An exploratory modelling and analysis protocol for identifying robust policy mixes for clean energy transitions: An exploratory analysis for Mexico

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Method Article

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Abstract

This protocol presents a systematic approach for conducting exploratory modelling and analysis (EMA) to identify robust policy mixes for clean energy transitions. It explores the effects of diverse policy alternatives and multiple uncertainties within energy transitions through computational experiments. The protocol comprises diverse steps, including Decision Framing, Policy Alternatives Generation, Experiment Setting, Performing Experiments, Policy Alternatives Analysis, Performance Metrics Analysis, and Medium and Long-term Policy Analysis. It also integrates analytical sub-processes such as Policy Objectives Analysis, Feature Scoring, Robustness Analysis, Vulnerability Analysis, and Trade-off Analysis. The effectiveness of this protocol is demonstrated through its successful implementation in Mexico. Targeted at researchers, policymakers, and energy analysts, it offers a comprehensive method for in-depth exploration of the potential effects of diverse policy alternatives and multiple uncertainties within energy systems. While acknowledging that the duration of completion depends on available computational resources, it provides a detailed approach to conducting EMA for energy transitions.

Introduction

Exploratory modelling and analysis (EMA) uses computational experiments to systematically explore the potential effects of diverse policy alternatives and multiple uncertainties within highly complex systems (e.g. energy systems) [1]. By simulating one set of hypotheses, one set of computational experimental results is obtained. If various hypotheses (or assumptions) about the system are correct, one computational experiment represents how the system would behave according to those various hypotheses encapsulated in one single model [2].

This protocol outlines a comprehensive and rigorous approach to conducting EMA for identifying robust policy mixes for clean energy transitions. After defining the policy system and identifying the objectives and constraints of the decision-making process (Step 0: Decision Framing), there are seven major steps. Step 1: Policy Alternatives Generation involves identifying or generating policy alternatives that have the potential to meet the policy objectives and constraints defined in the decision framing. In Step 2: Experiment Setting, we specify the performance metrics and curate the policy alternatives. In Step 3: Performing Experiments, we generate a series of prospective transition pathways using a transitions model as a scenario generator. In Step 4: Policy Alternatives Analysis, we examine the policy alternatives and modify or combine them as needed. In Step 5: Performance Metrics Analysis, we explore the performance of the policy alternatives in the face of uncertainties using exploratory modelling. Steps 6 and 7 are Medium-term (to 2030) and Long-term (to 2050) Policy Analysis, where the analysis of extensive simulation results is conducted using an exploratory thinking approach. To enhance the analysis, five analytical sub-processes have been incorporated: Policy Objectives Analysis, Feature Scoring, Robustness Analysis, Vulnerability Analysis, and Trade-off Analysis.

This protocol differs from other exploratory analysis protocols in two significant respects. Firstly, it focuses on using a policy system model as a scenario, facilitating the creation of a comprehensive array
of prospective transition pathways. Secondly, it integrates a suite of five analytical sub-processes, collectively contributing to a thorough exploration of the intricate interactions between policy alternatives and uncertainties in complex energy transitions.

Reagents

Equipment

Hardware requirements:

- Operating System: Microsoft Windows

Available at https://www.microsoft.com/

Microsoft Windows 10 Enterprise was used in this protocol.

- Processor: A modern multi-core processor.

- Memory: At least 4GB of RAM, but more is recommended for large models or complex simulations.

- Storage: At least 60MB of free disk space for Vensim DSS installation, plus additional space for storing simulation results and other files. For very large models, more disk space may be required.

The computational experiments (i.e. energy transition pathways) were conducted using a Melbourne Research Cloud (MRC) virtual machine instance with 80 CPUs, 720 GB of RAM, and 1 TB of storage.

Software requirements:

- Simulation software: Vensim DSS

Available at https://vensim.com/

Vensim DSS for Windows Version 8.0.9 Double Precision (64-bit) was used in this protocol.

Note: Vensim only works on Windows.

- Programming language interpreter/compiler: Python

Available at https://www.python.org/ or through Anaconda at https://www.anaconda.com/

python 3.10.9 (64-bit) was used in this protocol.

Note: If you have 64-bit Vensim, you need 64-bit Python. If you have 32-bit Vensim, you will need 32-bit Python.
The conceptualisation and contextualisation of the policy system and its boundaries were selected based on previous studies [2–7] and are briefly explained as follows.

Policy system structure: This study used a modified configuration of the latest version (v3.3.1) of the Energy Policy Simulator (EPS) model for Mexico, developed by Energy Innovation LLC [8]. The EPS is an open-source and peer-reviewed system dynamics (SD) computer model that quantifies the plausible effects of energy and climate policies on GHG emissions at a national or regional level. SD is a methodology that aids analysts and decision-makers in mapping the interaction of multiple variables in
complex systems and explore their behaviour in time by the use of simulation models [9]. The EPS allows users to control multiple parameters that affect energy use and production, as well as GHG emissions [10]. A public web-based version of the original model may be available at https://energypolicy.solutions/.

Although the EPS model integrates a myriad of variables for the energy system (over 380,000), the modelling approach adopted to model technological progress was recently identified as a key limitation for policy analysis (e.g. technological knowledge stock was not included) [4]. The EPS model uses a combination of exogenous and endogenous learning approaches to estimating technology cost developments depending on the maturity level of each technology [8]. In the case of endogenous learning, the EPS model adopts the one-factor learning curve (1FLC) approach, being installed capacity the only driver for future cost developments in the case of wind and solar PV. Following [4], we extended the approach by explicitly including technological experience and knowledge stock as the sources of learning based on a comprehensive analysis of how technological learning is modelled for energy policy analysis [7]. Thus, modifications to the EPS-Mexico model were implemented following [4] and learning rates were estimated based on [6,7] with data from [3]. The model was implemented in Vensim DSS, and simulations were run for the period from 2020 to 2050. The modified version of the EPS-Mexico model is available on Supplementary Files as part of this protocol (epsmexico3.3.1.1EMA.zip).

Deep uncertainty characterisation: Potential uncertainties relevant to our analysis and estimated initial values were identified through literature review and model analysis. Parametric uncertainty (i.e. range of possible values for uncertain parameters) was selected based on the literature review and is presented using the deep uncertainty characterisation matrix proposed in [2]. Additionally, to the three possible locations of uncertainty initially proposed in [2] (i.e. model structure, future conditions, and outcomes of interest), we have included policy planning elements (i.e. policy objectives and instruments) for completeness in the decision framing and experiment setting steps for conducting the EMA process. A total of 33 external factors, 43 policy instruments, 19 outcomes of interest, and 8 policy objectives are included for EMA, using the modified version of the EPS model as a transition pathways generator. The deep uncertainty characterisation matrix is available on Supplementary Files as part of this protocol (EMADeepUncertaintyMatrix.xlsx).

We used the EMA Workbench [11] to conduct the exploration process. EMA Workbench is an open source Python library aimed at providing support for designing experiments, performing the experiments, and analysing the results [11].

**Step 1. Policy Alternatives Generation**

This step involves identifying or generating policy alternatives that have the potential to meet the policy objectives and constraints defined in the decision framing step. A policy alternative represents a mix of policy instruments with specific values and implementation schedules. There are three general approaches for generating policy alternatives and therefore conducting the exploration process: framed
exploration, open exploration, and directed search. Framed exploration uses pre-specified policy instrument mixes based on policymakers’ interests. Open exploration and directed search explore alternative policy mixes not pre-defined by decision-makers [11]. This protocol focuses on open exploration and directed search.

In open exploration, sampling techniques (e.g., Latin hypercube, full factorial, partial factorial, or Monte Carlo) are used to generate policy alternatives. In this study, the decision space (i.e. policy alternatives) was sampled using Latin hypercube sampling (LHS) for the open exploration process (Step 1.1). LHS is more beneficial than other sample techniques (e.g. Monte Carlo, full factorial design) for long running models when computational resources are limited [12]. LHS forces the specified sample size to cover the whole experimental space (i.e. uncertainty space and decision space) by producing a sample that is random but relatively uniformly distributed over each dimension [12].

In directed search, optimisation techniques are used to generate a Pareto optimal set of high-performing policy alternatives (relative to a BAU scenario) [13]. This study uses a multi-objective evolutionary algorithm (MOEA) called non-dominated sorting generic algorithm II (NSGA-II) [14] to perform global optimisation and find high-performing policy alternatives for the directed search process (Step 1.1). MOEAs mimic natural evolution processes to iteratively evaluate strategies across multiple objectives until the best candidates are found. However, genetic algorithms incorporate stochasticity in their search process. As a result, the outcome of a single run may be influenced by randomness. To account for this, it is recommended to perform multiple runs with different random seeds and aggregate the results to obtain a more robust set of solutions (Step 1.2). We used the ε-NSGAII [15] to combine the results across the seeds for the optimisation runs into a single comprehensive set using an ε-nondominated sort. In addition, when utilising MOEAs, it is crucial to carefully monitor their convergence towards the optimal solutions. To achieve this, various metrics can be employed. In our study, we utilised epsilon progress, generational distance, epsilon indicator, inverted generational distance, and spacing to track convergence across different seeds used for optimisation. For details on these metrics see e.g., [16] and [17] for distance and additive ε -indicator; [18] for spacing; and [19] for ε -progress.

Step 2. Experiment Setting

In this step, we specify the performance metrics (or outcomes of interest) in addition to the policy objectives selected in Step 0. Performance metrics differ from policy objectives (i.e. performance targets) is that the former consider behaviour over time (i.e. time series outcomes) while the latter focus on values at a particular time (i.e. single values outcomes). We then curate the policy alternatives and define the number of scenarios for the exploration.

Step 3. Performing Experiments
Using the modified EPS-Mexico model as a scenario generator, we generate a series of prospective transition pathways based on the decision framing and experiment setting discussed in the previous sections. A scenario represents a point in the uncertainty space, while a policy alternative represents a point in the decision space. The combination of a scenario and a policy alternative is called an experiment (or transition pathway).

**Step 4. Policy Alternatives Analysis**

This step involves examining the policy alternatives that will be evaluated using the policy system model. Our goal is to gain a deeper understanding of these policy alternatives, identify new ones, and modify or combine them as needed. We may also organise them into different timelines and select the ‘best’ options.

**Step 5. Performance Metrics Analysis**

This step explores the performance of the policy alternatives in the face of uncertainties. We use exploratory modelling to conduct an exploratory analysis of a wide range of assumptions and scenarios. Our goal is to understand how each policy alternative would perform in terms of the outcomes of interest under various conditions. This analysis will provide valuable insights into the robustness of the policy alternatives.

**Steps 6 & 7. Medium-term (to 2030) and Long-term (to 2050) Policy**

The analysis of extensive simulation results using the modified EPS-Mexico model as a transitions generator (i.e. computational experiments) was conducted using an exploratory thinking approach. By adopting an exploratory approach, more realistic insights may be obtained using statistical techniques (e.g. envelop plotting and Kernel Density Estimates (KDE)) and data-mining techniques (e.g. feature scoring and scenario discovery) over numerous experiments [20].

Based on [2], an exploratory analysis includes three analytical sub-processes: robustness analysis, vulnerability analysis, and trade-off analysis. We have included two additional analytical sub-processes (i.e. policy objectives analysis and feature scoring) to explore the effects of policy alternatives on achieving medium and long-term policy objectives set by policymakers.

**Step 6.1 & 7.1 Policy Objectives Analysis**

In this step, we present a visualisation of the policy alternatives in relation to the policy objectives. This provides a clear and concise overview of how each alternative aligns with the desired outcomes and help
inform decision-making.

Step 6.2 & 7.2 Feature Scoring

This step focuses on understanding what policy instruments may have a stronger influence in meeting policy objectives under conditions of deep uncertainty. In this study, we implemented a random forest-based feature scoring approach [11]. Feature scoring is a family of techniques commonly used in machine learning for testing the effect that different regressors have on the target variable. This approach provides valuable insights into the relative importance of different policy instruments in achieving the desired outcomes.

Step 6.3 & 7.3 Robustness Analysis

Faced with deep uncertainty, policy decisions may be made using the principle of satisficing rather than optimising [21]. Robustness analysis is performed based on the satisficing measure adopted from [22]. Thus, robustness is defined in this study as the fraction of sampled scenarios (i.e. uncertainty space) in which a policy alternative meets policymakers’ performance requirements in one or more objectives. Policy alternatives can be ranked based on the performance thresholds established by policymakers to ‘accept’ a robust solution. When a policy alternative is ranked with 100%, the alternative satisfies the policy objective threshold in all plausible scenarios. On the other hand, a rank of 0% is assigned when a policy alternative cannot meet the established performance criteria in all plausible scenarios. The aim of using a robustness metric is to identify policy mixes that are both high-performing in terms of policy objectives and are relatively insensitive to future external changes (i.e. different scenarios) [1].

Step 6.4 & 7.4 Vulnerability Analysis

This step focuses on identifying regions of the large, multi-dimensional uncertainty space where robust policy alternatives are vulnerable to poor performance. Poor performance is defined in this study as situations when policy alternatives cannot meet the performance threshold set by policymakers (i.e. policy objectives). We used the patient induction method (PRIM) [23] as the algorithm to conduct scenario discovery [24]. PRIM is a factor mapping approach aiming at identifying sensitive ranges of uncertainties that are likely to cause a particular behaviour. It works by peeling away layers of the uncertainty space by constraining one dimension at a time, then evaluating how well those constraints capture the points of interest based on two metrics: coverage (the fraction of poor-performing scenarios that fall within the box) and density (the fraction of scenarios within the box that perform poorly) [13,22].
Step 6.5 & 7.5 Trade-off Analysis

Advanced visualisation techniques are required to communicate policy-relevant insights and to provide a clear understanding of trade-offs and potential consequences of diverse policy alternatives [2]. Thus, to present the performance of different policy alternatives, we use a three-dimensional scatter plot (including the full Pareto set in relation to the objective space with specific thresholds), a parallel axis plot (to show the robustness ranking of policy alternatives according to each policy objective), and Kernel Density Estimates (KDE) for non-constrained policy objectives (i.e. policy mix cost in this case).

Steps to reproduce the study:

a. Create a local folder with the name ema_analysis.

b. Download the compressed version of the model (i.e. zip file) named epsmexico3.3.1.1EMA.zip, available on Supplementary Files.

c. Unzip the model folder into the ema_analysis folder using a zip/tar files unpacking software (e.g. 7-Zip, WinZip). Make sure the name of the model folder is eps-mexico-3.3.1.1_EMA.

d. Download the Jupyter notebooks openexploration.ipynb and directedsearch.ipynb, available on Supplementary Files. Place these files into the ema_analysis folder.

e. Download the python file functions.py, available on Supplementary Files. Place this file into the ema_analysis folder.

f. Create the following folders within the ema_analysis folder: archives, Figures_DS, Figures_OE.

g. Open Jupyter Notebook and navigate to the ema_analysis folder.

h. Run the openexploration.ipynb file for an open exploration analysis and the directedsearch.ipynb for a directed search analysis.

Troubleshooting

Step 0

Problem: Errors when trying to run the EMA protocol due to incompatible or not installed software.

· Possible cause: Required software is not installed or is incompatible with the system.
· Proposed solution: Check that all required software is correctly installed and compatible with your system. Follow the software installation instructions to install or update any missing or incompatible software. Make sure that the versions of the software you are installing are compatible with your system and with each other.

Problem: Errors when running the Jupyter notebooks or python scripts.
· Possible cause: Incompatible software versions or missing dependencies.
· Proposed solution: Check that all required software and dependencies are correctly installed and up-to-date.

Problem: Errors when trying to import relevant libraries for conducting EMA.
· Possible cause: Missing dependencies.
· Proposed solution: Make sure that you have installed the relevant libraries and that the versions of the libraries are compatible with your version of Python. If you encounter errors when installing a specific library, try searching for the error message online to find potential solutions or consult the library’s documentation for troubleshooting tips.

Steps 1 to 7

Problem: The computational experiments take a long time to run.
· Possible cause: Insufficient computational power or resources.
· Proposed solution: Check that your computer meets the recommended hardware requirements for running the computational experiments. Consider upgrading your hardware or using a more powerful computer if necessary.

Problem: Difficulties visualising data or experiencing slow performance when working with large datasets.
· Possible cause: Not enough RAM memory available.
· Proposed solution: Check the amount of RAM memory installed on your computer and compare it to the recommended hardware requirements for running the EMA protocol. If you have less than the
recommended amount of RAM, consider upgrading your computer's memory or closing other programs and processes that may be using up memory. Alternatively, try working with smaller subsets of the data or reducing the complexity of your visualisations to reduce the amount of memory required.

Problem: Errors when running the computational experiments or analysing the results due to different variable names.

· Possible cause: Inconsistent naming of variables between different parts of the protocol or between the protocol and the data.

· Proposed solution: Carefully review the protocol and the data to ensure that all variables are consistently named. Follow the naming conventions and guidelines provided in the protocol to avoid errors due to different variable names. If necessary, rename variables in the data or in the protocol to ensure consistency.

Problem: Errors when saving the results or figures due to missing folders.

· Possible cause: Required folders were not created as stated in the steps to reproduce the study.

· Solution: Carefully review the steps to reproduce the study and ensure that all required folders have been created. Follow the instructions provided in the protocol to create any missing folders. Make sure that the folders are correctly named and located in the specified directories.

Please note that the problems and solutions listed in this troubleshooting section are not exhaustive and are intended to provide guidance on common issues that may arise when implementing the EMA protocol. Other issues may arise depending on the specific context and application of the protocol, and it may be necessary to adapt the troubleshooting strategies accordingly. If you encounter a problem that is not listed in this section, try searching for potential solutions online or consult the documentation of the relevant software or libraries for troubleshooting tips.

**Time Taken**

Refer to Figure 1

**Anticipated Results**

The implementation of this exploratory analysis protocol is expected to yield comprehensive insights into the potential effects of diverse policy alternatives and multiple uncertainties within complex energy
systems. By following the steps outlined in the protocol, researchers, policymakers, and energy analysts may gain a deeper understanding of how different policy alternatives would perform in terms of the outcomes of interest under various conditions. This understanding may provide valuable insights into the robustness of policy alternatives and help inform decision-making towards clean energy transitions in developing countries. Additionally, the analytical sub-processes integrated in the protocol, such as Policy Objectives Analysis, Feature Scoring, Robustness Analysis, Vulnerability Analysis, and Trade-off Analysis, are poised to offer deeper insights into the relative importance of diverse policy instruments in achieving the desired outcomes and unveiling the intricacies of trade-offs and potential consequences associated with each policy alternative. The protocol thus offers a robust framework for comprehensive analysis and informed decision-making within the dynamic landscape of energy systems.

The results of the practical implementation of the EMA protocol for identifying robust policy mixes in Mexico's clean energy transition are presented in [25].

References


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Figures
Figure 1

Figure 1. Exploratory modelling and analysis (EMA) protocol stepwise workflow, including running times in minutes.

Supplementary Files
This is a list of supplementary files associated with this preprint. Click to download.

- EMAResearchProtocol.pdf
- epsmexico3.3.1.1EMA.zip
- EMADeepUncertaintyMatrix.xlsx
- EMAOpenExploration.ipynb
- EMADirectedSearch.ipynb
- functions.py