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pIRP: A Probabilistic Tool for Long-Term Integrated Resource Planning of Power Systems

***Abstract*—The penetration of renewable energy resources (RER) and energy storage systems (ESS) into the power grid has been accelerated in recent times due to the aggressive emission and RER penetration targets. The Integrated resource planning (IRP) framework can help in ensuring long-term resource adequacy while satisfying RER integration and emission reduction targets in a cost-effective and reliable manner. In this paper, we present pIRP (probabilistic Integrated Resource Planning), an open-source Python-based software tool designed for optimal portfolio planning for an RER and ESS rich future grid and for addressing the capacity expansion problem. The pIRP tool's ESS and RER modeling capabilities along with its enhanced uncertainty handling make it one of the more advanced non-commercial IRP tools available currently. Additionally, the tool is equipped with an intuitive graphical user interface and expansive plotting capabilities. Impacts of uncertainties in the system are captured using Monte Carlo simulations and lets the users analyze hundreds of scenarios with detailed scenario reports. A linear programming based architecture is adopted which ensures sufficiently fast solution time while considering hundreds of scenarios and characterizing profile risks with varying levels of RER and ESS penetration levels. Results for a test case using data from parts of the Eastern Interconnection are provided in this paper to demonstrate the capabilities offered by the tool.**

***Index Terms*—Capacity expansion planning, energy storage, integrated resource planning, renewable energy, resource adequacy**

I. Introduction

It is well known that the integration of renewable energy resources (RER) and energy storage systems (ESS) into the power grid has gained great momentum in recent times, primarily due to climate change. The characteristics of RER and ESS are different from conventional sources of power, like synchronous generators, due to their variability and intermittency. Hence, specialized power system planning frameworks and tools are required as increasing volumes of RER and ESS are integrated into the grid. Integrated resource planning (IRP) is a class of problems that deal with efficient and economical long term integration of such resources into the grid, while ensuring emission targets set by regulatory authorities are satisfied.

While IRPs and the traditional capacity expansion planning frameworks both aim to ensure long-term resource adequacy, the latter typically resorts to deterministic approaches for allocating sufficient generation to meet the peak load forecasts. Such methods are not effective in the handling multiple sources of uncertainties, characterizing risks and ensuring reliability with RER-rich portfolios. In addition, with increased RER in the grid, risks of resource unavailability over longer periods raises resilience concerns. The aforementioned resilience and reliability concerns can be alleviated with the help of enhanced ESS modeling and uncertainty handling, thus paving the way for the development of new tools. This paper presents one such tool, the probabilistic integrated resource planning (pIRP) software, that utilizes a stochastic framework for optimal portfolio planning for a future grid dominated by RER and ESS.

A. Literature Review

Several tools exist today for the purpose of IRP. The most relevant tools are discussed here for the purpose of comparison with the pIRP software. Calliope [1] is an open-source Python based software that is designed to analyze energy systems with high shares of renewable energy. This software offers flexibility in modeling a range of spatial and temporal resolutions and has a detailed ESS modeling capability. However, this tool does not consider uncertainties in renewable generation, load or other system variables, which is a critical aspect of the future power grid integrated with high volumes of RER. In addition, this tool is designed as a Python package and does not offer a graphical user interface (GUI), which limits the usage of this software to Python-users. The European Electricity Market Model (EMMA) [2] is a techno-economic model of the integrated European power system developed using the General Algebraic Modeling Software (GAMS). It estimates the future capacity-mix of a system along with hourly prices, generation, storage dispatch, and cross-border trade. This tool is primarily built for the European electricity markets and is not suitable for universal power system modeling. Also, it is a fully deterministic model and has limited ESS modeling capabilities. Switch 2.0 [3] is a Python-based tool for planning transitions to low-emission electric power systems which can be used for IRP, research, and economic, technical and policy analysis. Its capabilities include modeling multiple investment steps over several decades and sequential modeling of individual hours of operation. However, like most existing IRP tools, it does not have a GUI and also does not consider uncertainties. CapacityExpansion [4] is an IRP tool developed as a Julia package. This tool has the distinctive feature of using a clustering algorithm for identifying similar time-series data. The disadvantages of this tool include the absence of a GUI, ignoring uncertainties of the system, and the lack of result visualization options. The Renewable Energy Deployment System (ReEDS) is a long-term expansion planning model developed in GAMS by the National Renewable Energy Laboratory (NREL) [5]. This model is capable of modeling several utility scale ESS technologies including pumped storage hydro, lithium ion batteries, and compressed air energy storage. Although this model is capable of handling several future scenarios, there are limitations in the process to set up and analyze the scenarios and in the range of uncertainties that can be modeled [6]. The Renewable Integration Solutions model (RESOLVE) is a long-

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term power system planning model developed by Energy and Environmental Economics, Inc. [7]. RESOLVE is a Python-based model that seeks to address RER integration challenges in the planning process and optimizes investments and operational costs for the California Independent System Operator. The model has desirable features such as modeling energy storage, assessing flexible loads, and selecting and weighting representative days for operational modeling. Limitations of the model include lack of a GUI and test cases.GenX [8] is a Julia-based capacity expansion planning model which offers extensive flexibility in temporal and spatial modeling for IRP purposes. However, GenX assumes perfect information and foresight of the decision-maker, which does not capture the effects of uncertainty and forecast error in grid operations. Besides the open-source tool described above, several commercial tools exists, such as Plexos and Encompass.

B. Contributions

The pIRP tool contributes new features, modeling capabilities, and computation efficiencies over the existing IRP tools. It comes with an intuitive GUI, which is not available in most of the existing open-source tools. Users can input their own data related to RER profiles using the interactive GUI and commonly used file types. It also offers extensive data visualization options, some of which are presented later in the paper. In terms of modeling capabilities, some of the key contributions of pIRP include flexible options for modeling different ESS technologies, and long and short duration ESS. ESS capacities and durations are considered as decision variables in the optimization framework and hence the ESS requirements are co-optimized with the other resources, unlike most existing tools. A resilience constraint is also included in the model, which considers temporary (e.g. multi-day) loss of resources in the planning horizon. Impacts of uncertainty are captured through Monte Carlo simulation (MCS) techniques and Latin Hypercube sampling (LHS) [9]. Users can also activate or deactivate specific sets of constraints depending on the type of the planning problem. In terms of computational efficiency, pIRP offers sufficiently fast solution time even when considering numerous scenarios due to its linear optimization framework. This allows the user to simulate hundreds of scenarios for a twenty year problem within a few hours (e.g. five zone model with about a hundred resources in less than two hours).

C. Organization

Section II provides a brief summary of the optimization framework developed in pIRP and describes the objective function and key constraints. Section III describes the tool architecture and highlights the features and workflow. Section IV demonstrates the efficacy of the pIRP software, where it is used to optimally select a portfolio of traditional resources, RER and ESS for a five-zone model, considering resilience and reliability constraints. Section V presents some concluding remarks.

II. Problem Formulation

The core of the pIRP tool builds upon foundations similar to the ones used in typical generation and transmission capacity expansion planning problems [10]. Since this paper focuses on tool architecture and applications, a concise description of the core formulation is presented below. The key parameters and variables are presented in Tables I and II, respectively.

TABLE I
KEY pIRP PARAMETERS

n_{res}	number of resources
n_{years}	number of planning years
n_{periods}	number of periods per year
n_{zones}	number of zones
n_{lines}	number of tie-lines

TABLE II
KEY pIRP VARIABLES

C	Capacity
R	Resource retirements
A	Resource additions
P	Power dispatch
F	Inter-tie flows
W	Tie-line capacity
T	Transmission hosting limit
D	Distribution hosting limit

A. Objective Function

The objective function of the pIRP, as presented in (1), seeks to minimize the sum of the following cost components: (i) fixed O&M cost (FOM), (ii) installed cost (IC), (iii) tie-expansion cost (TC), (iv) transmission hosting cost (THC), (v) distribution hosting cost (DHC) and (vi) production cost, consisting of variable O&M (VOM) and fuel cost (FC).

$$\min \text{ Cost} = \text{FOM} + \text{IC} + \text{TC} + \text{THC} + \text{DHC} + \text{VOM} + \text{FC} \quad (1)$$

B. Constraints

Capacity addition and retirement: Constraints on capacity, addition and retirements need to be considered for the generating resources. Capacity build-out constraints include restrictions on maximum capacity and the build-out rate. Also, constraints ensure that for a particular resource, the tool cannot retire more than the existing capacity.

Power dispatch: The dispatch from each resource is restricted by its maximum capacity. For power balance, the sum of zonal generation and imports/ exports over tie-lines must equal zonal demand.

Tie-lie limits: Each physical tie line is modeled in pIRP as two unidirectional flows. Tie-line flows between zones are limited by maximum tie-line capacities and expansion limits set per year.

Renewable profiles and zonal requirements: For renewable resources, the predicted yearly RER forecasts are taken as inputs. Power dispatch for each resource is restricted by the potential maximum production.

Local capacity requirements (LCR): The sum of capacities (adjusted by capacity credits) of available resources must be greater than the product of the maximum demand and the local generation requirement (e.g., 30%).

T&D hosting capacity: T&D hosting capacity constraints ensure that the hosting capacities respect the build-out rates and the maximum allowed capacities in each zone.

Reserve allocation: The sum of capacities (adjusted by capacity credits) of available resources must be greater than the sum of the maximum demand and a pre-specified headroom (e.g., 10%).

Ramping flexibility: The ramping capability is represented as a fraction of the maximum capacity of the resource. The aggregate ramping capability (obtained by applying capacity factor and average dispatch) from dispatchable resources must be greater than the aggregate ramp from RER and ESS.

Energy storage constraints: State of charge (SOC) and charge/discharge constraints for ESS are considered.

Resilience: Supply interruptions are modeled using this constraint. Loss of one or more resources might lead to an energy deficit in a particular zone. When such an event occurs, the resilience constraint helps in finding the set of resources which are not at risk and also the possible energy deficit values. Constraints are enforced in each zone to compensate for the energy deficit using the resources which are not at risk.

In addition to the constraints mentioned above, maximum allowable limits can be set for dispatch from RER.

III. Tool Architecture

The pIRP tool comprises three main components: (a) A model file in a Microsoft Excel worksheet (.xlsx file), (b) the core engine written in Python and (c) a GUI, also written in Python. The required data and parameters can be provided using the model file. The model file is then loaded using the GUI. The main GUI page with an example model is shown in Figure 1. The GUI allows making adjustments to model parameters, solver options, and load and RER profiles. When all necessary adjustments are completed, the core engine, which uses the Pyomo package [11] for modeling the optimization framework, is used to solve the IRP problem. Reports and plots are then generated through the GUI for visualization of the results.

It should be noted that while the tool requires 8760-hour load and RER profiles as inputs, the 8760 hours are partitioned by the tool into representative "time buckets" for faster execution time. The time buckets are characterized by seasons (winter, spring, summer and fall), day/night, weekday/weekend and peak/off-peak. The hours of the day are then mapped into the appropriate time buckets. For example, January 10, 2021 evening 7-9 pm is characterized as a winter-weekday-night-peak. The tool offers flexibility in how the user can construct the time buckets. A base construct is provided in the model file, which the users can use as a reference for creating their own time buckets.

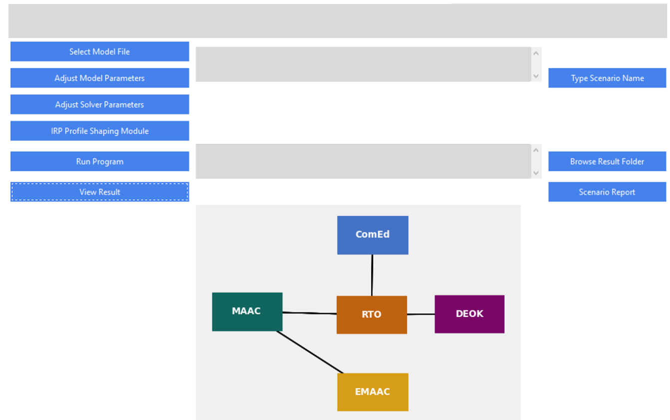

Fig. 1. pIRP main GUI with an example model (logos and affiliations have been greyed out for the peer-review phase).

A. RER profile handling

The tool allows the users to import their own load, wind and solar profiles using .csv files. Separate profiles can be imported for each zone. New profiles can also be generated by applying random swapping, regression or averaging techniques on the imported profiles.

B. Scenario generation using uncertainty

The pIRP tool stands out from other existing IRP tools due to its ability to generate multiple scenarios by considering the stochastic behavior of certain system variables. Fuel cost, load and RER profiles, capacity credits of RER, and zonal loads can be represented by random variables. These random variables can follow Normal, Uniform, LogNormal, or Weibull distributions, as deemed fit by the user. The users also have the options of providing certain parameters of the distributions as inputs, e.g., mean, variance, min, and max. Table III provides an example of an uncertainty table that the user can modify using the model file.

TABLE III
Uncertainty Model Inputs

Variable	Identifier	Distribution
Peak load	ComEd	Normal
Profile	Solar	Normal
Profile	Wind	Weibull
Capacity credit	Solar	Normal
Fuel cost	Coal, Nuclear	logNormal

C. Optimization Module

The pIRP core engine offers several options to the users in terms of solvers and problem parameters through the GUI. A number of solvers like GLPK, Gurobi, and others can be selected depending on the user's preferences. The user can choose which constraints they want to activate. The number of scenarios for the MCS can also be selected by the user. A series of optimization problems are solved sequentially after the parameter selection process is completed.

D. Outputs

A wide range of zonal and system-wide plots illustrating installed capacities of different generating resources, RER and ESS additions, retirements of fossil fuel units, inter-tie flows, and other variables for the planning horizon are available through the GUI once the solution process is complete. If a user performs MCS, a dashboard with histograms of results are also shown. The GUI provides a solution report which can be used to display results from a current or saved case study. This is available in a table format and can be exported to EXCEL. Users also have the option to view the back-end data consisting of .csv and .npz files for customized analysis.

E. Applications

The pIRP tool can be used to typically solve the following problems: (a) capacity expansion planning, (b) reliability and resilience planning under uncertainties, and (c) optimal investments in short, medium and long duration storage alternatives.

IV. Case Studies and Results

A modified PJM system consisting of the following five zones, as shown in Figure 1, is considered: ComEd, RTO, DEOK, MAAC and EMAAC [12]. The generation, tie-line and load information for the system have been simplified to attain a tractable yet representative model. The resource types include gas turbines (combined cycle, combustion turbine), coal power plant, nuclear power plant, biomass, geothermal, utility-scale solar PV, distributed solar PV, wind farm, hydroelectric plants, fuel cells, demand response, energy efficiency and ESS. ESS types include 1-, 2-, 5-, and 10-hour duration batteries, referred to as ESS-1, ESS-2, ESS-5 and ESS-10, respectively in the tool. Four bi-directional tie-lines have been considered, i.e., ComEd-RTO, RTO-DEOK, RTO-MAAC, MAAC-EMAAC. The peak load for the overall system is assumed to be at 161.3 GW in Year 2022 and a 1% load growth is assumed for all zones during each year of the 20-year planning horizon (2023-2042). For more details, readers can refer to the GitHub page for pIRP [13], where the tool will be hosted.

TABLE IV
Resilience - Supply Risks

Zone	Resource 1	Resource 2	Interruption
ComEd	Wind	Solar	3 days
ComEd	Hydro	Solar	5 days
RTO	Solar		2 days

Case Studies: Two cases are studied to demonstrate the efficacy of the tool: the base case and an MCS case with 25 scenarios. For the base case, a target of 75% RER for the ComEd and EMAAC zones and 50% for the RTO, MAAC, and DEOK zones is set for the year 2042. Supply risks are considered for different zones and resources, as summarized in Table IV. Resilience constraints are activated to ensure resources are allocated accordingly.

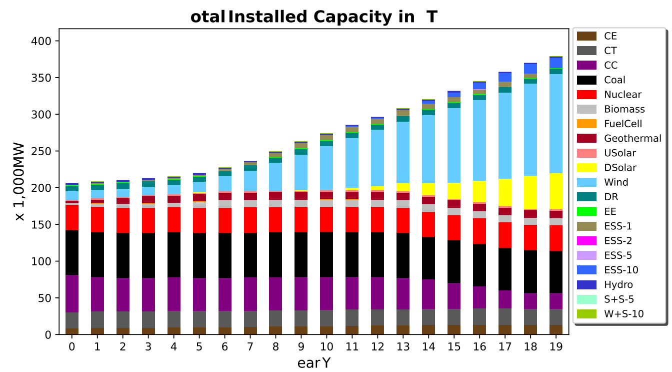

Fig. 2. Installed capacity of resources by year.

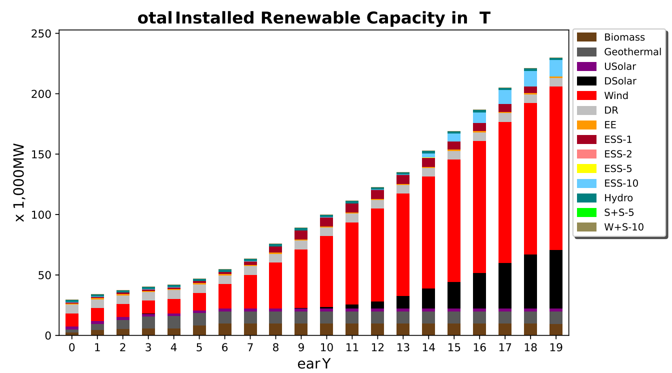

Fig. 3. System-wide renewable capacity by year.

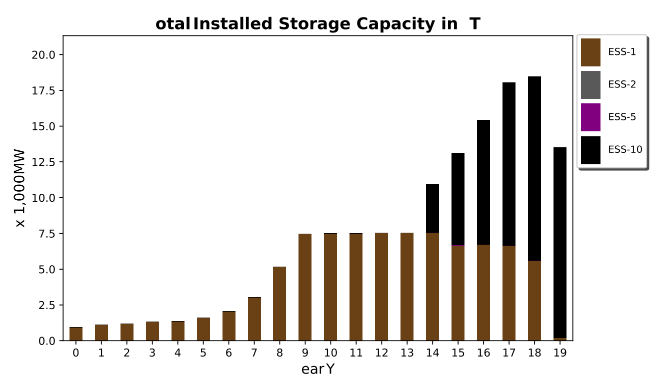

Fig. 4. System-wide storage capacity by year.

Results: The base case was solved using Gurobi in ∼2.5 minutes and using GLPK in ∼7 minutes. Results show the levelized cost of electricity (LCOE) value to be $37.8/MWh and ESS capacity addition in total for the overall system to be 21.1 GW. The yearly installations for different resources are shown in Figure 2. Figure 3 shows the yearly RER capacities. It should be noted that installed capacities for both wind and solar have grown significantly to meet the target penetration levels. Figure 4 shows the yearly installed ESS capacities and it can be observed from the figure that ESS-1 and ESS-10 were primarily selected by the tool along with a negligible

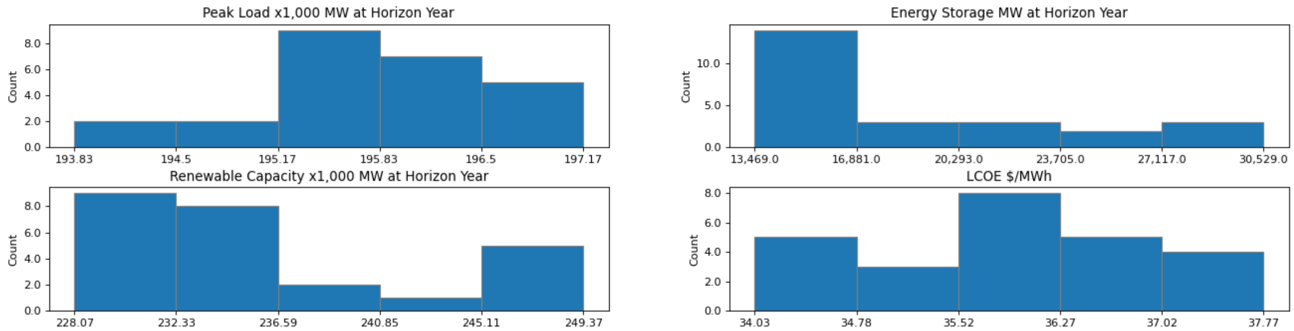

Fig. 5. MCS results - histograms of peak load, renewable capacity, energy storage capacity and LCOE.

portion of ESS-5. ESS-1 was chosen during the initial years to support reliability and ramping constraints. In years 14 and beyond, the tool preferred investments in ESS-5 and ESS-10 since with increasing RER penetration, supply risk resilience constraints need to be satisfied with sufficient long duration storage. ESS-1 resources were eventually retired due to the asset-life constraints and presence of longer duration storage.

Next, the MCS study was performed using 25 samples with parameter values related to profiles, peak load, capacity credit and fuel costs generated using LHS. Histograms in Fig. 5 show that depending on the peak load and renewable uncertainty scenarios, the required storage and LCOEs can vary over a wide range. Finally, the resource dispatches can also be analyzed by samples and zones (e.g. Fig. 6).

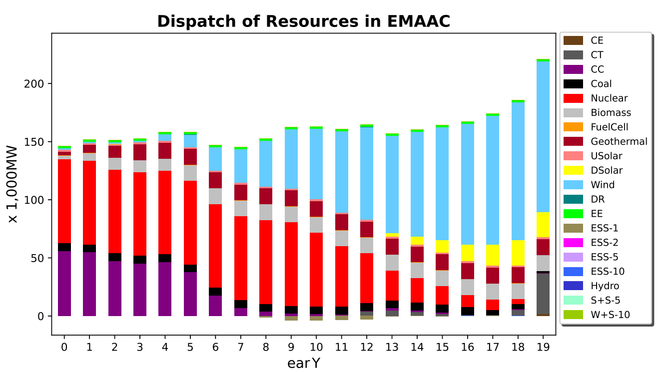

Fig. 6. Dispatch of resources at a specific region (e.g. EMAAC).

V. Conclusions

In this paper, the pIRP tool, a freely available Python-based software designed for optimal portfolio planning for an RER- and ESS-rich future grid, has been presented. Compared to existing open-source IRP tools, key advantages of pIRP include its enhanced uncertainty handling, intuitive GUI and result visualization. In terms of modeling, some of the key contributions of pIRP include flexible options for modeling different ESS technologies (short, medium and long duration ESS), and inclusion of resilience constraints, which considers temporary loss of resources within the planning horizon. Uncertainty models can be considered for a diverse range of system parameters and studied using MCS and LHS. Two case studies have been presented to demonstrate the key features and performance of the software.

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