Co-optimized Expansion Planning and Validation for Wind/Solar–Centric Power Grids

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***Abstract* – Integration of renewable technologies dominates grid transformation in the contemporary world. Power system planning tools such as Adaptive Co-Optimized Expansion Planning (ACEP) have evolved to address this challenge. However, methods of evaluating and validating such plans have largely remained underdeveloped as ACEP can only account for about seven futures before being computationally intractable. This paper presents Folding Horizon Simulation (FHS), a validation tool to test ACEP outcomes against additional uncertainties not accounted for in the initial model. The FHS software exposes ACEP baseline plans to 50 scenarios for each of the eight identified planning uncertainties, generated using Markov chain simulation. It evaluates metrics such as load shedding and systemic penalties like CO_2 and Renewable Portfolio Standard (RPS) and proposes reinvestments in the most cost–effective manner. The FHS analysis showed that higher values of β lead to notable reductions in load shed, regulation costs, and both generation and transmission reinvestment costs.**

***Terms* – Folding Horizon Simulation, plan validation, future, uncertainty, scenario.**

I. Introduction

Integration of renewable energy technologies has dominated electric grid transformation in the contemporary world. These technologies are deemed as potential measures of curbing carbon emissions and hence slowing down global warming and climate change. For this reason, United States has adopted multiple policy options to encourage electric power industry to seek clean energy portfolios. Economic incentives such as the Inflation Reduction Act (IRA) have fueled investments in wind and solar energy [1]

Power system planning must adapt to the growing reliance on renewable energy sources [2]-[4]. However, many Regional Transmission Organizations' (RTOs) planning processes lack rigorous systematic, climate–informed methods for projecting wind/solar variability and demand over 10–20 years. In the past, the planning reserve margin (PRM) accounted for the loss of the largest generator in the system [5]-[7], but a wind/solar–centric grid may require PRMs to consider the largest drops in renewable generation. Therefore, the overall planning process must evolve to encompass tools which are both capable of adapting power system plans to specific futures as well as those that evaluate such plans to function efficiently under realistic future conditions. While there are tools capable of adapting power system plans to futures such as a highly decarbonized grid, evaluating such plans proves difficult without ways to integrate weather and climate data. The new planning process this paper proposes encompasses futures selection, Adaptive Co–Optimized Expansion Planning (ACEP) and Folding Horizon Simulation (FHS), the evaluation tool, as presented in Figure 1.

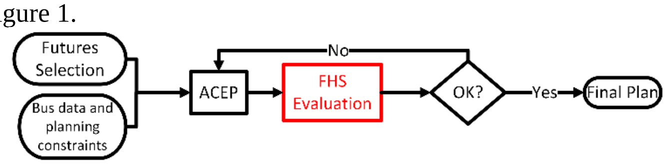

Figure 1: High Level Diagram of the planning process with evaluation tool

A. Futures Selection

Futures refer to possible long–term trajectories a power system may undergo based on uncertainties. Cognizant of this, Federal Energy Regulatory Commission (FERC), in order 1920[1], mandates that long-term transmission expansion planning must consider at least three realistic future outcomes. For instance, if load growth is treated as a planning uncertainty with possible values of *Low*, *Medium*, and *High*, this alone would result in three distinct futures. Introducing another uncertainty, such as the growth of Distributed Energy Resources (DER), which also has three possible levels, expands the total number of futures to nine (3^2). In general, futures are a function of both uncertainties and the scenarios constructed from them. For example, with eight uncertainties, each with three outcomes, this work yields a total of 6,561 unique futures. This number becomes computationally intractable for optimization. To address this, a subset of seven

[1] https://www.ferc.gov/news-events/news/fact-sheet-building-future-through-electric-regional-transmission-planning-and

representative futures was selected to balance model fidelity and computational feasibility. The selection process gave higher selection probabilities to the three MISO (Midcontinental Independent System Operator) futures (1A, 2A, and 3A) due to their regional relevance, while the remaining four were selected randomly but with equal probability from the remaining pool. This selection process was implemented using the SCENRED2 algorithm in GAMS, which identifies a set of scenarios that best represent the overall uncertainty space. Figure 2 presents the final seven futures chosen through this process, each capturing distinct combinations of uncertainty.

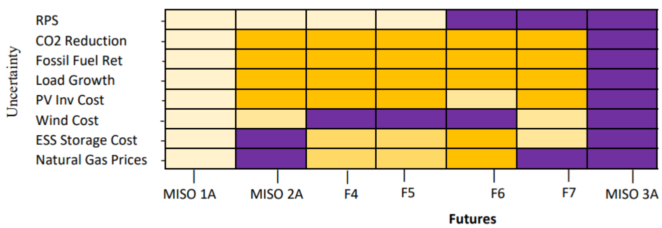

Figure 2: Seven futures chosen by the algorithm

B. Adaptive Co–Optimized Expansion Planning

Co–Optimized Expansion Planning (CEP) is the simultaneous optimization of multiple aspects of grid expansion within a single optimization problem [8]. CEP is a power system planning tool which seeks to identify the best future investments options for both transmission and generation while minimizing the overall cost and satisfying all constraints. For cases where future scenarios, such as a wind/solar–centric grid are highly probable, planners utilize Adaptive Co–Optimized Expansion Planning (ACEP), which adapts the CEP outputs to specific predicted future conditions. Therefore, ACEP is a stochastic formulation of the form in equation 1 which evaluates multiple futures in the planning horizon [9]. For a set of futures, f ∈ F and investment years, y ∈ Y, the objective function of ACEP is comprised of core investment plus adaptation investment represented as A, operational adaptation represented by O and a probability, P, of each future happening. There is, β, a robustness factor which determines how the plan performs under various uncertainties.

$$Min \sum_{y}^{Y} (\text{Core Inv} + \beta * (\sum_{f}^{F} \text{PA} + \sum_{f}^{F} \text{PO})) \qquad (1)$$

subject to:

- Network flow limits, generator limits
- Reserve requirements
- Environmental policy constraints
- Investment targets
- Reliability constraints

ACEP is an optimization model which combines future uncertainties, bus data and constraints as inputs to produce an optimal investment plan. This limits its ability to be computationally viable for more futures, thus, validating the efficacy of its outputs is a challenge [9], [10].

To tackle this challenge, Iowa State University (ISU) developed FHS as a validation tool. The authors of [9], [10] originally developed FHS as a general evaluation tool for power system planning. The author of [9] further refined FHS to apply to the MISO (Midcontinental Independent System Operator) MTEP (MISO Transmission Expansion Planning) process. This work further advances the FHS tool by adapting it to evaluate plans under heavily decarbonized futures and grounding it as an indispensable step the planning process. For each combination of future, uncertainty, and investment year, as outlined in Section II, FHS evaluates whether ACEP meets the planner's performance thresholds. If the thresholds are not satisfied, FHS revises the selection of futures and constraints, then triggers a re-execution of the ACEP. Three major enhancements to FHS in this work, building on the foundation in [9], include:

- Integration of Energy Storage Systems (ESS) as a reinvestment option,
- The introduction of the Resource Variability Index (RVI) to assess the ramping capability of ESS and justify Planning Reserve Margins (PRMs),
- The expansion of FHS to select futures.

With these enhancements, the FHS framework in this work, therefore, emphasizes balancing renewable energy curtailment through ESS deployment before adjusting PRMs or pursuing additional grid reinforcements.

While this works uses the Plan Iowa Energy[2] project as its case study, its outcomes and methodology are applicable to similar power system planning efforts. The structure of this paper is as follows: Section II provides a detailed description of FHS; Section III presents key results; Section IV offers discussion of results and Section V provides conclusions.

II. FOLDING HORIZON SIMULATION

Folding Horizon Simulation (FHS) is an algorithm designed to iteratively evaluate ACEP plans across a broad range of uncertainties, especially those not originally modeled in ACEP [9]. Since ACEP outcomes depend on stochastic future conditions, testing them in a realistic context poses challenges [10]. Given that ACEP models can only account for a limited number of scenarios and uncertainties due to lack computational tractability, FHS acts as an evaluation tool to expose the investment plan to additional uncertainties. This broadens the uncertainty space, offering planners crucial insights into the robustness and performance of the ACEP–modeled plan [10]. FHS addresses these challenges by testing ACEP outputs against a wider variety of scenarios to assess performance. Unlike optimization tools, FHS is solely evaluative, which makes it more time efficient. It can evaluate ACEP plans across 50 uncertainties faster than ACEP can compute seven. This efficiency has made FHS a desirable tool

[2] https://home.engineering.iastate.edu/~jdm/pie/Project%20abstract.pdf

for ACEP plan evaluation [10]. Figure 3 shows the high–level overview of the FHS process which is performed in 5 steps explained as follows.

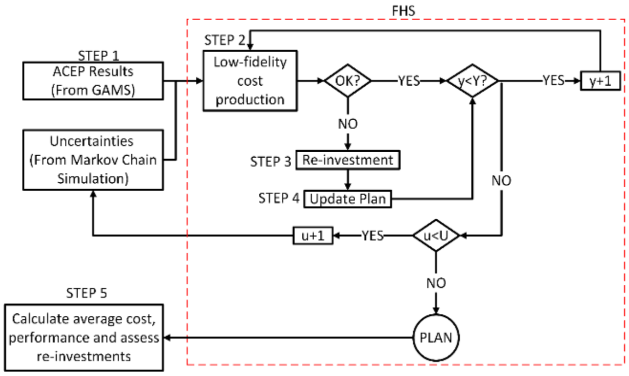

Figure 3: Folding Horizon Simulation Process

A. STEP 1 – Initial Inputs

ACEP model is set up using GAMS programming and solved with the optimization solver, CPLEX. Its initial output is an ACEP plan which only satisfies initial constraints such as basic Kirchoff's laws, initial PRM parameters, and non-negative variables. The plan at this stage is a baseline estimate which needs to be further tested. It is combined with uncertainties not initially modeled while generating ACEP to be the input of the plan evaluation and validation software–the Folding Horizon Simulation (FHS). FHS performs evaluation over time–steps, Y and uncertainties, U until the plan meets all the constraints. Construction of uncertainties, U, is done using Markov chain simulation [9], [10]. Eight uncertainties including Renewable Standard Portfolio (RPS), CO_2 emission reduction, load growth, natural gas prices, fossil fuel retirement, PV investment, land wind investment and Energy Storage System (ESS) costs were simulated in Markov chain; each predicted to take any of the 3 values*: HIGH*, *LOW* or *MEDIUM*. The planner can have as many scenarios as desired for each uncertainty. However, generating an infinitely large number of scenarios makes computation intractable. Thus, we limited simulation to 50 scenarios to balance computational efficiency.

B. Step II – Production Cost Simulation

This is the step where FHS exposes the baseline plan to uncertainties. It evaluates the plan to determine if it meets load conditions under each uncertainty throughout the planning horizon. This production cost simulation involves minimizing the generation operational costs, along with any associated penalty costs. Therefore, the production cost simulation is a deterministic approach that does not permit generation and transmission expansion. It only seeks to make the core ACEP plan meet realistic conditions of the grid.

Penalties are applied to assess the overall performance of the investment plan under simulated uncertainties. These penalty costs are incorporated into the objective function to highlight potential shortfalls in the plan under evaluation. The penalties cover areas such as load shedding, Renewable Portfolio Standard (RPS) requirement shortfalls, carbon dioxide (CO_2) emission reduction shortfalls, and capacity reserve shortfalls. Additionally, penalties are heavily weighted, making their violation the least economical option within the optimization framework of the FHS [9]. The information obtained from evaluating the ACEP against stipulated shortfalls is used in the reinvestment decisions.

C. Step 3 – Reinvestment Options

If the evaluation does not meet the planner's threshold, FHS seeks reinvestment options to strengthen the grid. Such reinvestment options focus on enhancing generation and transmission capacity to decrease load sheds and reduce overall systemic penalties such as failure to meet carbon dioxide (CO_2) obligations.

D. Step 4 – Updating the Core Plan

This step consists of updating the plan with the additionally obtained investment portfolios. The FHS repeats for the next year, y, in the planning horizon and then the next uncertainty, u. Therefore, the FHS ensures that the planner's thresholds are met for each uncertainty every single year of the planning horizon.

E. Step 5 – Calculation of Average Cost

This step includes determining the average costs of load shedding and reinvestment for each plan assessed in the FHS. This allows the planner to compute the performance metrics of the core plans against the uncertainties, U. It facilitates a crucial comparison between the total investment costs and reinvestment costs.

III. Results

As illustrated in Figure 3, the FHS algorithm uses ACEP base case and Markov Chain simulation results as its primary inputs. In this study, ACEP results were first evaluated using the General Electric's Multi–Area Reliability Simulation (GE–MARS). This step was taken to ensure the base ACEP meets reliability criterion of Loss of Load Expectation (LOLE) not exceeding one day in ten years (0.1/year). Whenever GE–MARS produced a LOLE above this threshold, the ACEP investment parameters were reconfigured, and the simulation was iterated until the required reliability standard was achieved.

For robustness parameters (β) of 0.1 and 1, the GE–MARS evaluations converged after 16 and 11 iterations respectively. Consequently, for FHS evaluation, the 1^{st} and 16^{th} iteration were selected for the $\beta = 0.1$ case, while the 1^{st} and 11^{th} iteration were used for the $\beta = 1$ cases.

As shown in Figure 4, generation, and transmissions core costs, along with their corresponding adaptations investment costs, were obtained from the ACEP cases. On the other hand, fixed operations and maintenance (FOM), variable operations and maintenance (VOM), generation and transmission reinvestment costs, fuel costs, load shed cost and regulation cost were obtained from the FHS evaluation tool. Regulation costs include penalties from both CO_2 and RPS. In the plot, costs from ACEP are represented by dotted colors in the legend, while FHS–derived costs are shown using corresponding colors with sliding bars. All costs are cumulative across the seven ACEP futures.

From Figure 4, when $\beta = 0.1$, both transmission and generation core costs are initially low, as the system prioritizes satisfying DC power flow constraints over LOLE

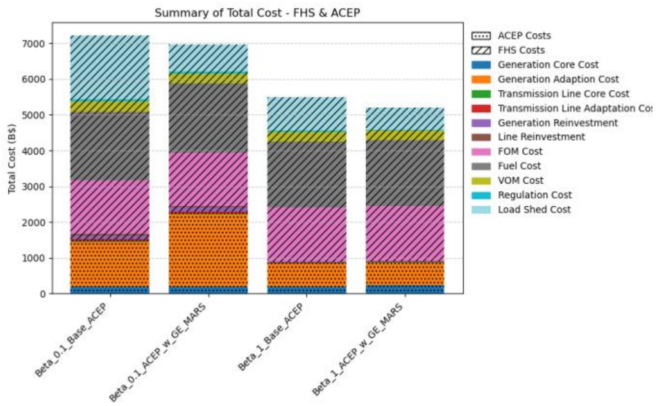

Figure 4: Total costs from the FHS and ACEP simulations for various β values under different GE–MARS Iterations

requirements. However, as GE–MARS iterations progress to enforce LOLE constraints, adaptation investments rise significantly, as seen in the second bar. When exposed to FHS, additional reinvestments in generation and transmission are introduced, which help reduce both load shed and regulation costs. While core investment costs for generation and transmission increase from the 1st to the 16th iteration, the change is relatively modest. Since β remains constant, the model focuses on meeting reliability and operational constraints through increased adaptations and reinvestments rather than increasing core investments. This explains the closeness in the values of core investment costs across early iterations and the growing trend in adaptation costs across higher GE–MARS runs with the same β value.

When β is increased to 1, generation and transmission core investments also increased with a significant reduction in adaptation costs. When the 1st and 11th iteration cases are exposed to uncertainties through FHS, there is a significant decrease in regulation and load shed costs, respectively. Additionally, both adaptation and reinvestment costs decline with higher β values and also across GE–MARS iterations.

Figure 5 and Figure 6 are the graphical representation of FHS reinvestments across different values of β and GE–MARS iterations within the MISO footprint. The algorithm also identifies investments in select seam tie lines between MISO and PJM. Each legend entry specifies the type of investment and whether its cost exceeds $1 billion. Thick colored lines represent transmission reinvestments above $1 billion, while thinner lines indicate those below this threshold. Generation reinvestments, categorized by type, are also shown, and labeled in the legend.

Figures 5 and 6 display generation and transmission reinvestments for β = 0.1 and β =1 at the 1st and 11th GE–MARS iterations, respectively. The maps are densely marked with numerous transmission lines.

To ensure the final plan is highly decarbonized, the generation technologies considered for reinvestment include Wind, Storage (STO), Natural Gas Turbine (Gas_GT), Solar, Natural Gas Combined Cycle (CC), Natural Gas Combined Cycle with Carbon Capture (CC_CCS) and Distributed Solar (DPV).

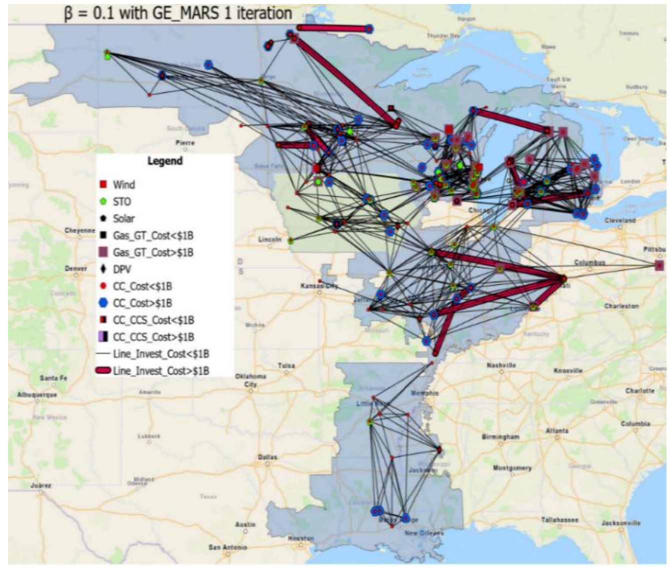

Figure 5: FHS Reinvestment MAP for ß=0.1, GE–MARS iteration=1

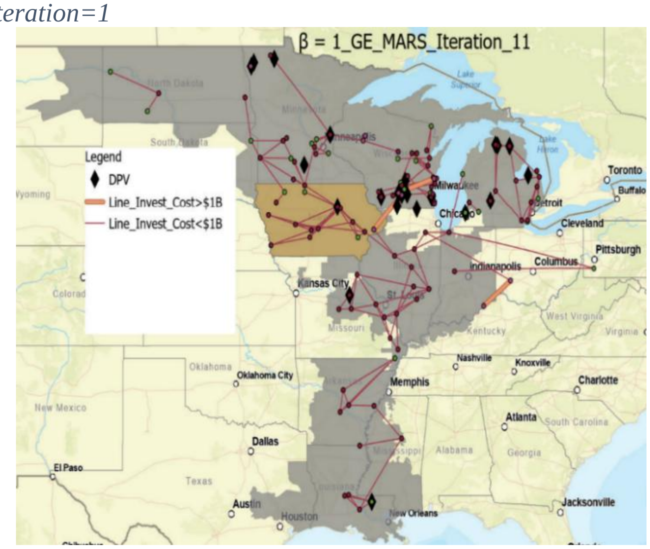

Figure 6: FHS Reinvestment MAP for ß=1, GE–MARS iteration=11

Both generation and transmission reinvestments decreased with higher β values and, more importantly, with higher GE–MARS iterations. In Figure 3, to meet the CO_2, load shed and regulation constraints, the FHS algorithm prioritized generation reinvestments in DPV, Gas_GT and natural gas technologies. The cost of transmissions reinvestment reduced significantly, with the number of lines having investment costs above $1B decreasing from 13 in Figure 5 to 3 in Figure 6. To minimize transmission reinvestments and meet CO_2 constraints, FHS reinvestment for the 11th iteration was exclusively DPV generation.

IV. Discussion

The FHS software has proven effective as an evaluation tool, exposing plans to uncertainties not modeled in ACEP [9],

[10]. As explained by [9], this tool can be integrated into MISO's MTEP process, allowing planners to evaluate and select the optimal plan. The PIE project is anchored on five visions each aligning with futures identified in the report [3]. According to [9], the FHS algorithm is ideal for selecting the value of β, representing the system's robustness at its initial investment. This work has shown that FHS can also help planners choose the future and vision with the most desirable investment characteristics. Whether investors prioritize costs, reliability, or robustness, FHS provides detailed results that simplify decision–making.

Figure 7 is the representation of ACEP performance when exposed to FHS at GE–MARS 11^{th} iteration of $\beta = 1$. The FHS–calculated investment costs for each future indicate that Future 6 is the most economical of the seven.

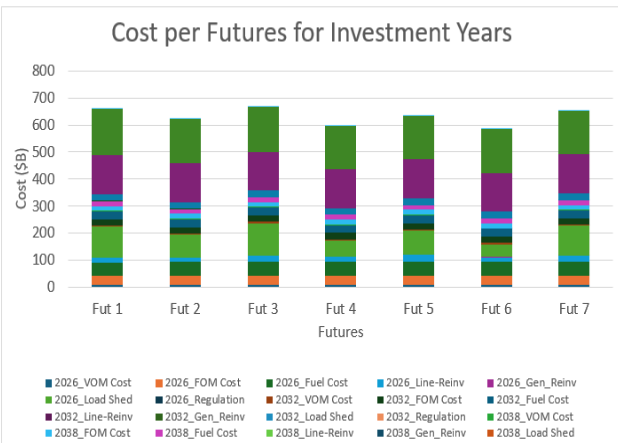

Figure 7: Cost per future for investment years

While the most economical future has the lowest overall costs, the best performing future is defined by the least load shed and regulation costs. This feature of FHS enables planners to choose a vision based on both economic viability and engineering performance. Tradeoffs may occur depending on RPS, CO_2 and load shed regulations. For this work, load shed and RPS are heavily weighted, which prevents the optimizer from choosing them over reinvestment. However, in jurisdictions with relaxed decarbonization regulations, planners may prioritize economic efficiency and reinvest only if the uncertainties arise. In such cases, reinvestment decisions shall only be made based on real–time grid conditions. Contrarily in regions like United States, that impose stringent penalties, planners may be forced to prioritize reliability over costs. In general, FHS remains an excellent tool for evaluating and making investment decisions.

Without using GE–MARS for reliability evaluation, FHS could stand in its place. While GE–MARS assesses ACEP base investments against LOLE standards, FHS evaluates the same against broader criteria including, load shed, RPS, and CO_2 penalties. This allows FHS to offer a more comprehensive evaluation, providing robust outputs for investment decisions without necessarily requiring the GE–MARS step.

V. Conclusion

Folding Horizon Simulation (FHS) is an evaluation tool designed to test the efficiency of Adaptive Co–optimized Expansion Planning (ACEP) outcomes by exposing them to expected uncertainties in a realistic environment. To achieve this, Markov chain simulation was used to generate 50 scenarios for each of the eight planning uncertainties that form the basis of ACEP plan evaluation. While a higher number of scenarios certainly improves the accuracy of FHS outcomes, computational tractability makes 50 scenarios an efficient choice.

The FHS analysis showed that higher values of β and more GE–MARS iterations lead to notable reductions in load shed, regulation costs (combination of RPS and CO_2 penalties), and both generation and transmission reinvestment costs. These results signify FHS as a good evaluation tool that enables planners to choose robustness of the systems as well as the future and visions that well fit their planning needs. Depending on their priorities, planners can choose to build a more resilient system from the outset or opt for a less robust one which commands reinvestment when uncertainties arise, each of which would represent a future and/or a vision. As this work demonstrated, FHS functions well in an integrated planning model where it both works as a reliability evaluation as well as an adaptational validation tool. With this, its application in the planning process to develop plans for highly decarbonized futures is more critical in planning the future grids.

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