**Sensitivity Analysis**

**Background:** Sensitivity analysis in system dynamics generally refers to the method of evaluating how sensitive a model’s behavior or policy recommendations are to assumptions in the model, parameter values, initial conditions, etc. The basic approach underlying any sensitivity analysis is to simulate the model over a range of values and then study the resulting distributions. Because system dynamics models simulate very quickly even on a laptop computer, it is feasible to consider a large number of uncertainties in a model. To automate this task, Stella includes tools for designing and running sensitivity analyses.

The automated procedure takes one or more parameters and draws values for these parameters from either a predefined list of numbers or random distribution of your choice. A sensitivity analysis is then run by sampling these values and running a simulation for each combination. The results are available using the graphs and analysis tools, and can be used to generate confidence intervals on simulation results.

While this procedure is designed to conduct sensitivity analysis of behavior and policies, it often used to also conduct policy experiments when one is interested in running all possible combinations of interventions. Although this is technically not a sensitivity analysis, the procedure is the same.

There is an extensive set of features in setting up sensitivity, including the selection of distributions, defining and saving different analyses, and combining a sensitivity analysis with optimization. See the [Stella online documentation](https://www.iseesystems.com/resources/help/v1-6/default.htm#05-Running_Models/Sensitivity_analysis/Overview_Sensitivity_analysis.htm%3FTocPath%3DRunning%2520models%7CSensitivity%2520analysis%7C_____0) for more extensive documentation on setting up and running a sensitivity analysis.

**Purpose:** Togain exposure to the use of sensitivity analysis tools to explore the impact of multiple interventions.

**Instructions:** For this exercise, we’ll use a simple one-stock model of the opioid epidemic (Opioid example.stmx). The model is an oversimplified representation of an otherwise very complicated and complex problem with three basic flows: initiation, quitting, and overdose deaths (see below).

The model allows for three basic types of interventions: decreasing the rate of initiation (primary prevention), increasing the rate that people are quitting (secondary prevention), and decreasing the rate of overdose deaths as a consequence of people using opioids and overdosing (tertiary prevention). The size or magnitude of these interventions is represented as an effect size (ES) that corresponds to a proportion of change where positive values are in the desired direction. For example, an effect size of 0.5 for reducing the risk of initiation corresponds to a 50% reduction in initiation.

The actual interventions are implemented with STEP functions. This is somewhat unrealistic as most interventions, if successfully implemented, tend to follow an s-shaped implementation curve. However, it is generally easier to see the impact in the simulation model if the simulated change introduces a discontinuity in the derivative of the curve. This generally has no effect on the evaluation of our intervention points.

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**﻿**Average\_duration\_of\_use = INIT\_Average\_duration\_of\_use\* IP\_average\_duration\_of\_use

UNITS: Years

DOCUMENT: The average duration of opioid use.

ES\_average\_duration\_of\_use = 0

UNITS: Dimensionless

DOCUMENT: Effect size (ES) of intervention to reduce average duration of use.

ES\_risk\_of\_initiation = 0

UNITS: Dimensionless

DOCUMENT: Effect size (ES) of intervention to reduce risk of initation.

ES\_risk\_of\_overdose\_death = 0

UNITS: Dimensionless

DOCUMENT: Effect size (ES) of intervention to reduce risk of overdose

death.

INIT\_Average\_duration\_of\_use = 14.2251544898335

UNITS: Years

DOCUMENT: The average duration of opioid use.

INIT\_Risk\_of\_initiation = 0.276555372037922

UNITS: Person/person/year

DOCUMENT: The risk or hazard rate of initiation is represented as a fractional rate of the number of persons initiating opioid use per person using per year.

INIT\_Risk\_of\_overdose\_death = 0.0596297050790344

UNITS: Person/person/year

DOCUMENT: The risk of overdose death from using opioids is represented as a hazard rate or fractional rate of persons dying from overdose deaths per person using per year.

Initial\_users = 3463.7815094916

UNITS: People

DOCUMENT: The initial number of users in Ohio in 2000.

Initiation = Risk\_of\_initiation\* Users {UNIFLOW}

UNITS: People/Years

DOCUMENT: The rate of initiating opioid use through casual use, prescription to relieve pain, and drug depdence.

IP\_average\_duration\_of\_use = 1 - STEP(ES\_average\_duration\_of\_use, TS\_average\_duration\_of\_use)

UNITS: Dimensionless

DOCUMENT: Intervention to reduce reduce average duration of use.

IP\_risk\_of\_initiation = 1 - STEP(ES\_risk\_of\_initiation, TS\_risk\_of\_initiation)

UNITS: Dimensionless

DOCUMENT: Intervention to reduce risk of initation.

IP\_risk\_of\_overdose\_death = 1 - STEP(ES\_risk\_of\_overdose\_death, TS\_risk\_of\_overdose\_death)

UNITS: Dimensionless

DOCUMENT: Intervention to risk of overdose death.

Overdose\_deaths = Users\* Risk\_of\_overdose\_death {UNIFLOW}

UNITS: People/Years

DOCUMENT: Opioid overdose deaths.

Quitting = Users/Average\_duration\_of\_use {UNIFLOW}

UNITS: People/Years

DOCUMENT: The rate of people quitting use of opioid including discontinuing prescriptions, recovery from addiction, etc.

Reference\_mode\_BAU = GRAPH(TIME)

(2000.00, 190), (2001.00, 200), (2002.00, 240), (2003.00, 290), (2004.00, 370), (2005.00, 450), (2006.00, 530), (2007.00, 660), (2008.00, 790), (2009.00, 890), (2010.00, 970), (2011.00, 1080), (2012.00, 1230), (2013.00, 1450), (2014.00, 1600), (2015.00, 1740), (2016.00, 1880), (2017.00, 2020), (2018.00, 2230), (2019.00, 2390), (2020.00, 2580)

UNITS: People/Years

Reference\_mode\_Hope = GRAPH(TIME)

(2000.00, 190), (2001.00, 200), (2002.00, 240), (2003.00, 290), (2004.00, 370), (2005.00, 450), (2006.00, 530), (2007.00, 660), (2008.00, 790), (2009.00, 890), (2010.00, 970), (2011.00, 1080), (2012.00, 1230), (2013.00, 1450), (2014.00, 1600), (2015.00, 1740), (2016.00, 1880), (2017.00, 1890), (2018.00, 1890), (2019.00, 1770), (2020.00, 1670)

UNITS: People/Years

Risk\_of\_initiation = INIT\_Risk\_of\_initiation\* IP\_risk\_of\_initiation

UNITS: Person/person/year

DOCUMENT: The risk or hazard rate of initiation is represented as a fractional rate of the number of persons initiating opioid use per person using per year.

Risk\_of\_overdose\_death = INIT\_Risk\_of\_overdose\_death\* IP\_risk\_of\_overdose\_death

UNITS: Person/person/year

DOCUMENT: The risk of overdose death from using opioids is represented as a hazard rate or fractional rate of persons dying from overdose deaths per person using per year.

TS\_average\_duration\_of\_use = 2015

UNITS: Years

DOCUMENT: Time that the intervention to rreduce average duration of use starts.

TS\_risk\_of\_initiation = 2015

UNITS: Years

DOCUMENT: Time that the intervention to reduce risk of initation starts.

TS\_risk\_of\_overdose\_death = 2015

UNITS: Years

DOCUMENT: Time that the intervention to reduce risk of overdose

death starts.

Users(t) = Users(t - dt) + (Initiation - Overdose\_deaths - Quitting) \* dt {NON-NEGATIVE}

INIT Users = Initial\_users

UNITS: People

DOCUMENT: The number of people in Ohio currently using opioids, including both illegal drugs such as heroin and synthetics opioids such as fentanyl, and legally available by prescription pain relievers such as oxycodone (OxyContin®), hydrocodone (Vicodin®), codeine, morphine, and many others (source: NIH/NIDA https://www.drugabuse.gov/drugs-abuse/opioids)

{ The model has 22 (22) variables (array expansion in parens).

In root model and 0 additional modules with 0 sectors.

Stocks: 1 (1) Flows: 3 (3) Converters: 18 (18)

Constants: 10 (10) Equations: 11 (11) Graphicals: 2 (2)

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1. Using the Opioid example.stmx model, design and run a sensitivity analysis to determine which combinations of interventions are most effective by sweeping the effect sizes for the three interventions (ES risk of initiation, ES average duration of use, and ES risk of overdose deaths) from 0.0 to 0.5 using an ad-hoc distribution. Then plot the distribution of the results using confidence intervals in a comparative graph to generate something like the graph shown below.   
     
   

Create a table for export that you can use to summarize the impact on opioid overdose deaths in response to the different conditions, and then export the graph and include output variables to generate the following (this example has been reformatted in Word).   
  
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|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Run | ES risk of initiation | ES average duration of use | ES risk of overdose death | Overdose deaths |
| Run 1 | 0 | 0 | 0 | 3679 |
| Run 2 | 0 | 0 | 0.5 | 2123 |
| Run 3 | 0 | 0.5 | 0 | 2613 |
| Run 4 | 0 | 0.5 | 0.5 | 1512 |
| Run 5 | 0.5 | 0 | 0 | 1867 |
| Run 6 | 0.5 | 0 | 0.5 | 1082 |
| Run 7 | 0.5 | 0.5 | 0 | 1310 |
| Run 8 | 0.5 | 0.5 | 0.5 | 762 |

**Using these results and assuming that we cannot do all three interventions equally well, but perhaps we can do 2 out of 3, which two recommendations would you endorse based on this model? Why?**

The run number 6 shows to us the lowest level of overdose deaths suing just two out of 3 interventions equally well, so I would recommend go with ES risk of initiation and ES average duration of use.