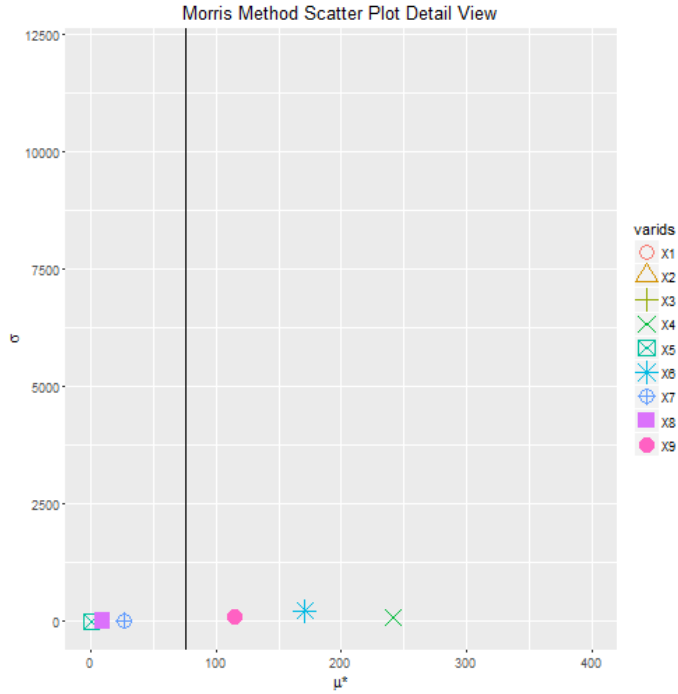


Figure 113 - X8D36/Singapore Morris Scatter Plot Detail

Table 54 - MGPTS-M/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	7928.953	7928.953	15201.243
X2	3664.535	1337.359	4984.461
X3	566.628	566.628	234.951
X4	276.553	-276.553	101.773
X9	99.676	99.676	79.832
X6	89.444	88.347	117.102
X5	74.826	74.826	41.105
X8	65.963	-24.302	80.996
X7	13.978	12.882	13.757

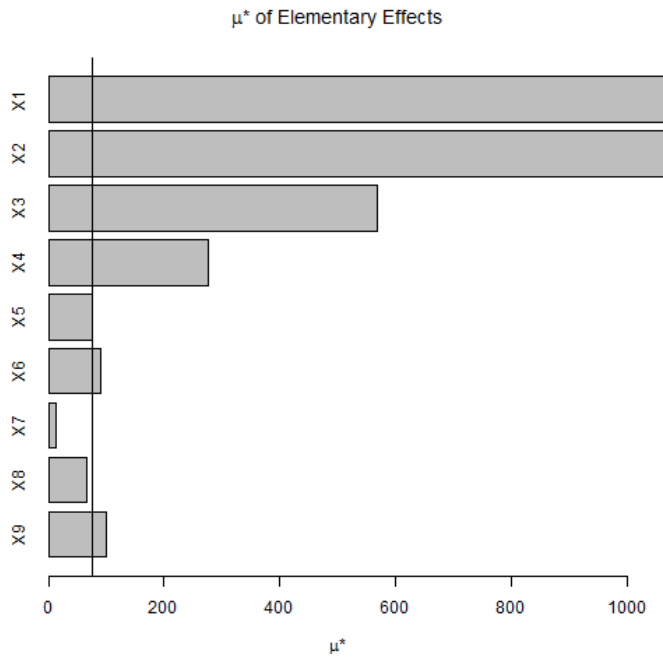


Figure 114 - MGPTS-M/Kharga Sensitivity Bar Plot

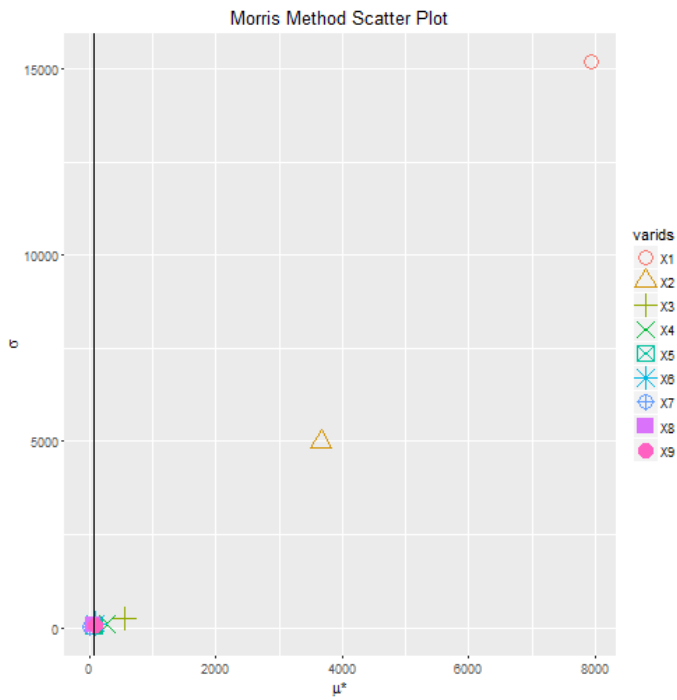


Figure 115 - MGPTS-M/Kharga Morris Scatter Plot

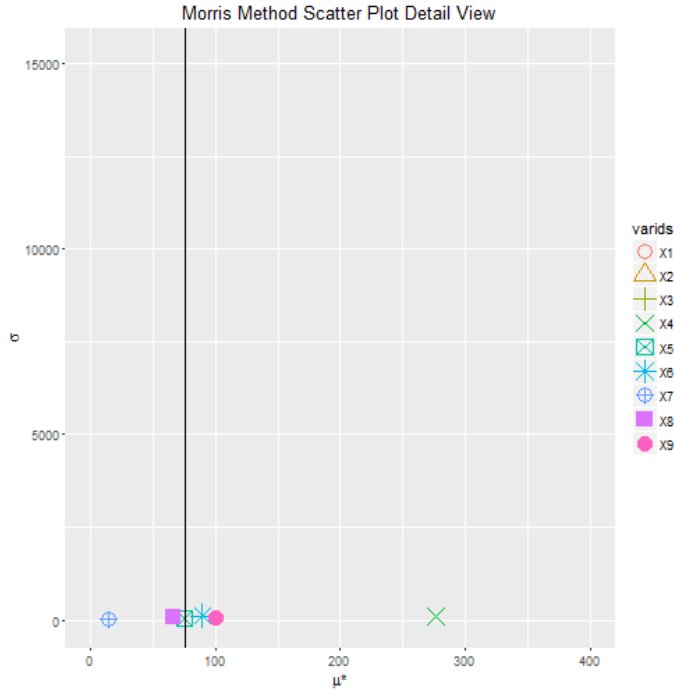


Figure 116 - MGPTS-M/Kharga Morris Scatter Plot Detail

Table 55 - MGPTS-M/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	5518.364	5518.364	11240.587
X2	3266.927	2202.01	4625.88
X5	310.814	310.814	108.612
X6	297.841	297.841	356.444
X3	202.55	-127.085	242.717
X4	84.693	-84.693	44.892
X7	42.483	42.483	39.582
X9	30.424	-1.188	49.534
X8	29.967	-11.694	38.156

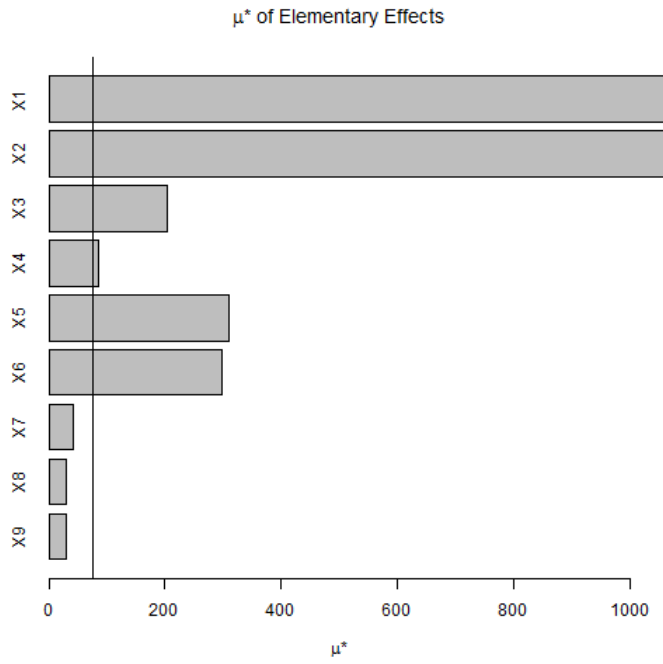


Figure 117 - MGPTS-M/Chongjin Sensitivity Bar Plot

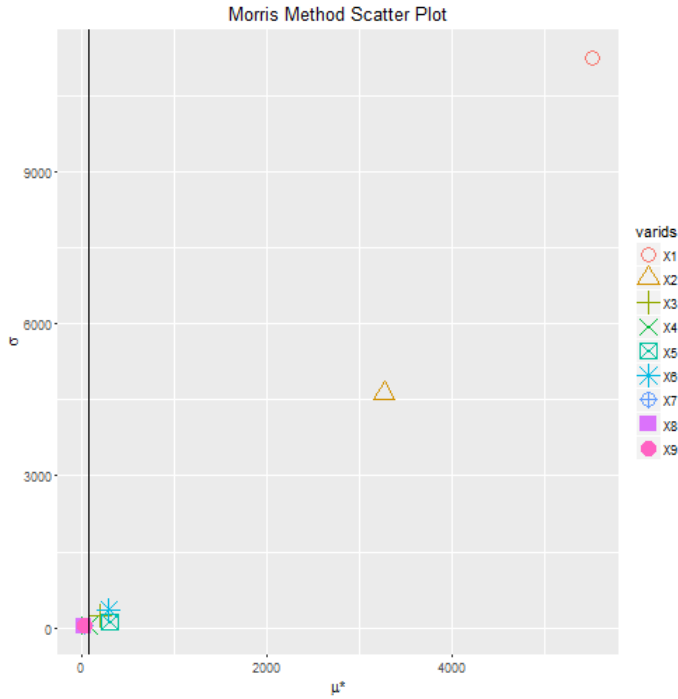


Figure 118 - MGPTS-M/Chongjin Morris Scatter Plot

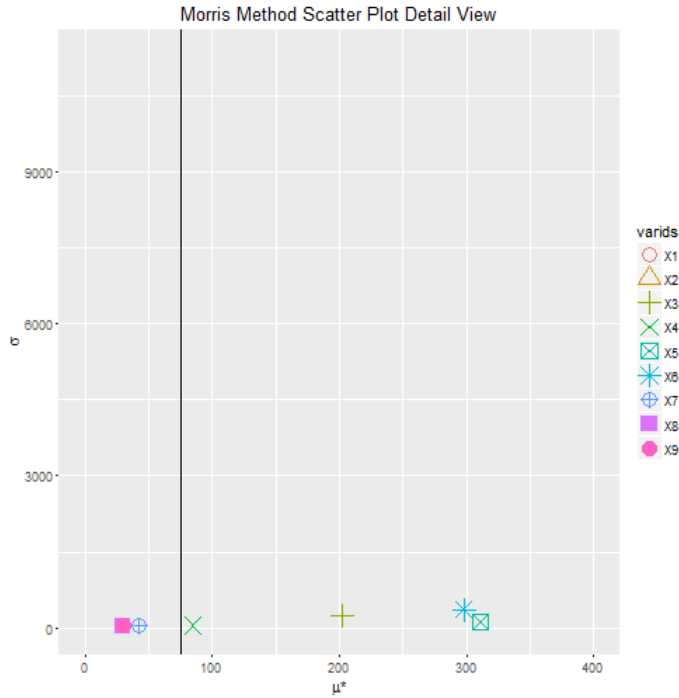


Figure 119 - MGPTS-M/Chongjin Morris Scatter Plot Detail

Table 56 - MGPTS-M/Singapore Sensitivity Results

Variable	μ^*	μ	s
X2	8468.447	6173.43	20338.01
X1	8175.631	8175.631	15146.338
X5	4712.184	4712.184	21073.529
X3	1118.912	1118.912	394.519
X4	370.382	-370.382	143.806
X6	238.638	238.638	338.259
X9	143.256	143.256	95.727
X7	36.271	36.271	27.394
X8	25.855	-8.131	28.508

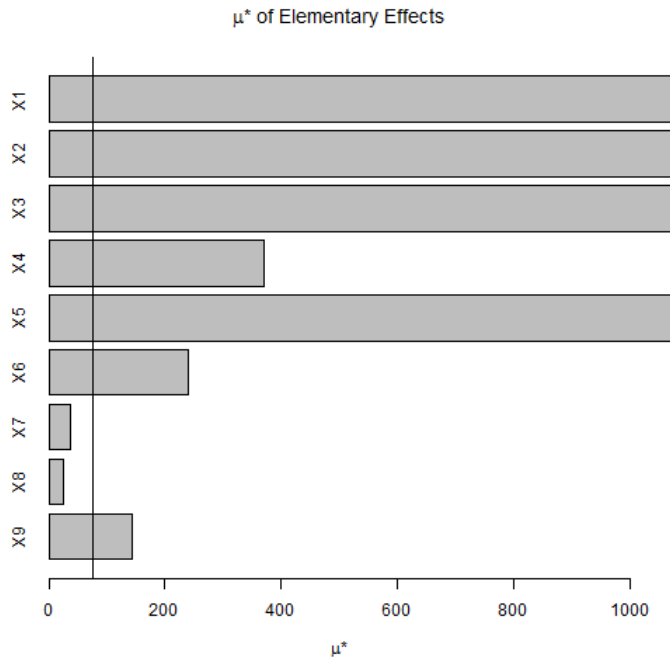


Figure 120 - MGPTS-M/Singapore Sensitivity Bar Plot

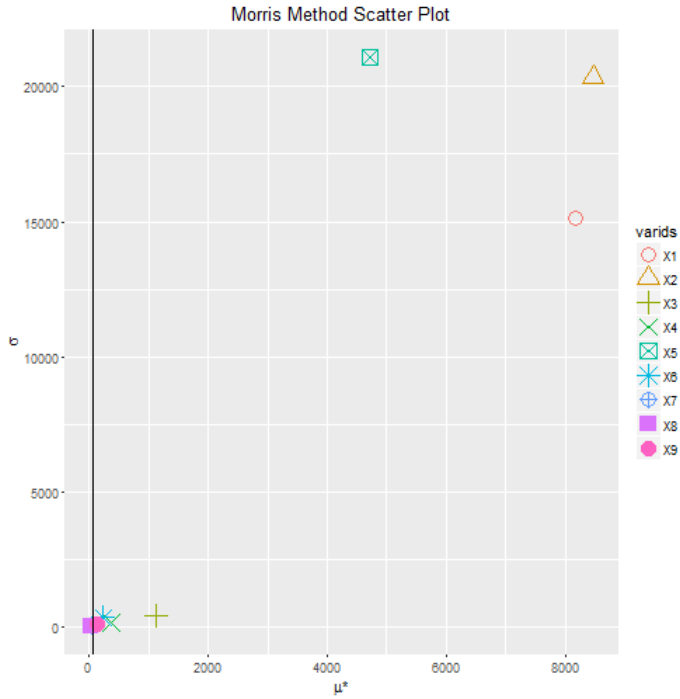


Figure 121 - MGPTS-M/Singapore Morris Scatter Plot

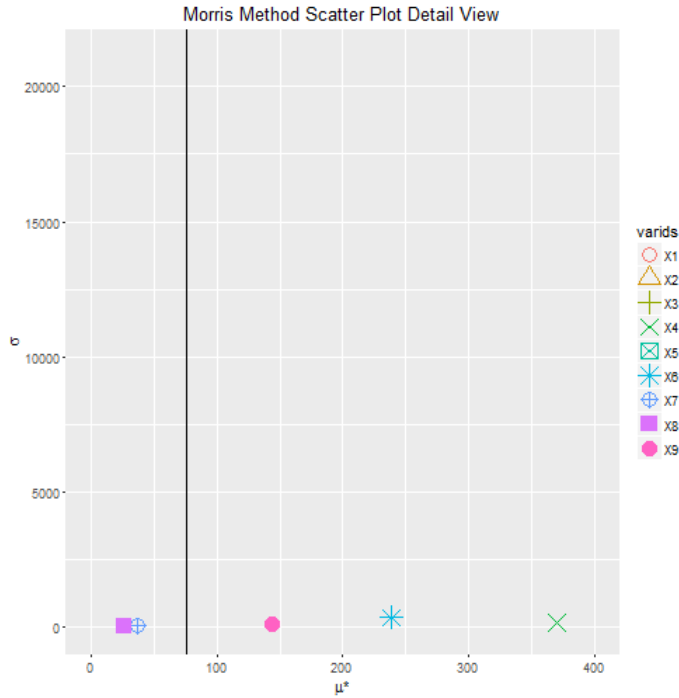


Figure 122 - MGPTS-M/Singapore Morris Scatter Plot Detail

Table 57 - MGPTS-L/Kharga Sensitivity Results

Variable	μ^*	μ	s
X1	5031.739	5031.739	9659.377
X2	3072.386	1352.464	3741.05
X3	312.032	312.032	151.275
X4	212.63	-212.63	82.571
X5	76.196	76.196	38.281
X6	61.091	61.091	82.661
X8	60.238	-25.277	73.686
X9	57.193	56.949	47.4
X7	9.014	9.014	8.608

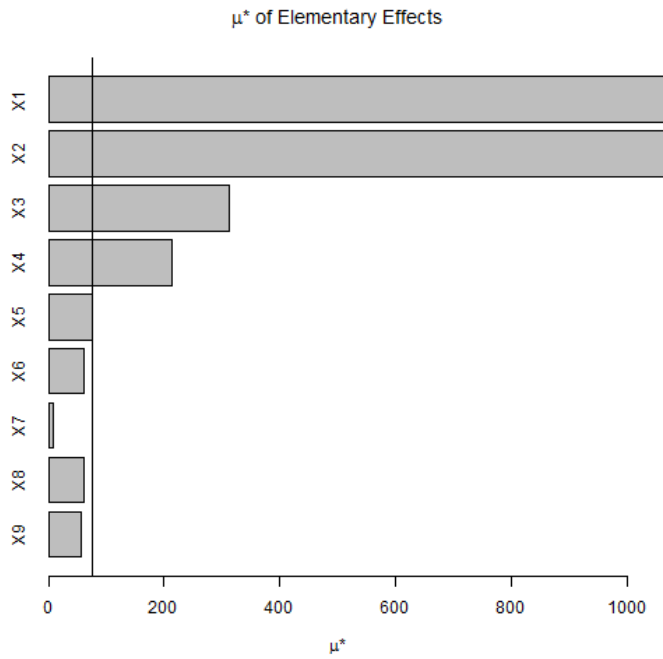


Figure 123 - MGPTS-L/Kharga Sensitivity Bar Plot

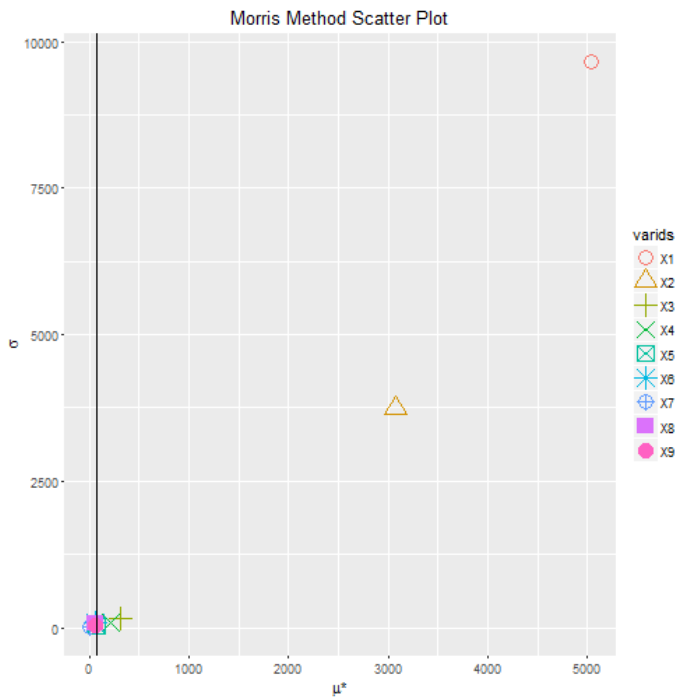


Figure 124 - MGPTS-L/Kharga Morris Scatter Plot

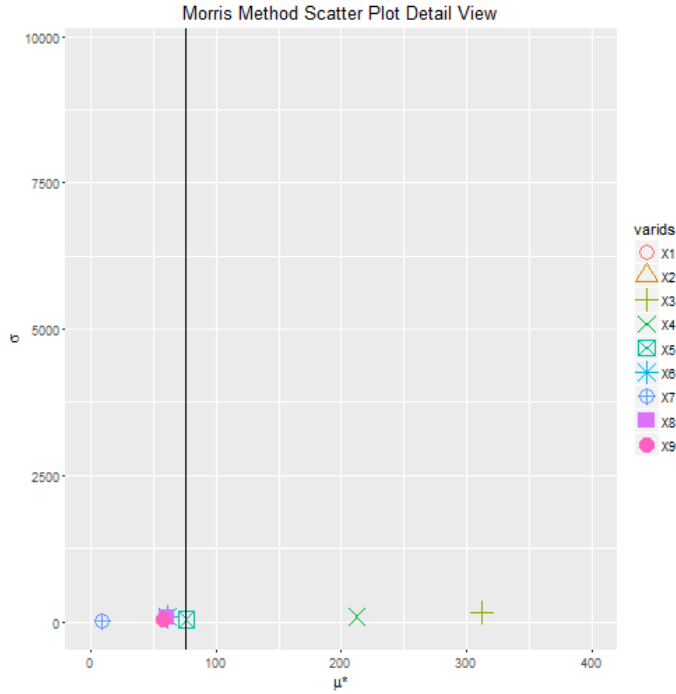


Figure 125 - MGPTS-L/Kharga Morris Scatter Plot Detail

Table 58 - MGPTS-L/Chongjin Sensitivity Results

Variable	μ^*	μ	s
X1	3232.027	3232.027	6543.141
X2	2790.687	1830.897	3826.213
X5	270.858	270.858	97.034
X6	199.718	199.718	254.027
X3	140.88	-112.984	136.951
X4	61.7	-61.7	29.381
X7	28.992	28.992	26.552
X8	28.566	-7.979	37.36
X9	18.699	-6.517	26.205

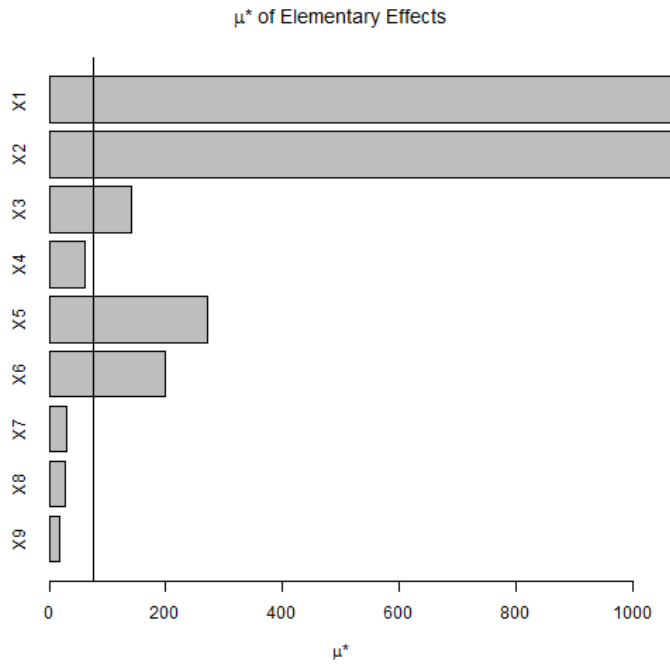


Figure 126 - MGPTS-L/Chongjin Sensitivity Bar Plot

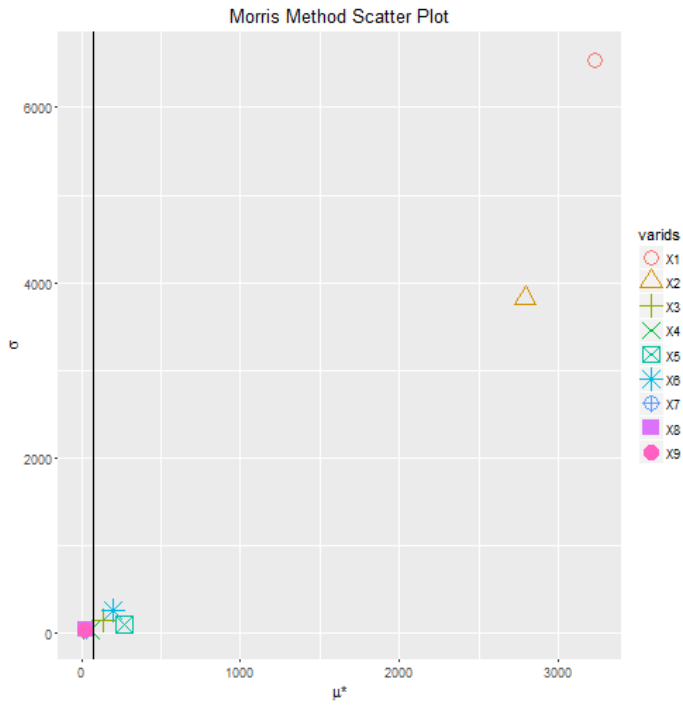


Figure 127 - MGPTS-L/Chongjin Morris Scatter Plot

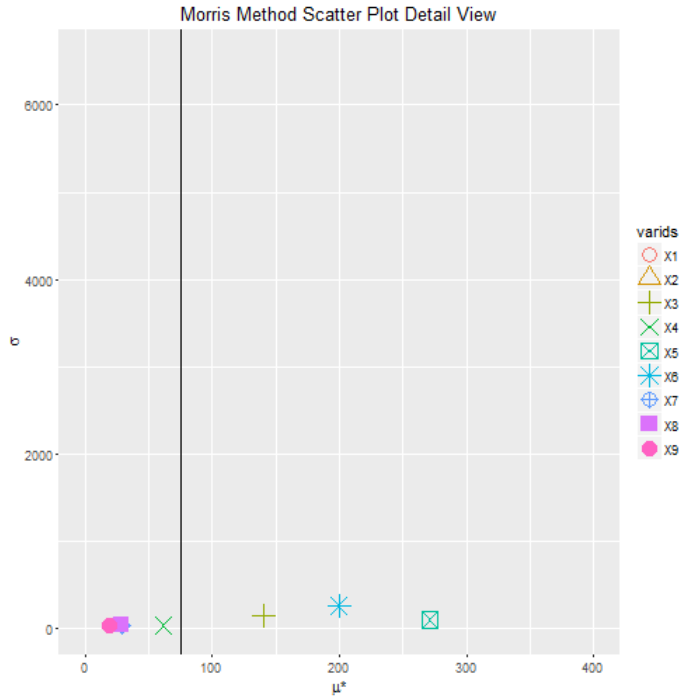


Figure 128 - MGPTS-L/Chongjin Morris Scatter Plot Detail

Table 59 - MGPTS-L/Singapore Sensitivity Results

Variable	μ^*	μ	s
X1	5375.078	5375.078	9929.619
X2	3216.921	1227.785	4389.473
X3	718.594	718.594	266.534
X4	324.701	-324.701	137.545
X6	152.148	152.148	220.384
X9	90.144	90.144	61.698
X8	36.423	-12.669	39.228
X7	23.693	23.693	18.251
X5	0	0	0

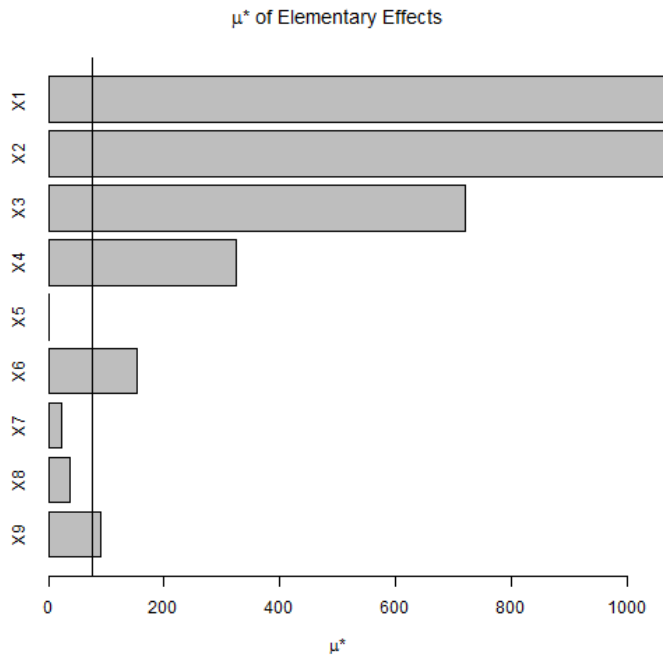


Figure 129 - MGPTS-L/Singapore Sensitivity Bar Plot

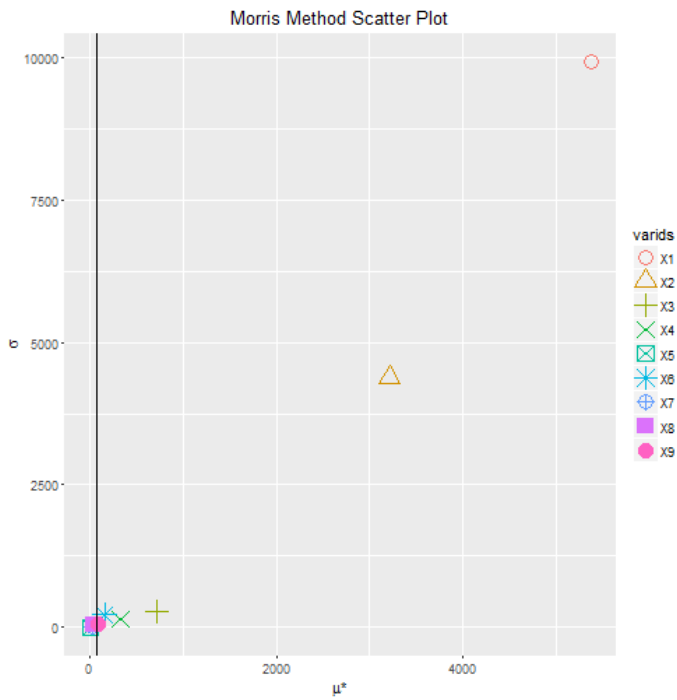


Figure 130 - MGPTS-L/Singapore Morris Scatter Plot

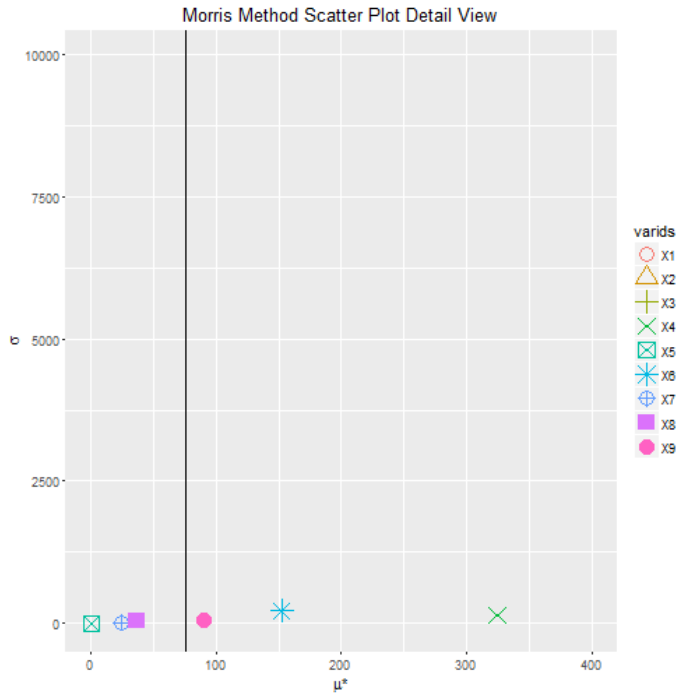


Figure 131 - MGPTS-L/Singapore Morris Scatter Plot Detail

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