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# Economic Parameter Uncertainty Quantification Demonstration

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**Gabriel J. Soto**
**Paul Talbot**
*Idaho National Laboratory*

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Gabriel J. Soto
Paul Talbot

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**Idaho National Laboratory**
**Integrated Energy Systems**
**Idaho Falls, Idaho 83415**

**http://www.ies.inl.gov**

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# EXECUTIVE SUMMARY

Integrated energy systems (IES) combine power, in mutually beneficial ways, from variable renewable energy sources and nuclear power plants (NPP) to produce multiple commodities and improve economic viability under uncertain market conditions. The open-source Framework for Optimization of Resources and Economics (FORCE) tool suite, developed at Idaho National Laboratory (INL), has enabled comprehensive modeling and simulation of IES. The capabilities within FORCE include grid portfolio optimization through the Holistic Energy Resource Optimization Network (HERON) and the transient process model analysis library HYBRID, among others.

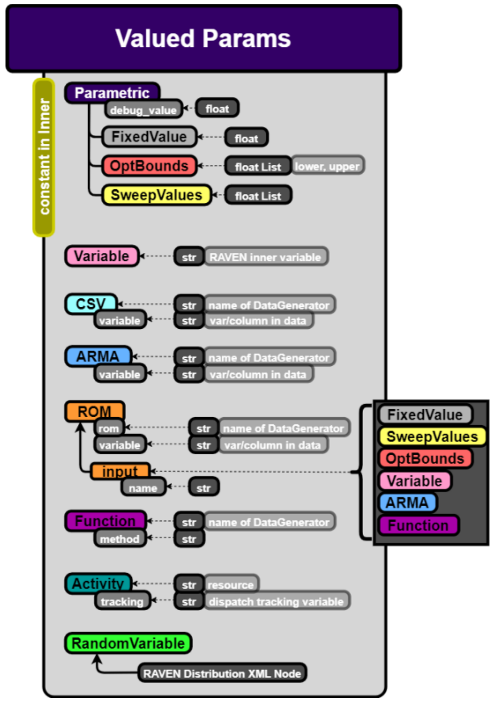
HERON has recently added uncertainty quantification capabilities for economic parameters. Users may now associate a distribution with certain cash flow parameters to simulate uncertainty in cost or other economic inputs. For example, a user may want to capture the uncertainty of capital expenditures of an advanced NPP because public data are hard to find or is not available yet. This new addition allows users to account for that uncertainty.

***Refresher on HERON:*** HERON's standard workflow (the bi-level, Risk Analysis Virtual Environment (RAVEN)-runs-RAVEN stochastic optimization) already provides uncertainty quantification when users run techno-economic simulations with trained auto regressive moving average (ARMA) or time series analysis (TSA) reduced order models (ROMs): market uncertainty. The outer RAVEN level determines values for variable component capacities:

- In ***opt*** mode via stochastic gradient for component capacities with `*<opt_bounds>*`
- In ***sweep*** mode via iterating over a grid of values for component capacities with `*<sweep_values>*`

Values from each "step" in the outer level are held constant in the inner level, where decisions over resource dispatch are optimized for different market scenarios. Each scenario/realization takes a time series sampled from the included ARMA or TSA ROM using a Monte Carlo sampler. In this way, HERON can incorporate uncertainty over market pricing, hourly load demand, wind, and solar availability, etc.

***New Features:*** Users can now add uncertainty to cash flow parameters alongside ARMA/TSA ROM runs. This is particularly useful for components such as advanced nuclear reactors which do not have settled, publicly available cost numbers for capital expenditures (CAPEX), operations and maintenance costs, etc., and may instead have a certain range or distribution.



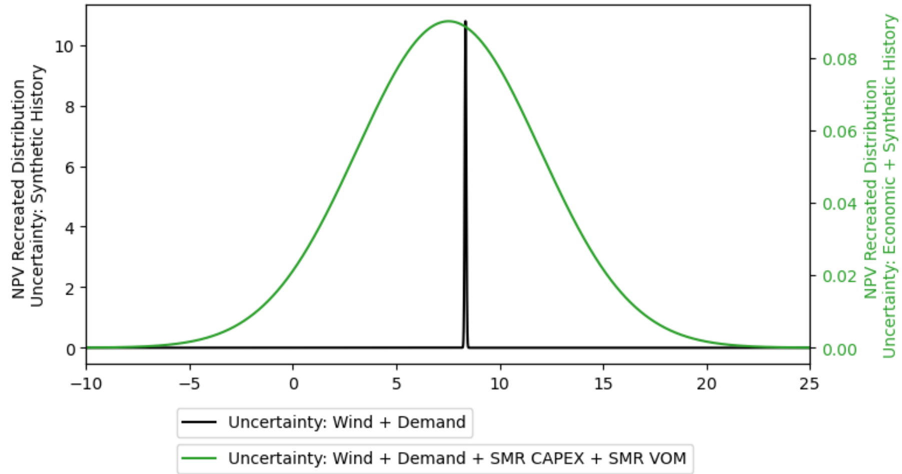

*List of available HERON ValuedParams*

The uncertainty is applied as a distribution for a cash flow parameter (e.g., the reference price or cost). In the HERON standard workflow, when the Monte Carlo sampler generates a synthetic history from the ARMA/TSA ROM, it will also sample from the provided distribution(s) a new cost value or cash flow parameter for each realization. HERON may now produce results such as the expected value of net present value (NPV) given uncertainty in market conditions *and* uncertainty in component costs.

```
<Components>
  <Component name="SMR">
    <produces resource="electricity" dispatch="independent">
      <capacity resource="electricity">
        <sweep_values debug_value="5">30,32.5</sweep_values>
      </capacity>
    </produces>
    <economics>
      <lifetime>60</lifetime>
      <CashFlow name="capex" type="one-time" taxable="True" inflation="True" mult_target="False">
        <driver>
          <variable>SMR_capacity</variable>
        </driver>
        <reference_price>
          <uncertainty>
            <Normal name="SMR_capex_dist">
              <lowerBound>1_867_000</lowerBound>
              <upperBound>9_467_000</upperBound>
              <mean>5_700_000</mean>
              <sigma>3_800_000</sigma>
            </Normal>
          </uncertainty>
          <multiplier>-0.1</multiplier>
        </reference_price>
      </CashFlow>
```

*Example of HERON input script with uncertain ValuedParam as price.*

***How to use it***: Users must include an `*<uncertainty>*` node below the desired cash flow parameter; this uncertainty node is a new ValuedParam (e.g., “fixed_value,” “opt_bounds,” “ARMA,” “Function”) internally called “RandomVariable.” Within the `<*uncertainty*>` node, users must include a distribution XML node—with the same syntax as the ones in RAVEN (e.g., “Normal,” “Uniform,” “Beta,” “Weibull”)—to represent the uncertainty in the parameter. Above is an example of adding uncertainty to the CAPEX cost/reference price cash flow; it is assumed to be a normal distribution with a mean of 5.7$M and a standard deviation of 3.8$M which were assumed for an small modular nuclear reactor. The difference between a 50-sample HERON simulation with and without *economic* uncertainty is shown below.




*Difference in final net present value distributions with and without economic uncertainty for a small modular reactor, wind, and battery integrated energy system*.

Economic uncertainty can be specified only for the following parameters:

- ○<*reference_price*> *(sometimes referred to as ‘alpha’)*
- ○<*driver*>
- ○<*reference_driver*>
- ○<*scaling_factor_x*>

Economic uncertainty is also only available when using an ARMA or TSA ROM, in the future it will also be available when using a static history or comma-separated value (CSV).

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# CONTENTS



# FIGURES

# TABLES

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# ACRONYMS

| | |
|---|---|
| ARMA | auto regressive moving average |
| CAPEX | capital expenditures |
| CSV | comma-separated value |
| FOM | fixed operation and maintenance |
| FORCE | Framework for Optimization of Resources and Economics |
| HERON | Holistic Energy Resource Optimization Network |
| IES | integrated energy systems |
| INL | Idaho National Laboratory |
| IRR | internal rate of return |
| LMP | locational marginal price |
| LSCOE | levelized system cost of electricity |
| MACRS | modified accelerated cost recovery system |
| NPP | nuclear power plant |
| NPV | net present value |
| PDF | probability density function |
| PI | profitability index |
| RAVEN | Risk Analysis Virtual Environment |
| ROM | reduced order model |
| SMR | small modular reactor |
| TEA | techno-economic analysis |
| TEAL | Tool for Economic Analysis |
| TSA | time series analysis |
| UQ | uncertainty quantification |
| VOM | variable operation and maintenance |
| VP | valued param |
| VRE | variable renewable energy |
| WACC | weighted average cost of capital |

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# 1. Introduction

Techno-economic analysis (TEA) of integrated energy systems (IES) answers questions of economic viability of various technologies working together to meet regional demand of various commodities or resources. IES produce energy from various sources–including variable renewable energy (VRE), nuclear power plants (NPP), and secondary storage. IES leverages the baseload reliability of NPP-produced electricity and the peaking, daily, and seasonal intermittency of VRE to cleanly and reliably meet power demands from grid operators. Residual power after meeting power demands can be rerouted for storage, secondary commodity production, residential heating, or other industrial applications that can be facilitated with excess energy. Storage of either electricity, thermal energy, or other commodities from IES can also be used for arbitrage in their respective markets. Strategic charging and discharging of storage components can take advantage of fluctuations in energy prices for added revenue and profits.

Traditional plants operating in regional deregulated markets with a large mix of VRE generation often struggle with volatile pricing and market conditions. Periods of oversupply from VRE and low demand for electricity often result in low, even negative, electricity prices in deregulated markets [1]. Baseload suppliers without the technical ability or economic incentive to quickly ramp up production are not as competitive in these markets. Inversely, when demand is high but weather conditions are not favorable, baseload suppliers are necessary to carry out grid functions. The composition of IES, with a mix of baseload and variable resource supply, is designed for resilience and responsiveness in these circumstances. Simulations of economic performance, however, must incorporate the fluctuations and general volatility of these markets to truly capture an expected outcome for these systems.

The Framework for Optimization of Resources and Economics (FORCE) toolset via the Holistic Energy Resource Optimization Network (HERON) plugin and the Risk Analysis Virtual Environment (RAVEN, recipient of the 2023 R&D 100 award) software conduct stochastic optimization to incorporate the uncertainty of these markets and determine the optimal capacity sizes of different technologies in a grid portfolio [2,3,4]. This uncertainty and stochastic optimization takes the form of a bi-level optimization problem: the first stage or outer level is tasked with solving for the technology capacity sizes which optimize some expected economic metric, the second or inner level is tasked with determining the optimal dispatch of resources to maximize that economic metric.

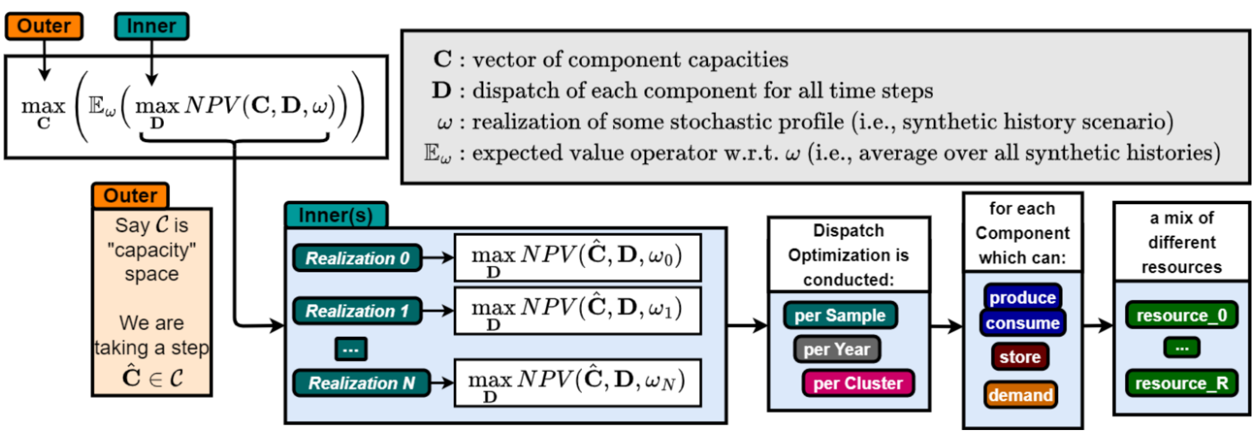



*Figure 1. Bi-level optimization scheme used in HERON with multiple realizations in the inner levels.*

The inner level takes the form of multiple instances (sometimes hundreds or thousands) of market conditions and the associated dispatch or utilization of resources to optimize an economic metric. The inner level then returns a distribution of these economic metrics—a common one being the net present value (NPV) of the technology, a sum of annualized positive and negative cash flows—to which the outer level optimizes over some statistic—commonly the expected value—of the distribution.

The inner optimization simulates multiple instances of market conditions using trained reduced order models (ROMs) of time series data pertinent to regional markets. These time series data consist of features such as hourly load demand for a resource like electricity, wind, and solar utilization factors, or settled locational marginal prices (LMP) for deregulated markets [4]. Through a catalogue of transformation and characterization time series analysis (TSA) algorithms—e.g., normalizations, fitting of Fourier modes for detrending, auto regressive moving average (ARMA)—the ROM captures inherent, sometimes correlated, statistics and dynamics in the time series [5,6,7]. Once trained, the TSA ROM can be used to synthesize new time series data with the same inherent characteristics and statistics of the training set. Each instance, often referred to as scenarios or realizations, in the inner level uses a set of unique, synthetic time series for each type of signal. Through the resultant distribution of economic outcomes, with enough realizations and sufficiently well-trained ROMs, the simulated expected value of a metric like NPV for a given portfolio of technologies will approach the true expected value given the uncertain nature of potential market conditions.

One additional uncertainty which has previously not been addressed in HERON and is the newest feature to be added in fiscal year (FY) 2024 is economic uncertainty within the cashflows. The next generation of advanced reactors (e.g., sodium or lead-cooled fast reactors, small modular reactors, microreactors) have promising futures in the clean energy landscape of the country but, historically, capital costs have taken a large proportion of total costs and are a major obstacle to future deployment of these crucial technologies [8]. Within this pre-deployment phase, any projected capital costs (CAPEX), fixed-yearly or variable operation and maintenance costs (FOM and VOM respectively) have different ranges depending on assumptions from manufacturers.

This uncertainty in cost can and is now modeled within HERON alongside market uncertainty. In this report, we will describe the initial implementation of economic uncertainty quantification (UQ) within the HERON bi-level optimization and parametric sweep schemes. In Section 2, a basic background of HERON and the different options available for input parameters to users will be outlined. In Section 3, the economic UQ features will be described. In Section 4, future work within the remainder of the FY will be proposed.

# 2. HERON Workflow

The HERON bi-level optimization is structured with different categorical indexing which will be described in this section. These include time regimes for the TSA ROMs for which dispatch optimization is solved (Section 2.1), resource pools and components which interact with the resources (Section 2.2), and cash flows to map activity to economic performance (Section 2.3). Dispatch optimization determines the optimal time-dependent utilization and allocation of resources amongst the different components leading to an optimal economic outcome for a given time window (Section 2.4). Different technical and economic inputs are then described with a catalogue of "ValuedParam" from which they receive their values, evaluated either prior or during the inner level (Section 2.4). The bi-level optimization scheme is then revisited in the context of HERON inputs and ValuedParams (Section 2.6).

## 2.1 Time Indexing

Time indexing within HERON is dictated by the time series resolution of the trained TSA or Synthetic History ROMs. Typically, these are organized by yearly data files with an hourly time resolution; interpolation methods are available for missing yearly data to estimate required features for characterizing algorithms such as the ARMA [7]. Parallel efforts at Idaho National Laboratory (INL) within the IES program are focusing on multi-resolution time series analysis, but for now the standard is to conduct dispatch optimization at a single time scale such as hourly. A depiction of the scenario, or realization which will be used interchangeably, time indexing is featured in Figure 2. The example in the figure shows a simulation where there are four inner realizations or scenarios. Each scenario has 5 years' worth of time series; each year is 15 data points.

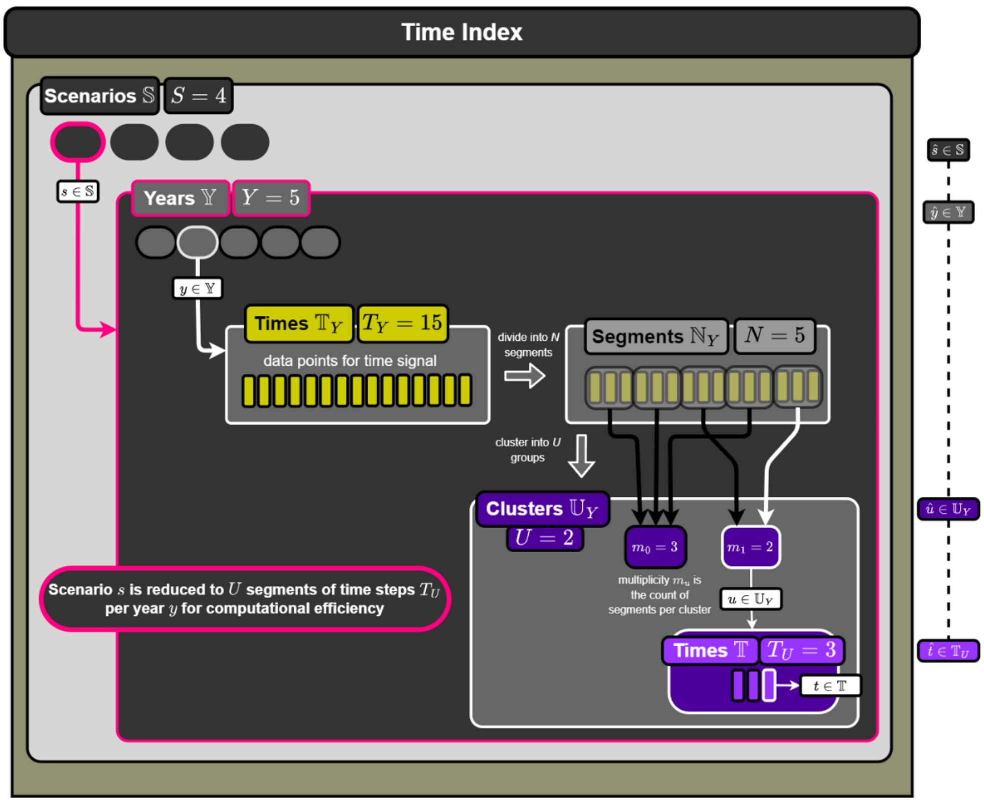



*Figure 2. Time series and dispatch indexing based on a collection of scenarios or realizations, each with multiple years and the same number of data points per year. Segmenting and clustering of different time points are also shown.*

Nominally, dispatch optimization would be conducted for all data points in the year. Due to computational constraints (since sometimes hundreds of parallel inner realizations would be run for a single step in the outer level), methods are implemented to conduct dispatch optimization over time windows with similar characteristics. All yearly time points are optionally subdivided into segments; the new smaller number of data points is now the optimization window. Additionally, these segments can be clustered via a classification algorithm into a smaller set of time window groups. Dispatch optimization is then conducted over each unique cluster while tallying a multiplicity factor for all segments each cluster is meant to represent.

## 2.2 Resources and Components

After establishing the time indexing of the inner optimization problem(s), users have the option to define multiple components for their IES as well as the resources pools on which they act. Three different types of components are available to select from: a producer, storage, or demand component. These are depicted in Figure 3.

Producers create a specified resource up to a certain capacity that is either known a priori or solved for in the outer level; they may also consume resources to produce others via a defined transfer function. These transfer functions are defined either in ratios akin to a balanced chemical equation or with the coefficients of a polynomial expression [9]. Production and consumption of a certain resource is depicted graphically as adding to or drawing from a generalized resource pool common to all IES components. Producers are a representation of common generators in a grid like NPPs, VREs, natural gas plants, etc. Storage components store quantities of a certain resource up to a capacity either known or solved for. Storage levels are changed via charging and discharging of the resource; these are also graphically depicted in Figure 3 as drawing from and adding to a resource pool, respectively. Common storage components include batteries for electricity or thermal energy storage for thermal power. Demanding components only consume a designated resource and are meant to represent grid operators or other markets that require either time-dependent or time independent quantities of a resource.

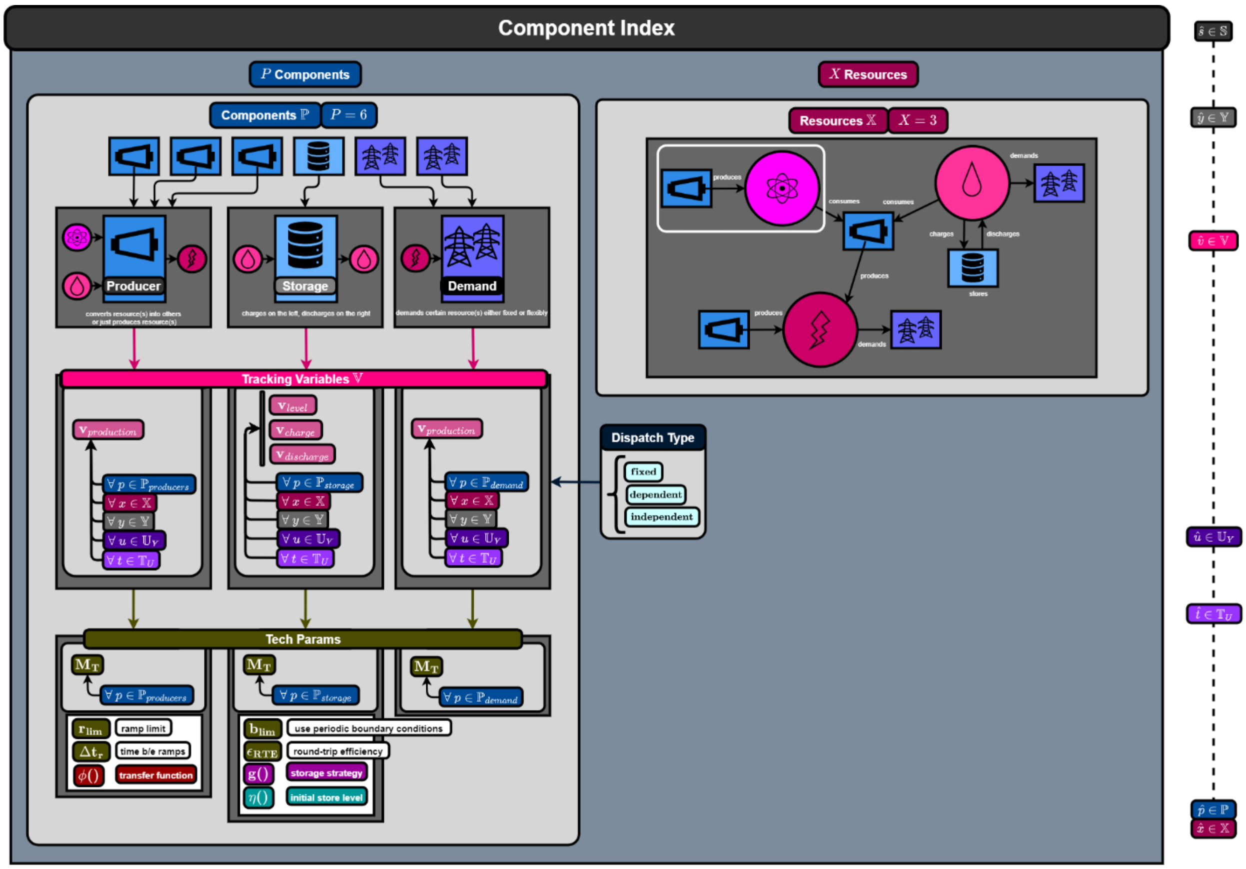



*Figure 3. Overview of all IES component types, with technical parameter inputs and variable types (left). A depiction of resource pools is also shown (right).*

Dispatch types are also specified per component by the user. Production, storage, or demand can be either fixed or independent. Fixed dispatch is constrained to be equal to the capacity of the component; independent dispatch are variables to be solved for, per time step, in the dispatch optimization problem.

## 2.3 Cashflows and TEAL

Cash flows are defined to map resource-dependent component activities, capacities, and market uncertainty to economic values. The engine for calculating economic metrics is the Tool for Economic Analysis (TEAL) which is a plugin in the FORCE toolset. Cash flows are defined by a universal formula:

$$\hat{F} = \alpha \left(\frac{d}{d'}\right)^{\chi}$$

where $\alpha$ is the representative price or cost, $d$ is the driver of the cash flow, $d'$ is the reference driver associated with the cost, and $\chi$ is a scaling factor representing economies or diseconomies of scale for $0 \leq \chi \leq 1$ and $\chi > 1$ respectively. A diagram of the different cash flows is shown in Figure 4.

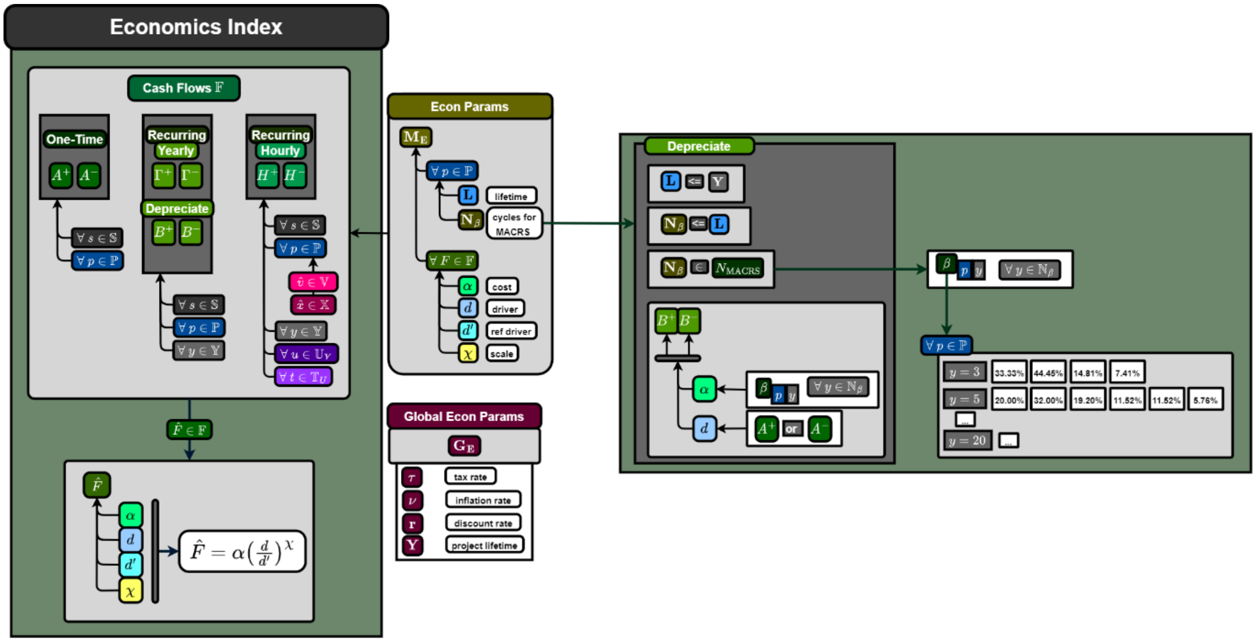


*Figure 4. Overview of cash flow types used in HERON and TEAL.*

Three distinct groups of cash flows are defined in TEAL: a one-time, recurring yearly or recurring hourly cash flow. Each follow the same universal formula with different values or sources of values for the $(\alpha, d, d', \chi)$ set. One-time cash flows (e.g., CAPEX) are applied once per lifetime of the component. Drivers for these cash flows are typically the capacity of the component; costs are then usually defined as $ per unit of capacity. Recurring yearly and hourly cash flows are repeated per the specified time frame. Drivers for these may also be the component capacity or, in the case of the hourly cash flows $H$, the dispatch activity of the resource. Costs are often fixed values or can take time series values from a trained TSA ROM for a LMP signal in a deregulated energy market.

Cash flows can be modified based on tax rates and inflation rates per year of the project simulation. Additionally, a discount rate or weighted average cost of capital (WACC) can be introduced to determine the present value of future cash flows. Final cash flows can be summarized with the following formula for a given year $y$:

$$F_y = \frac{(1-\tau)\hat{F}}{(1+\nu)^y(1+r)^y}$$

where $\tau$ is a tax rate, $\nu$ is the inflation rate, and $r$ is the discount rate or WACC. An additional cash flow for depreciation is available in TEAL based on a modified accelerated cost recovery system (MACRS) or custom yearly depreciation schedule. Here, the driver is the CAPEX cash flow. Two resultant cash flows are created to represent the recovery of the capital cost of an asset in the United States: a negative value depreciation, treated as a loss, and a positive depreciation tax credit.

Once all cash flows are calculated and evaluated, TEAL can then combine them into a single economic metric for the given realization. Among the different available economic metrics are the NPV, the profitability index (PI), and the internal rate of return (IRR). The PI metric is the NPV normalized by all CAPEX cash flows. The IRR metric essentially solves for the discount rate or WACC $r$ such that the sum of cash flows is 0, answering the question “what must the rate of return be to break even?”. An additional economic metric which has now been configured to work with HERON is the levelized system cost of a resource X, commonly used for electricity as levelized system cost of electricity (LSCOE) [10]. This is distinct from some of the uses of the same metric in literature in that it considers the “break even” cost of any cash flow but in the context of the entire defined IES configuration.

## 2.4 Valued Params and HERON Inputs

HERON offers users multiple ways to define the values of the different components and cash flow inputs. For most cases, the input values are static or fixed values. However, some technical or economic inputs may be dependent on the evaluation of method or a ROM within the inner dispatch optimization; some inputs may also be dependent on decisions made in the outer level. Two distinct sets of value entities are available in HERON: "ValuedParams" (VPs) and Transfer Functions. The latter are used to define the conversion of consumed resource(s) to produced resource(s) for the Producer components only. Available VPs are shown in Figure 5.

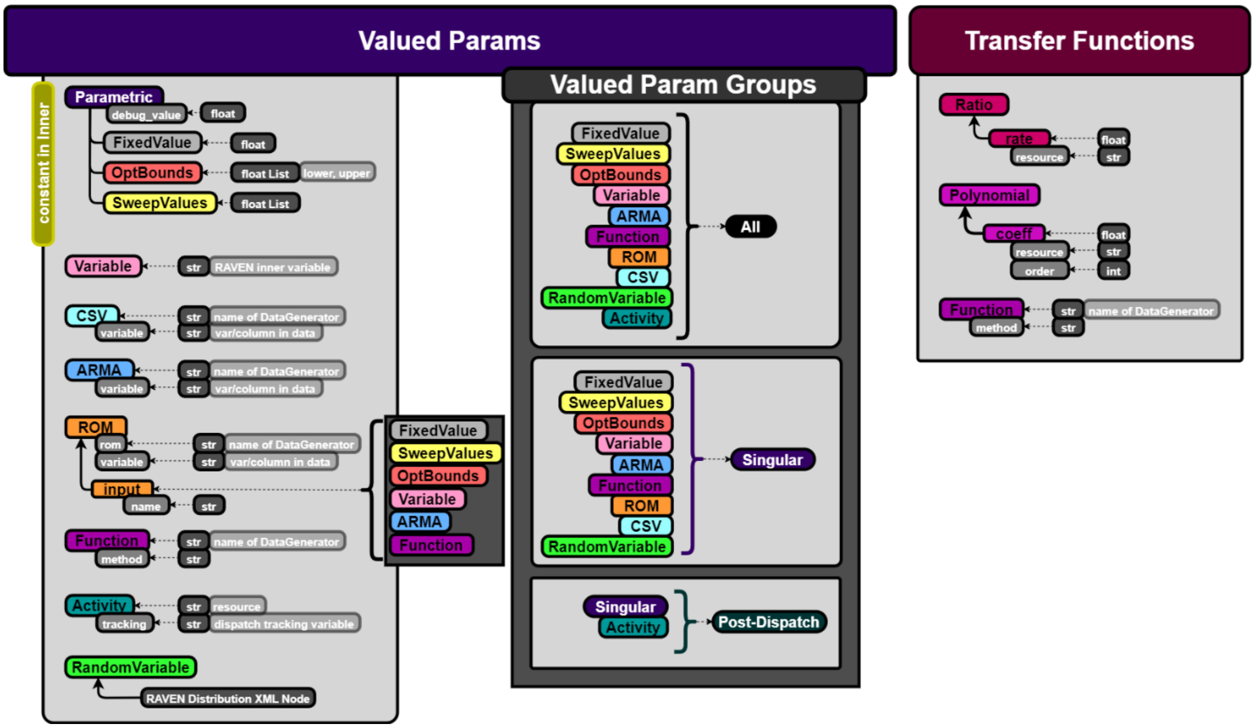



*Figure 5. List of available HERON ValuedParams and TransferFunctions. ValuedParams Groups also shown.*

Parametric VPs define values which are taken from outer level decisions and are therefore constant across a set of inner realizations. The Variable VP is used to reference another variable (such as a component capacity) defined within HERON. ARMA and comma-separated value (CSV) are used to designate values taken from evaluation of a TSA ROM (a unique time series per inner realization) or from a static time series in a CSV file, respectively. The ROM VP is reserved for usage of a non-TSA model that may additionally take inputs from other VPs; the evaluation of the ROM also takes place at each inner step, though the results may be deterministic relative to the inputs as opposed to the ARMA VP which is stochastic in nature. The Function VP is a more straightforward evaluation of a custom Python method given by the user, also evaluated in each inner step. Finally, the Activity VP is the resultant optimal, time-dependent dispatch of a resource and "tracking" variable (e.g., for Producers, the production and for storage, the discharge of a resource or the charge level). The new RandomVariable VP will be discussed in Section 3.

A separate list of inputs is also defined within HERON, some of which can be associated with a VP. These are shown in Figure 6 in three main groups: component production inputs, technical parameters and economic parameters. The component production inputs include the component capacities, an optional minimum bound for resource utilization, and an optional capacity factor for time-dependent modifier on the installed component capacity. Capacities and minimums can take any of the "Singular" group of VPs;

capacity factors only accept CSV or ARMA VPs. Additionally, capacity factors must range between 0 and 1. Technical parameters are inputs associated with the dispatch optimization and are subdivided between the different component types.

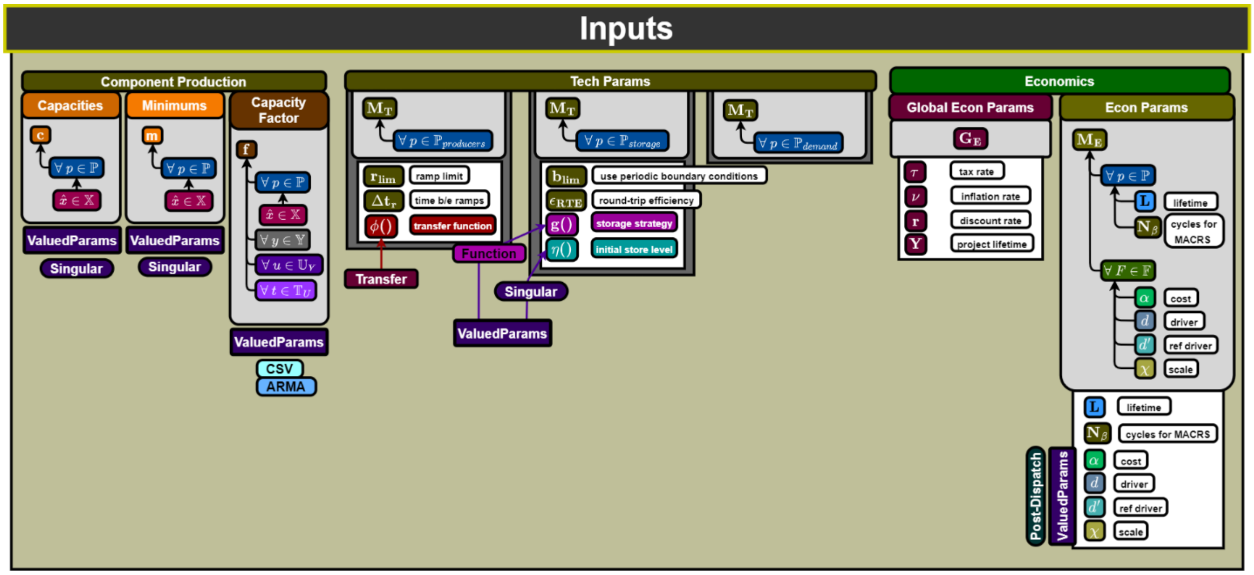



*Figure 6. List of available HERON inputs and the allowed ValuedParams from which each can source their value from. Note that not all inputs can derive their value from a ValuedParam.*

Economic parameters are inputs passed through to TEAL after the dispatch optimization portion of each inner call. These are also subdivided into two groups: global economic parameters that define the full IES configuration (e.g., tax rate, inflation) and regular economic parameters used for cash flows. The component lifetime and an optional MACRS schedule (defined by the number of years to depreciate) are scalar inputs for each component. Then numerous cash flows can be defined based on the three types described in Section 2.3. Each cash flow requires a $(\alpha, d, d', \chi)$ set of which each entry can take VPs as value sources. The hourly cash flow $H$ can use the optimal dispatch results as a driver.

## 2.5 Dispatch Optimization

Dispatch optimization is conducted for every instance of the inner level as shown in Figure 7. More specifically, each dispatch optimization occurs for every inner realization, for every year, for every cluster or segment of that year. Then, each dispatch optimization takes into account all *hourly* cash flows $H$, for all components $P$, all resources $X$, and all tracking variables $V$ (i.e., the way each component is defined to interact with that resource). This is conducted over all time steps $T_U$ in the segment or cluster. The dispatch decisions that maximize some objective function are recorded for each cluster and assigned as the Activity VP to all inputs that requested it. The objective function when using more economic metrics is the summation of all positive and negative $H$. However, when using the levelized system cost metric, this inner objective function is the same summation normalized by $\left(\frac{d}{d'}\right)^{\chi}$ of the cash flow chosen to be levelized. In Figure 7, a schematic is shown for how the component capacity and minimum are used as upper bounds, with an optional modifier given by the time-dependent capacity factor.

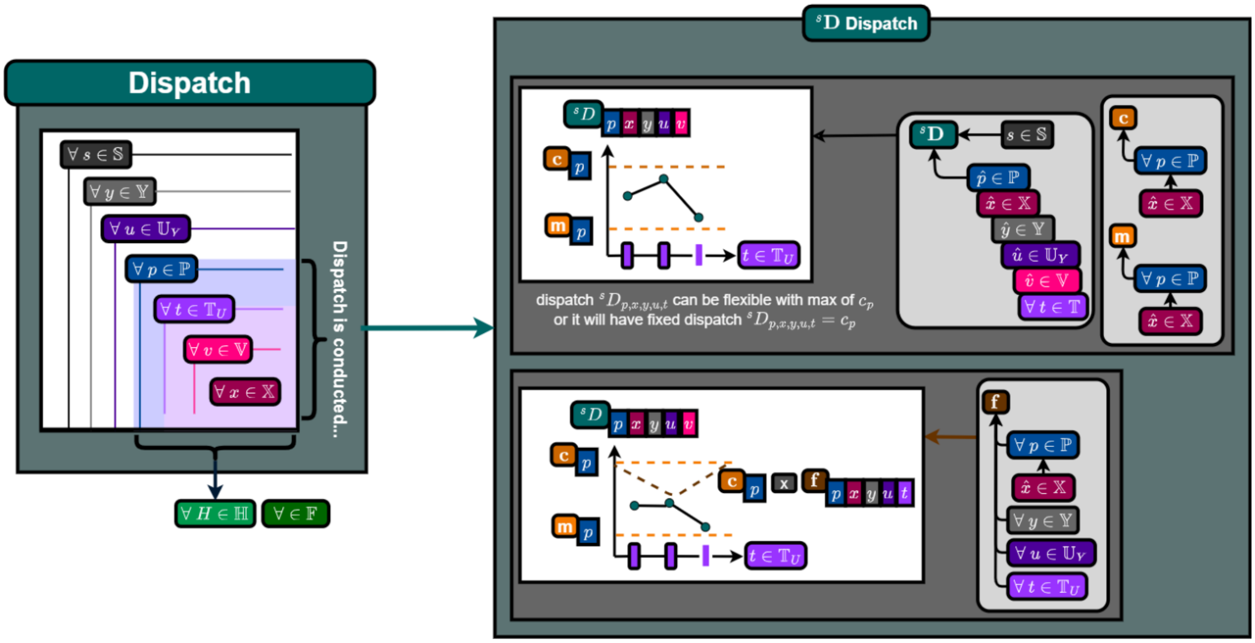



*Figure 7. Breakdown of dispatch optimization time window regimes.*

## 2.6 Bi-Level Workflow

In the context of the two separate lists of inputs to HERON and available VPs which can be matched together, it is worth revisiting the bi-level optimization workflow. Two modes are possible for this bi-level workflow: an optimization of the outer level or a parameter sweep of variables in the outer level. For the following examples, the parameter sweep will be considered. This scheme is shown in Figure 8.

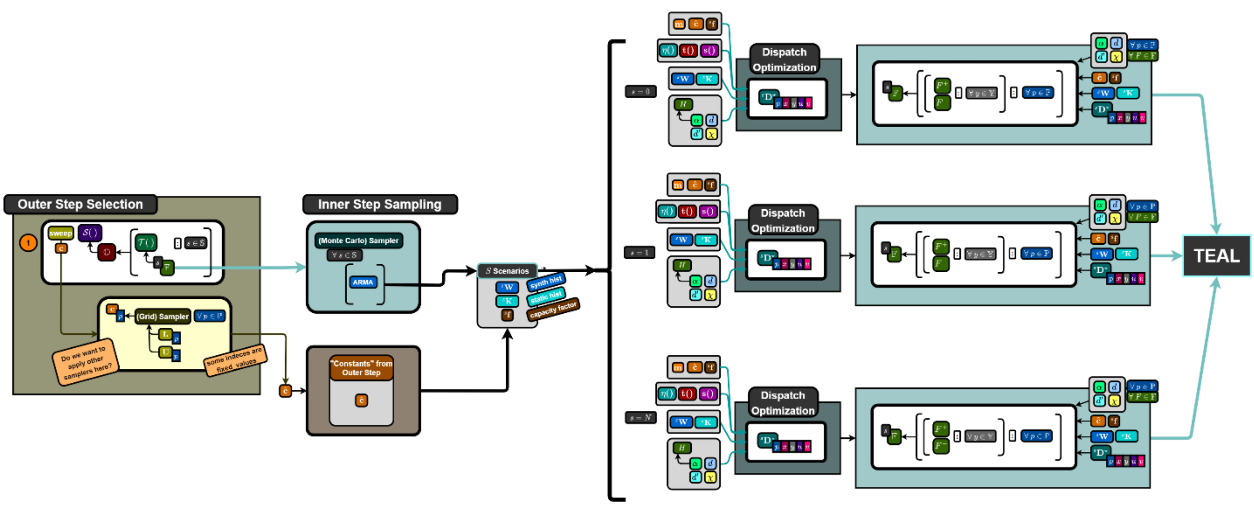



*Figure 8. Overview of bi-level parameter sweep in the context of ValuedParams.*

In the parameter sweep, a grid sampler is used to cycle through different component capacities over which to run inner simulations. The result from the outer at each step is:

$$\mathcal{S}(\mathbb{O})$$

where $\mathcal{S}(\cdot)$ is a statistic taken on a set of values and $\mathbb{O}$ is a set of economic metrics from TEAL. Examples of these, respectively, could be the expected value of NPV, the value at risk of NPV, or the minimum of LSCOE. In sweep mode, HERON also returns some additional basic statistics and other non-basic statistics requested by the user. The set of economic metrics is defined more rigorously as

$$\mathbb{O} = [\mathcal{T}(\,^{s}\mathbb{F}\,) : s \in \mathbb{S}]$$

where $\mathcal{T}(\cdot)$ are TEAL evaluations, taking as input a set $^{s}\mathbb{F}$ of cashflows for each scenario (or realization) s in the set of total realizations $\mathbb{S}$. Each collection of $^{s}\mathbb{F}$ cashflows requires an instance of the inner optimization as shown on the right of Figure 8. The grid sampler in the outer level selects capacities which are treated as constants in the inner level for each outer step. The inner step uses a Monte Carlo sampler to generate an evaluation of the ARMA TSA ROM, creating a synthetic time series for each trained signal. These synthetic time series signals can then be mapped via the ARMA VP to different inputs, such as a cash flow cost or driver, or a capacity factor.

For each inner step s, dispatch optimization is performed using all component production inputs, technical parameter inputs, and economic inputs for *hourly* cash flows—all with their associated VP or other valued input. If the Activity VP is designated for an hourly cash flow, each time step resource dispatch is solved for as described in Section 2.5. After dispatch, the remaining cash flows are evaluated in HERON and TEAL; in TEAL, the global economic inputs are used to calculate the final economic metric.

# 3. Economic Uncertainty Quantification Implementation in HERON

Economic UQ has now been implemented within HERON as shown in the newest VP within Figure 5 [11]. The new VP is named RandomVariable intended to represent a value sampled from a distribution. This is the method for quantifying the uncertainty in an economic parameter of the set $(\alpha, d, d', \chi)$ in the cash flows. At every instance of the inner level optimization, if one of the $(\alpha, d, d', \chi)$ entries is designated as an uncertain parameter *not* associated with a stochastic TSA ROM, it could instead take the form of a random variable sampled from a distribution of values. This schematic is shown in Figure 9. In the Monte Carlo sampler, the distributions are sampled simultaneously along with the stochastic ARMA ROMs at every inner level instance. Uncertainty in *hourly* cash flows is carried into the dispatch optimization; uncertainty in all cash flows is evaluated in TEAL.

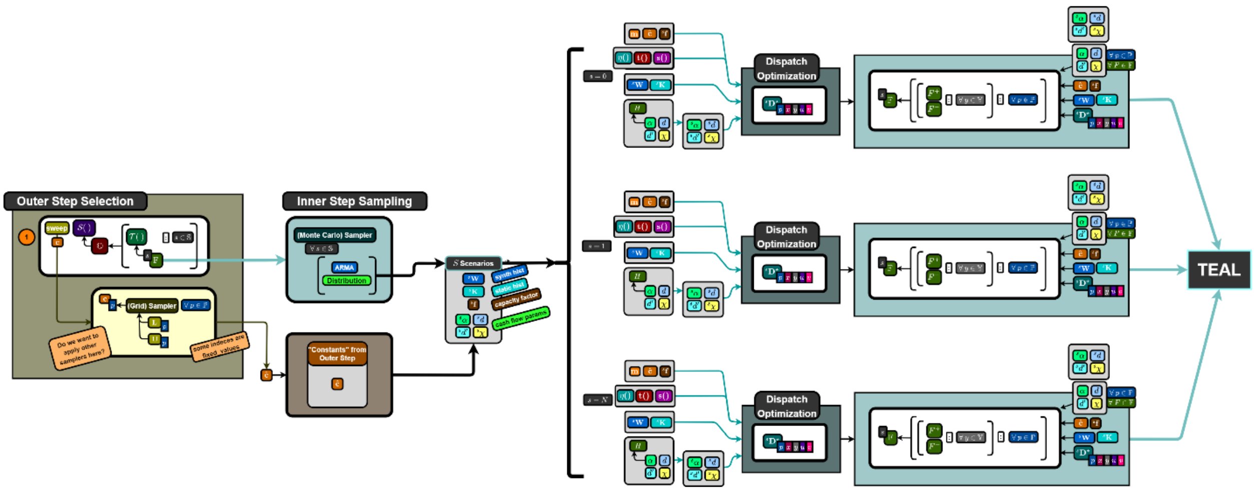



*Figure 9. Overview of bi-level parameter sweep in the context of ValuedParams with added RandomVariable VP.*

Users can invoke the RandomVariable VP using an extensible markup language (XML) subnode within the HERON XML input script under the economic input which is requested to be "uncertain" in the simulation. An example of this input script is shown in Figure 10. The subnode is labeled as *<uncertainty>* to designate the economic UQ. Within that node, users must provide an additional XML node for the distribution with which they wish to represent uncertainty of that parameter. In the example above, the uncertainty in CAPEX cost of the component "source" is represented with a normal distribution of mean 10,000 and variance of 2. The syntax of the distribution node must match that of the equivalent distribution found in the RAVEN user manual [2]. A current list of distributions is:

- 'Uniform'
- 'Normal'
- 'Gamma'
- 'Beta'
- 'Triangular'
- 'Poisson'
- 'Binomial'
- 'Bernoulli'
- 'Logistic'
- 'Custom1D'
- 'Exponential'
- 'Categorical'

- 'MarkovCategorical'
- 'LogNormal'
- 'Weibull'
- 'NDInverseWeight'
- 'NDCartesianSpline'
- 'MultivariateNormal'
- 'Laplace'
- 'Geometric'
- 'LogUniform'
- 'UniformDiscrete'

Usage of existing RAVEN “distributions” infrastructure over new infrastructure carries the benefit of automating syntax checks and other regression tests for validation of the code.

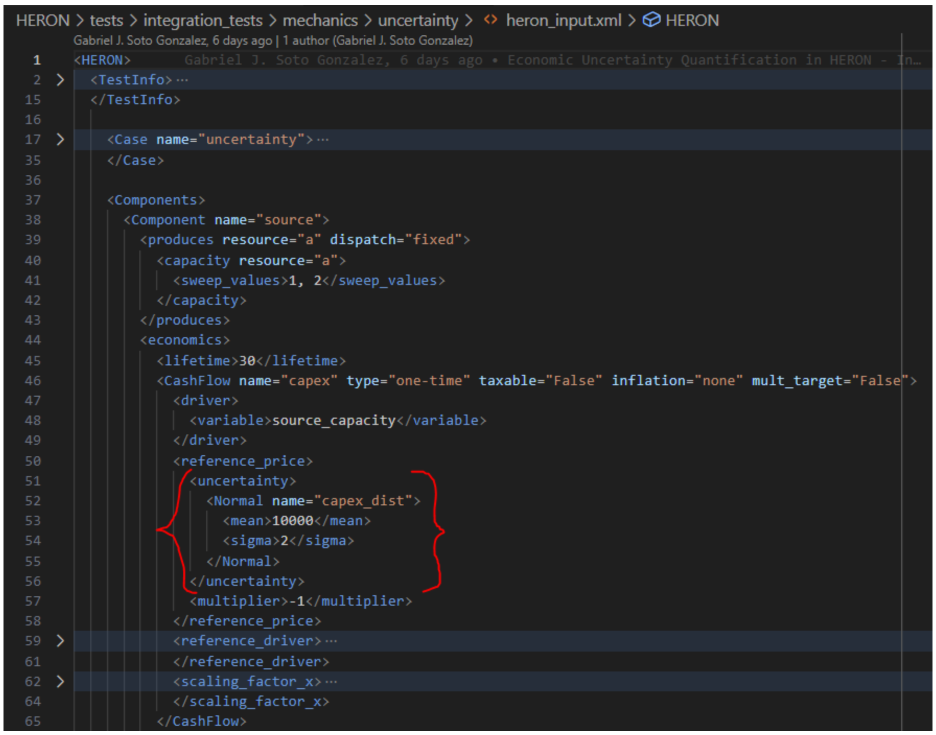
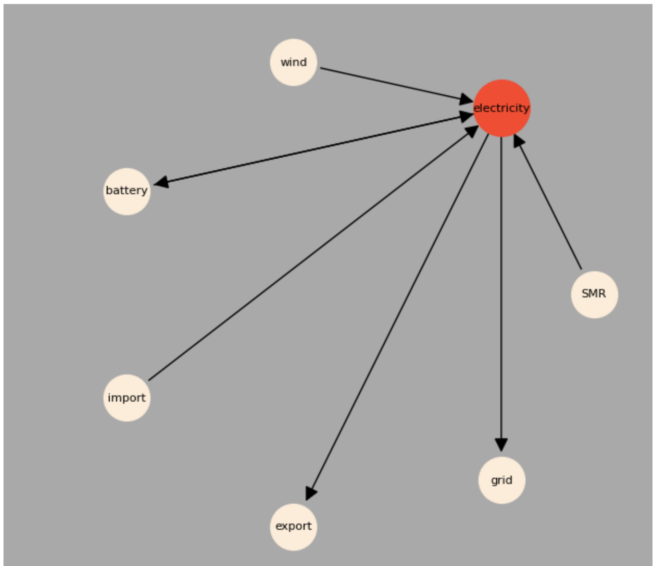



*Figure 10. Example of HERON XML input script with uncertain VP used as a reference price of CAPEX cash flow.*

Currently only the economic inputs $(\alpha, d, d', \chi)$ for any cash flow are allowed to have a RandomVariable VP. As new use cases for this uncertainty quantification present themselves, more inputs will be added to the compatibility list for the UQ VP. Additionally, this economic UQ has only been implemented alongside Monte Carlo sampling of the ARMA TSA ROMs. Evaluation of economic UQ with static history CSV VPs has not yet been implemented.

A simple use case was selected for demonstration of the new economic UQ feature. The IES configuration chosen is shown in Figure 11. It consists of a small modular reactor (SMR), wind farm, battery and grid which demands electricity. An additional import and export component are included as an extra source and sink for the electricity resource, aiding the computational efforts. Dispatch of electricity among the components is independent except for the grid, which demands exact amounts of electricity. Uncertainty is included in the hourly demand and wind capacity factor profiles using similarly trained synthetic history TSA ROMs from previous reports at INL [4,7]. A CAPEX cash flow was included for the SMR, wind and battery which scales with installed capacity (not capacity factor); the SMR had an additional VOM cash flow associated with production of electricity. A positive cash flow for the grid was included, assuming a mean $100/MWe for all supplied electricity. A high negative cash flow was also included for the import and export components to discourage their use. For ease in computation, simulations were run for a project time of 3 years; all CAPEX cash flows are scaled by a factor of 0.1 to approximate their effect from a full 30-year project within the span of the simulated 3 years.




| | Dispatchable? | Governed? |
|---|---|---|
| SMR | independent | False |
| wind | independent | False |
| battery | independent | False |
| import | independent | False |
| export | independent | False |
| grid | fixed | False |

*Figure 11. Network diagram of the simulated IES. The grid demands a fixed amount of electricity.*

Simulations (in parametric sweeps of different capacities) were performed for 50 samples of the TSA ROM to determine a distribution of NPVs and return a set of basic statistics such as mean and standard deviations. A similar set of simulations was then performed with added economic uncertainty. The CAPEX and VOM cash flows (calculated hourly) for the SMR were modeled as normal distributions reconstructed from values in a literature review of advanced reactor costs from INL [8]. The reconstructed distributions are shown in Figure 12 as probability density functions (PDF) and the actual span of values used in the simulations in the shaded areas.

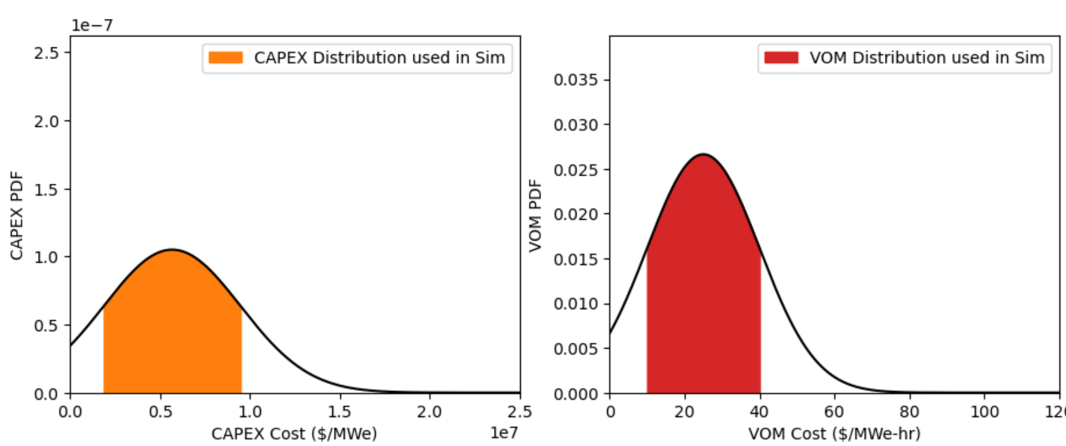



*Figure 12. CAPEX and VOM cashflow distributions (probability density functions) for the SMR in economic UQ simulations. Simulations use values within the shaded areas.*

Results from the parametric sweeps of simulations without and with economic UQ are summarized in Table 1. The simulations (50 samples) with only uncertainty in the wind and demand hourly profiles (i.e., "w/o Economic UQ") show a higher mean NPV with a smaller standard deviation than the simulations with economic UQ. The smaller standard deviation in the simulations without economic UQ are likely because of the higher SMR capacity which can meet most of the grid demand but requires some additional electricity from the wind and battery. After adding uncertainty in the SMR CAPEX and VOM, the standard deviation of the NPV results increases.

*Table 1. Regression test results for source and sink swept capacities using a deterministic Sine ARMA ROM and normally distributed uncertainty in cost.*

| Simulations (N=50) | SMR capacity | Wind capacity | Battery capacity | Mean NPV | Std NPV |
|---|---|---|---|---|---|
| w/o Economic UQ | 32.5 | 25 | 10 | $ 8,350,263.56 | $ 36,995.86 |
| w/ Economic UQ | 32.5 | 25 | 10 | $ 7,529,599.88 | $ 4,427,026.08 |

The NPV statistics from each type of simulation (without and with economic uncertainty, both with uncertainty in wind and demand) were used to reconstruct a normal distribution of NPVs shown in Figure 13. The shape of the NPV distribution without economic UQ has less spread than the one with economic UQ. Additionally, the distribution of NPV with economic UQ sometimes results in negative NPV due to higher sampled CAPEX and VOM costs surpassing any possible profit from electricity. A more detailed study of optimal capacity sizes with and without economic uncertainty will be performed in the remainder of FY24.

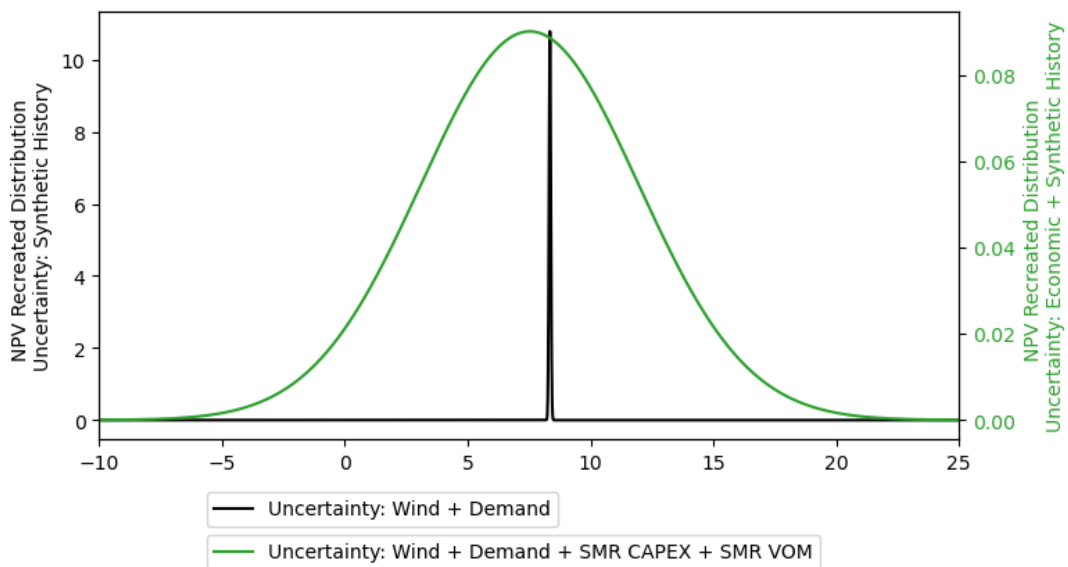



*Figure 13. Reconstructed NPV distributions from simulations with uncertainty in wind and demand capacity factors vs. simulations with an additional uncertainty in CAPEX and VOM.*

# 4. Planned Future Work

Some remaining tasks for the FY24 work package include implementation of the distribution sampling with static histories. This presented a challenge because static histories require usage of a Custom Sampler within RAVEN which was not as straightforward to modify as the Monte Carlo sampling technique for the ARMA VPs. Once static histories can be used alongside economic UQ, the regression test should be updated to use a static CSV VP rather than the deterministic sine wave ARMA.

Another pending task is to expand and limit usage of certain combinations of VPs with HERON inputs. For example, currently the SweepValues VP is only admissible for component capacities. However, it may be helpful to simply run a sweep over a discrete set of economic costs for a single cash flow. A more centralized inspection of HERON inputs and their associated VPs should be implemented with a VP registry.

Finally, it is important for users to not just incorporate uncertainty into TEA simulations but to also quantify how much each source is adding to the overall problem uncertainty. A new sensitivity analysis feature should be implemented within HERON to measure how sensitive the final economic metric result is to different factors. It would be important to quantify how much uncertainty the TSA ROM introduces into the IES configuration in the presence of other economic uncertainties, for example. Incorporation of ROM evaluation uncertainty is not straightforward, but some methods in the literature have been used to treat this as an epistemic rather than aleatoric or inherent uncertain process and therefore be able to isolate to measure contributions to the final stochasticity [12,13]. If the non-TSA ROM uncertainty exists in non-hourly cash flows, all uncertainties could be treated concurrently within the same inner evaluation since the dispatch optimization is independent of one-time or yearly cashflows. In that case, the sensitivity analysis can be conducted as an additional output for either the optimization or sweep mode. However, if uncertainty exists in an *hourly* cash flow, the dispatch optimization would not be independent of this uncertainty and therefore more than the original *N* number of inner realizations must be evaluated to properly isolate contributions from each process in a Sobol'-type sensitivity analysis. This sensitivity analysis may be introduced as a separate mode from optimization or sweep in that case.

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