Computational Experiment Design for Operations Model Simulation

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Abstract—Computer simulations that demonstrate the value of novel approaches are crucial to developing more flexible and robust power systems operations with high penetrations of renewable energy at multiple geographic and temporal scales. However, optimization-based simulations that depend on forecast data often face challenges in evaluating performance, reproducing results, and testing under realistic simulation scenarios. In this paper, we develop scientific computing best-practices for the validation and reproduction of power systems operational models. We then employ two case studies to demonstrate the proposed validation and reproduction framework.

Index Terms—Optimization, Power System Operations, Scientific Computing

I. INTRODUCTION

The study of power systems operations has evolved with the changing needs of the grid and the development of new analysis tools. Formerly, the discipline relied heavily on mathematical analysis of lower-dimensional, deterministic systems and presented limited computer simulation results. Today, the need to integrate large amounts of variable and uncertain resources from different technologies while maintaining reliability and economic efficiency has dramatically increased the complexity of studying power systems [1]. However, thanks to increases in available computational power, optimization-based models and computer simulation are standard tools used for research in systems of all scales, from bulk generation and transmission to micro-grids. This paper contributes a framework to facilitate using these tools in accordance with the principles of Scientific Computing.

Scientific Computing has emerged as a field that studies and promotes the application of principles such as reproducibility, transparency, and accuracy to experiments that are carried out using computer simulations. Although Scientific Computing has benefited from notable contributions regarding the theory and practice of reproducibility [2]–[5], and there have been crucial advancements in the systematic development of computational experiments for model and algorithm testing through simulations [6]–[8], its adoption is not widespread.

It stands to reason that enhancing Scientific Computing would carry significant implications for power systems, since computational experiments afford almost the only option for engineers to conduct empirical experiments about the operation of large-scale power grids. Computing is a fundamental tool for conducting operations research [9], and – by extension – power systems operation research. Improving the definitions and practice of Scientific Computing principles thus also stands to benefit both of these fields.

We propose an initial step towards a power systems framework that systematically applies Scientific Computing principles to the development and validation of operational models. The focus of this paper is operational models, i.e. short-run decision-making models, that commonly represent the system in a quasi-steady state and solved via optimization algorithms. However, the broader concepts and definitions are also applicable to power system dynamic models, electromagnetic transients and any other field that relies on computer simulations. The relevant contributions in this paper are: first, a template to facilitate the development of simulations and computational experiments; second, a consistent set of Scientific Computing definitions, practices, and implementation details to facilitate its application to power systems operations research; third, repositories with cases employing the techniques and definitions outlined in this paper.

The paper is organized as follows: in Section II, we present a description of Scientific Computing practices and definitions emphasizing their relevance to power systems operations research. The requirements to design a computational experiment focusing on the definition of variables, data, models, and metrics is presented in Section III. Section IV showcases a development pipeline required to implement the computational experiment in accordance with Scientific Computing principles. Section VI includes examples of the implementation guidelines discussed in Section III and IV. Finally, we include conclusions in Sections V.

II. SCIENTIFIC COMPUTING PRACTICES

The field of Scientific Computing includes a broad array of definitions and practices. The relative importance and specific

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application of any one of these varies according to discipline [10], [11]. Here, we review definitions and applications of Scientific Computing principles in power systems versus other disciplines in the context of the scientific process.

Incorporating new knowledge into established science relies on (1) reproducibility of the experiments and (2) the validity of conclusions derived. Although there are semantic distinctions across fields in the term reproducibility [10], [11], we define reproducibility as the ability to produce consistent results with repeated experiments while running the same software and using the same input data and simulation settings [12]–[14]. Validity also has a variety of definitions depending on the scientific context. Here, we refer to two types: (1) Internal validity, or the consistency that simulation results have with the experimental system, and (2) external validity, which might also be called “generalizability.” It is the ability to derive inferences about how specific results or relationships may hold over variations in settings and systems [10]. These definitions must hold even when the experiments are carried out through simulation in computational environments.

Interest in Scientific Computing as a field unto itself began with a focus on the precision aspects of computational numerical methods and the conditions required for algorithms to obtain consistent results [15]. But numerical precision is not a chief concern for power systems operation research as it is for other simulations approaches like dynamic modeling and the development of numerical integration algorithms. Researchers in this field usually employ third-party packages to solve Mathematical Programs (MPs), and therefore the responsibility of numerical precision lies with the solver provider. The only exception to this is power systems research focused on the development of algorithms (e.g., [16]).

Some of the most vocal advocates in the scientific community for the principles of reproducibility and validity are from the fields of medicine [13] and computational biology [5] which strive to derive consistent, verifiable results from field or laboratory experimental data. Power systems researchers would do well to take lessons applicable to modeling and simulation, since their work is conducted on the basis of numerous embedded assumptions [17].

Large amounts of resources and time are needed to fully reproduce experiments that are not accompanied by code. However, computational reproducibility requires more than access to the code used to run computational experiments. While documentation alone meets some minimum standard, it is often insufficient to achieve full reproducibility. The recent focus of Scientific Computing on institutionalizing “best practices” has included themes directly relevant to effectively sharing code and documentation. This includes guidance on code readability, the use of version control tools, and code sharing through platforms like Github. These basic tenets have come to define the baseline for “good” code [18]. In part, these are not practiced in power systems because most researchers are not trained in the Scientific Computing principles that would emphasize the why and how of reproducible code [19]. In many cases, power systems researchers have no intention of re-using code following paper publication.

In summary, according to the scale of reproducibility proposed by [15], most papers in this field thus fall in the category of “publication only” and can only be regarded as “reviewable” according to [10]. Implementation details are often deemed irrelevant, even when in many cases such details are crucial to understanding final results [20]. By contrast, consider the open source genetics software BioConductor [21], whose standard of reproducibility has generated more than 10,000 citations showing the value to the field of having certain common scientific practices. It has no equivalent in power systems, although researchers in this field do occasionally apply principles of Scientific Computing to specific areas, such as the use of Optimal Power Flow (OPF) benchmark cases for the development of new formulations [22].

III. DESIGNING THE EXPERIMENT

In this section, we contribute a logical process for designing power systems computational experiments based on general practices from empirical research. In a simulation context, the experiment consists of varying inputs and executing trials of the simulation processes to generate a sample of outputs. These samples are later used to compute relevant performance metrics or summary statistics. Figure 1 shows a breakdown of the experimental process organized into three different processes: data, computational modeling, and results sub-processes. Each of the sub-processes can present the researchers with many design choices. However, in this section, we review exemplary practices in the literature to guide
tackling common issues and best practices. We emphasize that using this framework supports a robust evaluation of operational models and provides a clear way for reviewers and readers to assess conclusions conditional on the researchers' experimental setup.

In [8], the authors define a simulation experiment as sampling the space of input variables over trials to characterize a system in the space of output variables. Exhaustive sampling is a viable strategy when the input space is small. However, power systems operational research typically features complex and large input spaces that includes time-series, network configurations, demand levels, and parameters of economic and physical subsystems. This motivates a sub-classification of the data inputs inspired by general empirical methods to help inform experiment design.

In our review, we find that a formal design approach and classification like this are rarely used. Researchers tend to implicitly focus on reporting a few key simulation results, and over-specify the case data and the experiment parameters, reducing external validity of conclusions.

A. Data

The experimental data specification requires selecting system parameters, a method for selection and use of trial data, and a definition of test-sets. A test-set is a collection of inputs used in the simulation that produces a corresponding output. The data defining a test-set is organized hierarchically with a single set of \textit{experiment parameters} that define the scope of the experiment, a number of sample sets of \textit{confounding variables} that delineate a particular trial, and for each trial, an instance of each of the \textit{independent variables} which are the primary objects of study with a hypothesized impact on the outputs. Table I shows the different types of data input along with descriptions and selection considerations.

The validity of results is closely tied to the researchers’ choices of both classifying and selecting these data. The more general and representative of other cases the experimental parameters are, the higher the external validity; while the more robust the sampling of confounding variables, the higher the internal validity. The simulation settings such as output interval, algorithm tolerances, convergence criteria are also part of the experiment parameters, and convergence criteria.

Confounding variables can be sampled either randomly or deterministically: sensitivity analysis, selecting sets of representative or extreme cases, and Monte Carlo simulation are all conventional methods [8]. In power systems operational research, independent variables often include or are directly the operational models themselves; e.g., the alternative Unit Commitment (UC) models in [23], [24] or the demand response recourse strategies in [25]. Confounding variables are often sets of time-series data, initial system state, renewable penetration or the test system.

In selecting data, there is often a tension between using real, benchmark, or synthetic data. Real systems and real data sets are often attractive because they have better internal validity. However, using any proprietary data with sharing restrictions can undermine reproducibility. Standardized test systems are by definition more reproducible and should yield more comparable results across studies, but the prevalence of “modified IEEE systems” show that these often do not capture all relevant features and there is a need for comprehensive test data sets. Synthetic network generation algorithms address some of these shortcomings [26], but do not eliminate the need for modification with time series and the addition of other devices. In these cases, the modification process must be transparent and unbiased, which can be done by providing all the details when defining the modifications necessary and generating the full modification with code. Capturing uncertainty in synthetic data sets, particularly in forecasts and realizations is a critical component in modern operations. [27] provides an overview of modeling uncertainty across parts of the power system.

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B. Simulation Models

In power systems research, computational models are both the subject of the research and the experimental apparatus for evaluating research, often leading to the conflation of different models within the experiment. In practice, most experiments are used to demonstrate the performance of a proposed decision model for taking an operational action. In our framework, this makes the decision model an independent variable. Following the process in Fig. 1 it is necessary to define at least one alternative test-set (i.e., a control) in the form of a baseline decision model, often representing a heuristic or current practice. To do this, and to have a valid representation, it is critical to delineate a decision model from an emulator model used as a representation of the real system defined as follows:

- Decision Model: The model used to obtain the desired system operation behaviour. The model that generates set-points or policies used to drive the devices in the system.
- Emulator Model: A model that mimics a specific real-world behaviour of the electric power system. The model produces outputs that resemble the system performance when operating under the resulting policies from the decision models.

The emulator yields the performance metrics to compare performance between decision models and should be consistent across all test-sets and trials.

In some cases, where the contributions are comprised of a combination of operational models and solution algorithms (e.g., [29], [30]) it is important to have a clear distinction between the modeling aspects and the algorithmic ones. In such cases, details of the model and implementation of the
algorithm should be clear and reproducible. For instance, update rates, constants, tolerances and heuristics need to be clearly stated.

The results commonly included in publication consist of the output of the decision model without showing whether the decision model has the hypothesized effect on the system. The emulator model is intended to enable the evaluation of the decision model’s performance in terms of the system’s behavior conditional on its output. Not having an emulator in the simulation process is particularly problematic in operations models intended to handle uncertainty like Stochastic Unit Commitment (SUC) and Robust Unit Commitment (RUC). It also complicates matters when the decision model must make simplifying assumptions to be computationally tractable. In [31], the authors explicitly point out the limitations of interpreting the results of their decision model, and propose a modification to make it more realistic. However, the standard should not be that a decision model accurately represents reality; rather, the effort is selecting a reasonably accurate emulator to capture the relevant system’s performance.

Separating the models in this fashion has been done in many highly cited works [23], [25], [31], though there are some exceptions [24]. Other examples are most readily found in receding and shrinking horizon model predictive control, often employed in microgrid Energy Management System (EMS). The stochastic EMS work in [32] uses an actual physical test system, while [33] exemplifies the computational approach using OpenDSS as the emulator, and [34] uses a Monte Carlo (MC) approach to test the robustness of the control.

Based on the aforementioned literature, we generalize three main characteristics that the emulator should possess to be used as the validation test-bed in simulations:

1) The emulator should be on the same or a faster time-scale than the decision model under study, and capture the phenomena that are significant on these time scales and relevant to the study. There needs to be a logical connection between the chosen emulator and the operational model.

2) The system representation should include as much detail as is necessary to test the effect of simplifying assumptions used to make operational models tractable. This often requires additional data and trials.

3) The emulator’s time-series realization data must be distinct from forecasts used in the decision model. The use of forecasts within decision models has become commonplace in power systems operations research, and in many cases the same data used to generate the decision are used to test the effectiveness of the decision model.

C. Performance Metrics

Metrics are measurements computed on outputs of the computing process in Fig 1. The relevant aspect to consider is that metrics should be reported and calculated in terms of the trials with a probabilistic sense. Commonly, metrics are reported only for a single test set or single trial. In a computational experiment conducted with repeated trials, the metrics should accurately demonstrate the internal and external validity of the conclusions. For instance, in [35], [36] the authors use total costs and Automatic Generation Control performance metrics (e.g., CPS2) to assess the value of improving forecasting accuracy in the system.

There are a vast number of possible metrics relevant to power systems operations that depend on the application of the decision model. However, it is possible to derive recommend three principles in the design of experimental metrics:

1) Consider the distribution of metrics across trials and analyze them statistically.

2) Disaggregate metrics rather than reporting total costs alone. Presenting the costs associated with here-and-now and recourse actions separately can yield more insight (neither can be omitted), and include physical metrics which provide a richer picture of phenomena left out of decision models but captured by the emulator (e.g., battery wear, insecure loading limits, etc.).

3) Include the computational times for the given environment. Metrics on computational performance tend to go unreported and they are critical for assessing the feasibility of incorporating research into real systems or further experiments, as well as indicating opportunities for computational performance improvement.

IV. IMPLEMENTING A REPRODUCIBLE COMPUTATIONAL EXPERIMENT IN POWER SYSTEMS

In practical terms, achieving reproducibility and validation requires operationalizing the principles of Scientific Computing. Here, we present a template for a reproducible scientific workflow for simulation of power systems operations.

### Table I

| Input Type                | Description                                      | Selection Considerations                                      | Examples                                      |
|---------------------------|--------------------------------------------------|---------------------------------------------------------------|------------------------------------------------|
| Experiment Parameters     | All data held constant through out the simulations, defining the scope of the experiment | Enables generalization of the experiment to other cases       | Test network, cost functions, boundaries of the confounding variable space |
| Confounding Variables     | Data varied across trials, used to test robustness of results | Unbiased sample coverage of the relevant space                | Forecast and realization time-series, reserve requirements |
| Independent Variables     | Variables compared within each trial, primary objects of study | Isolation of variable of interest, including a control or null case | Operational models, forecast accuracy, renewables penetration |
problems. Each step of this template weighs the two major components required for a computational experiment: the environment and the workflow.

- **Environment**: The collection of software, hardware components, and configurations used to implement a computational experiment [19]. The environment may include elements such as cloud-services, third-party software, file management scripts, and external tests.

- **Workflow**: The sequence of computing tasks, from data intake to summary of results via plot and table generation, which, as a collection, make up the scientific experiment and the analysis [37]. The development of a workflow is a requirement for validation and reproducibility.

The following template breaks down both the environment and the workflow of a power systems computational experiment into the three main stages: data process, computing process, and results and reporting process.

### A. Data Process

Often, preoccupations about data in the context of Scientific Computing are limited to data sharing, access concerns, and best practices for transparency by using raw data files in human-readable formats [18], such as CSV for tabular data. However, the very act of processing raw data into analytical data must itself be a reproducible procedure that can be validated. The two aspects necessary for achieving this are (1) the data model and (2) the data production process.

All computational experiments need to define, document, and automate the steps followed in processing and generating data, such that these procedures can be reproduced and validated by other researchers. Figure 2 showcases a simple workflow for data processing and generation, distinguishing between the raw input data that can be obtained from many different sources and may exist in a variety of formats, and the analytical data that has been parsed by the researcher to fit neatly into the organization of the data model.

1) **Data Model**: A data model is a way to organize data and standardize its internal relationships and properties, providing a structure for use in the computational experiment [38]. In power systems research, efforts to make standard data models have primarily focused on power flow data [39], and the Common Information Model (CIM) developed by industry for SCADA and control center automation [40]. Power systems' operational research requires richer data models, which can hold more information than just a representation of the system parameters. For instance, holding time series, confounding variables, and parameters is necessary for the execution of computational experiments.

Without a single, widely agreed-upon data model in power systems modeling for computational experimentation, researchers have to develop customized data models for individual applications. This process is time-consuming, and as a result, data models usually go underdeveloped. Researchers should first carefully evaluate whether a custom data model is necessary. If so, modern programming languages provide researchers with environments containing an extensive assortment of options to develop data models. Researchers can greatly increase the value of their contribution and convergence to new standards by publishing their data model and implementation code for re-use.

2) **Data Consumption**: In most cases, before the data can be arranged into the data model, some computations are necessary. Examples of such computations might include consistency checks, ensuring the anonymity of proprietary data, or adding more features to the original data. For instance, including ramp rates to model UC in data sets that were originally developed for Power Flow (PF). Such computations are part of the data processing pipeline, and must be recorded as part of the workflow.

In the context of the workflow depicted in Figure 2, synthetic data should be considered, along with “real” or observational data, to be a raw input to the model. Like real data, synthetic data may undergo parsing for use with a specific data model. When creating confounding data, all random number generators used should be seeded, and those seeds included in the data model. Further details concerning the process for generating synthetic data are outlined in Section III.

### B. Computing Process

The computing process is easily confused with the computational experiment itself. In fact, the experiment – as described earlier in this paper – is far more nuanced than the execution of a model. A computing process is comprised of a set of simulations used to test the effects on the test-set in the system using the emulator model as a proxy, as shown in Fig. 3. Each trial of an experiment constitutes a simulation case, which is characterized by the decision and emulator model executions.
and interactions. For instance, simulating a standard day-ahead UC over a year results in executing 365 daily decision models, each followed by another 24 hourly Economic Dispatch (ED) emulator executions.

Simulations can take many different configurations depending on the research objective and the experiment design. It is, therefore, not possible to pre-define a generic simulation setup that fits all applications. However, it is possible to establish some general definitions to help guide the development and facilitate the reproducibility of the simulation setup.

A simulation generally defines a chronology in which models execute, and information is passed between them. Although there are myriad configurations in power systems, there are two standard formats: 1) Synchronized, where the results of each time step \( t \) in model A is synchronized with the execution of model B such as the day-ahead example mentioned above (see Fig. 4), and 2) Receding Horizon where only the solution of \( t = 1 \) is used in model B such as Example 1 in Section V (see Fig. 5).

1) Model Execution: When an optimization model is executed, sub-processes relevant pieces to scientific workflow happen in the background that need to be accounted for in the computation workflow. Figure 6 shows the pipeline and the different components that make up the environment and workflow of a model execution.

- **Algebraic Modeling Language**: The Algebraic Modeling Language (AML) code describes the model’s MP. The models are generally expressed in terms of sets, parameters, variables, constraints, and an objective function. In this stage the optimization model is not being solved, rather its processed such that it can be used in the solver.
- **Optimization Model**: This is the AML output, the optimization model in standard form. Often AMLs make internal transformations to the MP to make it compatible with the solver. This include adding slack variables or constraint reformulations, and can occasionally hinder reproducibility when the AML changes.
- **Solver**: The solver performs the computations necessary to obtain the solution of the MP. Modern optimization algorithms can be heavily customized, and all the details of the solver parameterization must be accounted for.

C. Results and Reporting

The output of the computing process is the collected results of the simulations, which does not necessarily imply that it is the final result of the experiment. Figure 7 shows the workflow to compile the outputs of the model executions into a format suitable for analysis, finishing with the calculation of the selected metrics. Often, other libraries are required in the environment to process the outputs and calculate the results. The aggregation process has the potential to confound the effects of the proposed model. Hence, the raw output of the simulations should be archived, and the code to calculate the metrics should comply with the principles of reproducibility.

V. CASE STUDIES OF THE FRAMEWORK IMPLEMENTATION

We have included two example cases for the principles described in this paper. The cases are developed in MATLAB and Julia programming languages to showcase that the proposed framework is platform and language independent. The results shown here aim to exemplify the application of the principles in simplified case studies and not to derive specific conclusions about the models. The code for the case studies is archived in the public repository [https://github.com/Energy-MAC/PowerSystemsScientificComputing](https://github.com/Energy-MAC/PowerSystemsScientificComputing).

A. Case 1: Microgrid EMS with demand response

This experiment compares different predictive controllers to regulate power consumption through demand response in energy-constrained islanded microgrids.

1) Experiment Design: The hypothesis is that each controller improves a particular performance metric relative to a baseline of no control. Here, the choice of decision model used by the controller is the independent variable. We compared four controllers: a heuristic method that does not use forecasts, a predictive control using only a single average forecast, and two stochastic programming formulations.

We constructed a synthetic microgrid, synthetic forecasts of solar generation based on historical data, and synthetic electricity demand forecasts based on random simulation to be used as confounding variables. The system features multiple customers, distributed solar and battery storage.

The performance metrics are: Average Service Availability Index (ASAI), total customer utility from electricity consumption, and the realization of the objective of the decision model, which is a measure of benefit of electricity consumption that we construct. Since performance metrics include power availability and the impact of interruptions at the customer level, the emulator must capture the effect on customers.

2) Implementation: This environment is MATLAB 2018a and Gurobi 9.01 as the solver using the Gurobi MATLAB API. The experiment uses a custom data model for data input/output and for the experimental parameters. The controller makes a decision to send energy and power limit signals to customers every 4 hours with a receding horizon of 2 days. The emulator model includes a customer decision to respond to the signal every 4 hours, and a model of the physical devices that runs on a 2-minute timescale. The controller assumes that customers will reduce consumption if necessary to comply with energy and power limits, but assumes they will reduce exactly to a limit, while in the emulator, customers make a discrete choice of which appliances to disconnect with some imperfect
knowledge of what their consumption will be. Then, the 2-
minute model simulates power sharing between generation
and storage, the evolution of thermostatically controlled loads
and battery state-of-charge, and interruptions when load power
cannot be met or customers exceed limits.

3) Results: Figure 8 shows the value of the metrics across
trials for each controller relative to the baseline of no control.
This illustrates the principles of displaying metrics statistically
and showing the side effects on multiple concrete emulator
metrics not explicitly optimized for in the decision model that
has an abstract objective. The design framework emphasizes
that these results are limited to the context of the experiment
parameters, particularly the interruption cost function in the
emulator customer model and the forecast and realization data.

B. Case 2: Stochastic UC and Bulk Power Systems

The experiment is designed to compare an SUC model with
a standard UC model. The detailed mathematical specifications
of the models used in these experiments are located in the
example repository.

1) Experiment Design: The hypothesis is that using SUC
achieves better hedging against wind power uncertainty and
reduces the occurrence of load shedding. In this example,
the independent variable is the day-ahead model which is the
choice of UC or SUC model. Given that the SUC requires
the use of scenarios, the complete test-set is made up of the
decision model-forecast pair. The SUC uses 100 scenarios
generated by sampling a truncated normal distribution with
a variance of 30%. To evaluate the hypothesis, an ED model
is used as the emulator with 5-minute resolution time-series.

The experiment includes 10 trials each for ranges of 30
consecutive days in the annual data in order to capture seasonal
variations through the year. For each trial, the metrics used
to assess the performance of the system are total fuel cost
and total energy not supplied. The models are tested in a
modified 5-bus test system [41] which has been enhanced with
piece-wise linear cost functions. The test system also features
an additional 3,600 MW of wind power generation and an
increased peak load of 14,400 MW. The system has been also
enhanced with yearly time series for load and wind power
from the data provided in [28].

2) Implementation: The experiment has been in Julia
v1.2.0, using the JuMP v0.20.0 as the AML with the Solver
Gurobi 8.11. Auxiliary *.toml files define the full experiment
environment by fixing other libraries’ versions in the
experiment. The code structure in the example repository has
been intentionally arranged consistently with the definitions
given in the paper. The data model is provided using the pack-
age PowerSystems.jl and the same is used to integrate
time series data into the load flow case. The commitment
decisions are synchronized with the ED model, which is
executed 24 times for every commitment model execution.

3) Results: The results showed that for most trials, the SUC
reduces the amount of load shedding in the system but also
has an increased fuel cost. The results are displayed as Box
Plots in Figure 9 that enable further exploration of the trial
results and derive more detailed insights about the model’s
performance. In this way, it is possible to notice that in two
outlying samples, the SUC resulted in more load shedding than
the UC. The result motivates exploring which circumstances
may lead to weaker performance from the SUC than the UC.

From the computational point of view, running multiple
trials allows us to evaluate if the relative differences in
computation speed are consistent between the model. Each
commitment model ran a total of 300 times; the SUC has an
average solve time of 59.18 s and a maximum of 158.98 s
compared to the 2.87 s and a maximum of 8.2 s of the UC
model; an order of magnitude faster than the SUC.

VI. CONCLUSIONS

- The power systems community has the potential for
  many benefits from the adoption of Scientific Comput-
ing practices. The current computational experimentation
  practices are lacking when compared to other fields.
- Developing novel operational models requires validation
  through computational experiments. Appropriate experi-
  ment design is critical in demonstrating models’ capabil-
  ity to handle large penetration of renewable energy.
- The software developed for power systems operational
  research must reproduce experimental results, which im-
 plies access to the input data, code access and consistent
  results when the experiment is replicated.
