doi:10.20944/preprints201808.0545.v1

Intercomparison between Switch 2.0 and GE MAPS models for simulation of high-renewable power systems in Hawaii

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ABSTRACT

Background: New open-source electric-grid planning models have the potential to improve power system planning and bring a wider range of stakeholders into the planning process for next-generation, high-renewable power systems. However, it has not yet been established whether open-source models perform similarly to the more established commercial models for power system analysis. This reduces their credibility and attractiveness to stakeholders, postponing the benefits they could offer. In this paper, we report the first model intercomparison between an open-source power system model and an established commercial production cost model.

Results: We compare the open-source Switch 2.0 to GE Energy Consulting's Multi Area Production Simulation (MAPS), considering 18 scenarios of renewable energy adoption in Hawaii. We find that after configuring Switch with similar inputs to MAPS, the two models agree closely on hourly and annual production from all power sources. Comparing production gave an R^2 value of 0.996 across all energy sources and scenarios, with R^2 values in the range of 69–100 percent for individual sources.

Conclusions: Although some disagreement remains between the two models, this work indicates that Switch is a viable choice for renewable integration modeling, at least for the small power systems considered here.

Keywords: model intercomparison, renewable energy, production cost modeling, security-constrained unit commitment, open-source software

Background

In recent years, numerous new, open-source or academic planning models have been introduced to assist in planning power systems with increasing shares of renewable power [1–16]. These have the potential to advance planning for smart power systems that integrate renewable energy, storage and demand response. Further, they can help bring a wider range of parties into the planning process for next-generation power systems, enabling replication of research findings and movement toward consensus among stakeholders [2, 17–19]. However, new, open-source models must compete for users' confidence with established, commercial models with a long history of use for grid and renewable energy studies [20–28]. Although the newer models are available at no cost and generally offer a richer treatment of new opportunities such as co-optimization of investment, operations, storage and demand response, they have do not yet have a track record of performing similarly to the more established models for basic power system analysis. This reduces their credibility and attractiveness to stakeholders, foregoing some of the benefits these new models could offer.

In this paper, we report a model intercomparison between Switch 2.0 and GE Energy Consulting's Multi Area Production Simulation (MAPS), considering 18 scenarios of renewable energy adoption in Hawaii. Switch is an open-source capacity expansion model, designed to optimize the construction of power systems with large shares of renewable power, storage and demand response. It was released as open-source software in 2008 [11, 29], and has subsequently been used for a number of long-term studies of renewable energy adoption [30–36]. Here we test Switch version 2.0, which was released in 2018 [1, 37]. GE MAPS is a commercial-grade power system production-cost model that has been widely used for renewable integration studies in Hawaii and elsewhere [20, 25, 26, 38–45]. It has also been calibrated against system operations in Oahu and Maui [46, 47], giving an extra element of "ground truth" to its findings.

We are not aware of any previous model intercomparison between open-source and commercial grid planning software, especially focusing on renewable energy integration. This gap may be partly because open-source grid planning models have only become widely available in recent years, and partly because few researchers have access to the inputs and assumptions that are needed to replicate professional integration studies. This study takes advantage of the unusual fact that detailed data are available on the inputs, assumptions and findings from the GE MAPS model, as run for the *Hawaii Renewable Portfolio Standards Study* (RPS Study) [48].

In other fields, especially climate modeling, intercomparisons between models are common, either to benchmark the accuracy of different models [49–51] or to identify areas of consensus and disagreement among the models [52–55]. This study takes the former approach, focusing on the question of whether a new, open-source model is able to provide similar results to an established and validated commercial model when modeling a real-world power system.

In the Results section, we compare the behavior of Switch and GE MAPS for all the power-production results presented in the RPS Study. This work focuses only on findings shown in the RPS Study because the full GE MAPS model and results are not available to the public. In the Discussion section, we discuss the implications of these results and possible sources of disagreement between the models. The Methods section and Supplementary Information describe how Switch was configured for the study. Assembling datasets and configuring Switch for this study required significant effort, and the data and model are now available via a public repository at https://github.com/switch-hawaii/ge_validation.

Results and Discussion

We compared the results from running Switch 2.0 to GE MAPS for 17 scenarios of interconnection and renewable resource adoption on the islands of Oahu and Maui previously studied with GE MAPS in the *Hawaii Renewable Portfolio Standards Study* (RPS Study) [48]. These had various amounts of wind and solar generating capacity and various combinations of inter-island transmission cables. Renewable resources ranged from 18 to 55 percent of total energy demand. New transmission options included a "grid-tie cable" to enable bidirectional sharing of power between the Oahu and Maui power systems and/or a "gen-tie" cable to carry power from wind farms on Lanai to the Oahu power system, without connecting to Lanai's local power system. Scenario 1 in the RPS Study considered the current power systems without significant changes. We configured Switch to match Scenarios 2–18, which represented future power systems. These are summarized in table S1 in the Supplementary Information.

Although the comparisons reported below use quantitative metrics where possible, the comparison is fundamentally qualitative, intended to help researchers identify the areas where the models may differ and attention must be given to produce satisfactory results. We used this approach because statistical significance is not applicable in this context – the models are deterministic and clearly agree more than could be expected by chance; however, researchers must make their own qualitative judgments of whether they are similar enough to meet their needs.

Annual power production from each class of generator

Figures 1 and 2 below show the annual power production from each major type of generator, in each of the 17 scenarios. Different energy sources are stacked in each column, and MAPS and Switch results are compaired in pairs for each scenario. The agreement is generally within 0.5% of total power production for all categories except for baseload production in scenarios the grid-tie-only scenarios, which differ by 1–2%. There are several patterns in the differences between GE MAPS and Switch (see Fig. 2):

- In scenarios with independent separate island power systems (scenarios 2–9, 10, 13, 16), Switch uses 23–72 GWh more of baseload generation on Oahu than MAPS, and correspondingly less cycling and peaking generation. This equates to 0.3–0.8% of total production. In these scenarios, Switch uses slightly more Maui peaking generation and slightly less Maui baseload generation than MAPS (7–8 GWh, corresponding to 0.1% of total production).
- In the scenarios with a grid-tie cable between the two islands but no gen-tie wind (scenarios 11, 14, 17), Switch uses 120-160 GWh more baseload generation on Oahu than MAPS (1.4–1.9% of total production). It also uses slightly more Maui peaking generation. These are matched by roughly equal decreases in baseload generation on Maui and cycling and peaking generation on Oahu.

- The pattern in the scenarios with gen-tie wind and a grid-tie cable (scenarios 12, 15, 18) is similar to the grid-tie-only scenarios (more Oahu baseload and Maui peaking, less of other thermal plants), but less pronounced. In these scenarios, Switch also curtails more Oahu wind than GE MAPS and accepts more Maui wind and solar, with a net decrease in renewable production of 0–35 GWh, 0.0–0.4% of total production.

The R^2 value (squared correlation coefficient) between results from MAPS and Switch across all energy sources and scenarios is 0.9999 for Oahu and 0.9963 for Maui. This indicates that the two models agree on nearly 100% of the variation between energy sources and scenarios.

Table 1 shows R^2 values across all scenarios for each individual energy source, indicating how well the models agree on the variation in production from each individual type of generator across the 17 scenarios. The R^2 value is above 99% for all the renewable power sources and is 69–100% for the thermal power plants. The lower values for the thermal plants appear to reflect differences in prioritization of the various thermal plants relative to each other, as shown in Figures 1 and 2.

Table 1. R^2 value (squared correlation coefficient) between total energy production in GE MAPS and Switch, across scenarios 2–17, for each power source and island

	Island	
Power Source	**Oahu**	**Maui**
Distributed Solar	1.000	1.000
Central Solar	0.999	0.991
Wind	0.994	1.000
Peaking	0.747	0.668
Cycling	0.652	0.976
Baseload	0.993	0.766
Firm Renewable	1.000	N/A

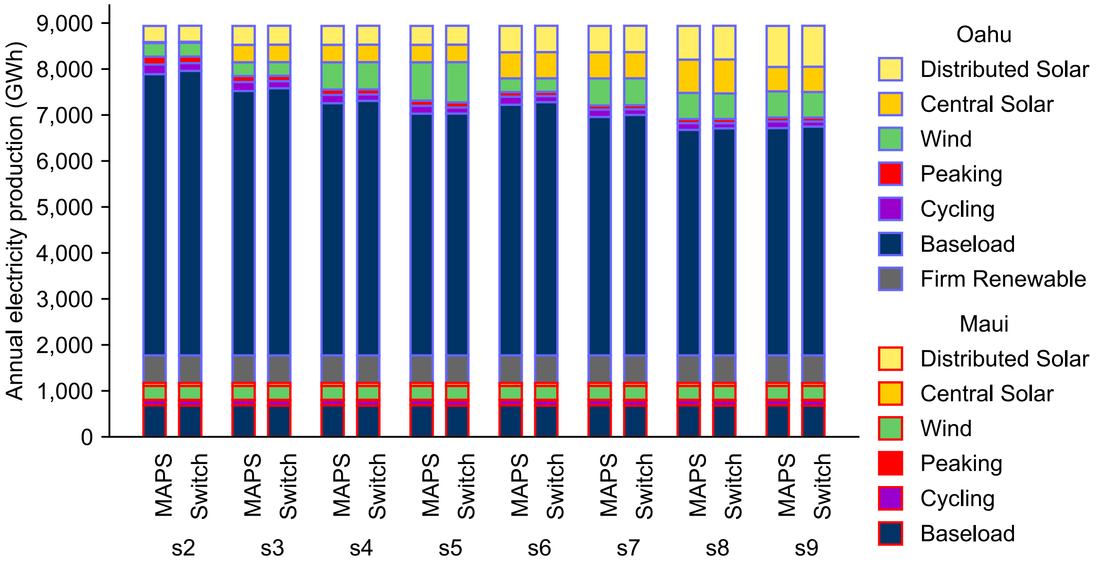

Figure 1. Annual production from each source in scenarios 2–9, as calculated by MAPS and Switch. Upper, blue-bordered rectangles show Oahu generators; lower, red-bordered rectangles show Maui generators

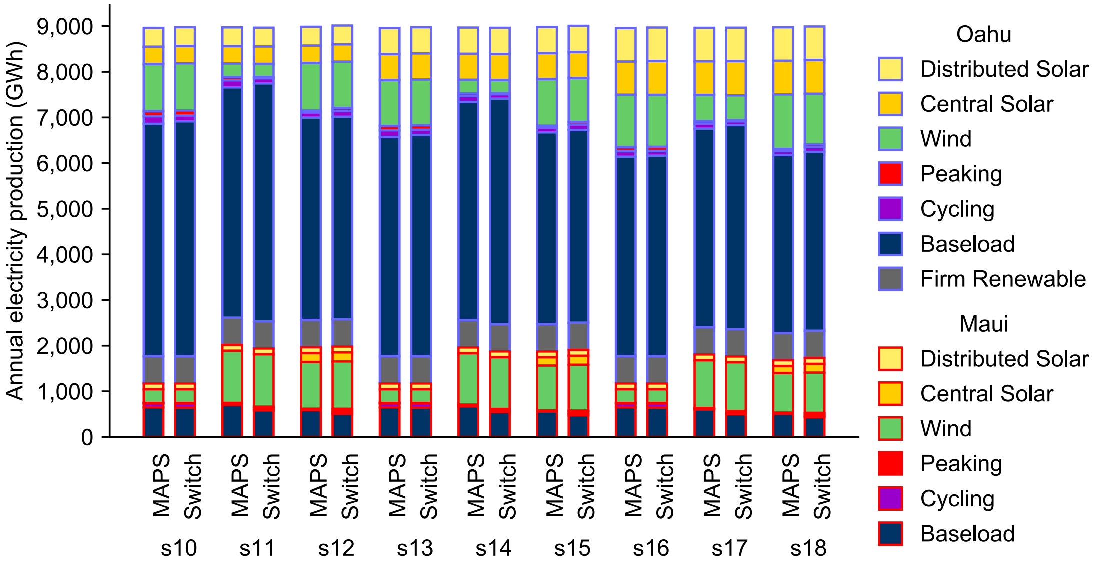

Figure 2. Annual production from each source in scenarios 10–18, as calculated by MAPS and Switch

Annual Curtailment in Each Scenario

Figure 3 compares the rate of curtailment of renewable power between Switch and MAPS modeling. Curtailment occurs at times when available wind and solar power exceeds system load net of generator minimum loads and down-reserve requirements. There is one colored marker for each scenario as modeled by Switch, and one black ring for the equivalent scenario in MAPS. The x values for each marker show the amount of wind and solar power that is potentially available in that scenario, found by summing the hourly potential reported by GE in [56]. The y values show the percentage of renewable power that was left unused due to curtailment in each scenario. These calculations include wind, distributed solar and utility-scale solar.

The comparison in Figure 3 mostly follows from the results discussed in the previous subsection. MAPS and Switch produce very similar results overall, with a median difference in curtailment of 0.13 percentage points and differences of less than 0.3 percentage points for all but three scenarios (5, 15 and 18). Overall, the R^2 between the two models is 0.973, indicating that Switch and GE MAPS agree on about 97% of the variation in curtailment between scenarios.

The biggest difference is in scenario 5, where Switch has 1.0% curtailment vs. 3.1% for MAPS. Scenario 5 is a relatively high wind scenario, and the difference is mainly due to curtailment of 41 GWh more of Oahu wind in Switch (about 0.5% of total power production, barely visible in Figure 1 in section 0).. Scenarios 15 and 18 have the highest levels of renewable deployment and include both gen-tie wind and an inter-island grid tie. In these scenarios, Switch’s curtailment was 0.6–0.7 percentage points higher than GE MAPS.

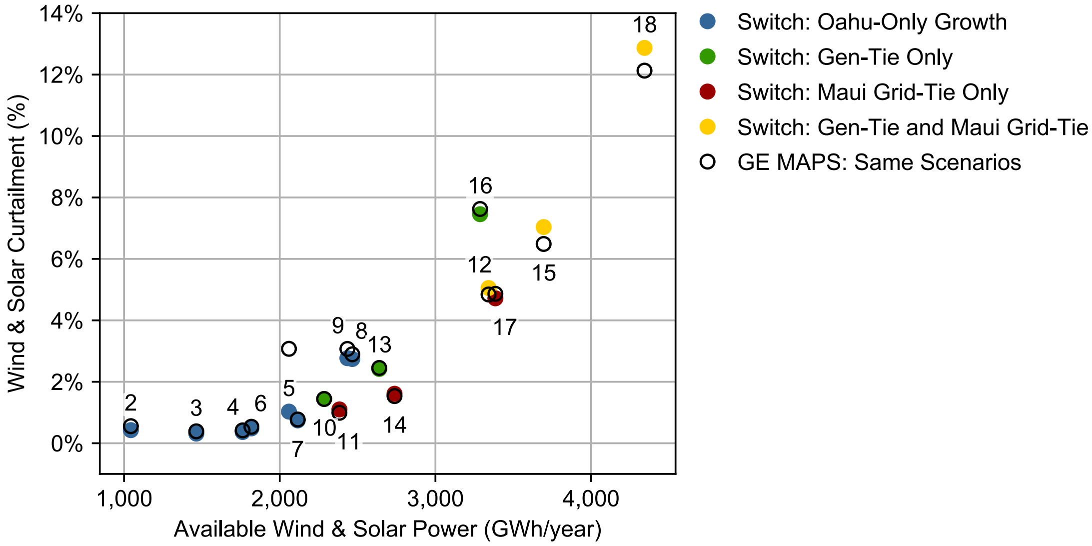

Figure 3. Curtailment rate calculated by Switch and GE MAPS in scenarios 2–18

Hourly System Operation

Figure 4 shows one week of hourly operation of the Oahu power system in a low-renewable scenario (#2), as reported for GE MAPS (upper plot, reproduced from the RPS Study [48]) and Switch (lower plot). Similar to the annual results, Switch uses less cycling generation (purple) and more baseload generation (blue/teal shades) than MAPS on the Saturday and Sunday. Specifically, Switch commits only one cycling plant from 11 am to 3:59 pm on the Saturday and 8 am to 3:59 pm on the Sunday, while MAPS commits two cycling plants during these times. In both cases the cycling plant(s) run at minimum load (22.5 MW each), and primarily provide reserves. Switch also decommits some Kalaeloa capacity earlier than MAPS on the last evening.

We could not identify a reason for the discrepancies in the hourly profiles from the two models. It is possible they are caused by different treatments of minimum up-/down-times for power plants (on the Saturday, one cycling unit exactly meets both of these limits), or MAPS may have been configured to optimize commitment beyond the minimum needed for load and reserves (Switch was configured to commit only the minimum required capacity).

We also note that MAPS slightly reduces output from Kalaeloa during the times of lowest power demand on Wednesday and Thursday nights, and this effect is slightly weaker in the Switch modeling. This suggests Switch may have used a lower minimum-load or down-reserve requirement for the Kahe and Waiau baseload units than MAPS.

Figure 5 compares hourly results for a high-renewable scenario (#16). Again the match is close overall, but Switch used slightly more baseload generation and less cycling generation than MAPS. For example, Switch decommits Kalaeloa 2 & 3 at midday on Tuesday, late morning on Wednesday and late evening on Sunday, while MAPS keeps them running. Switch also runs less cycling capacity (purple) than MAPS on Monday afternoon, Friday afternoon and at 6 pm on Saturday.

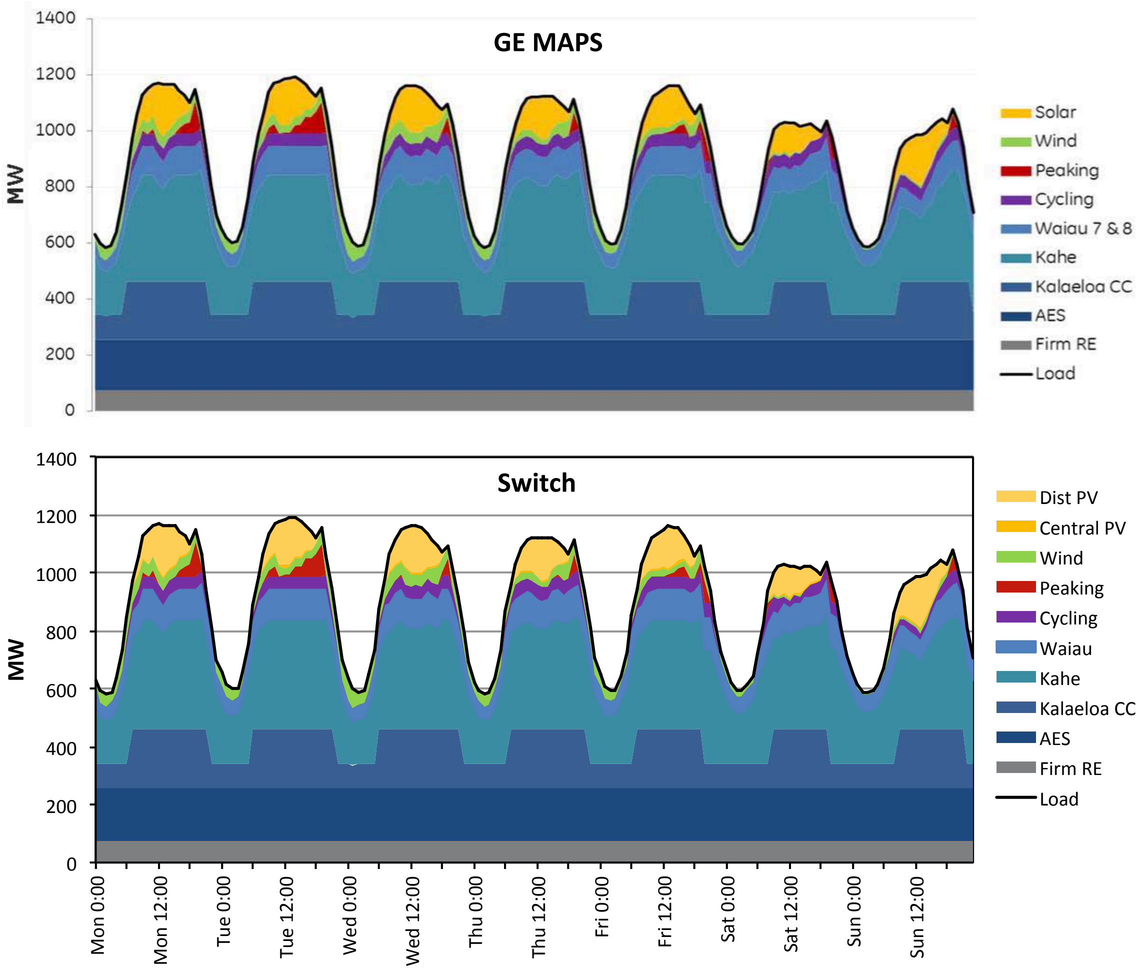

Figure 4. Hourly power production in Scenario 2 during the week of June 22–28, calculated by GE MAPS and Switch (plot begins on a Monday)

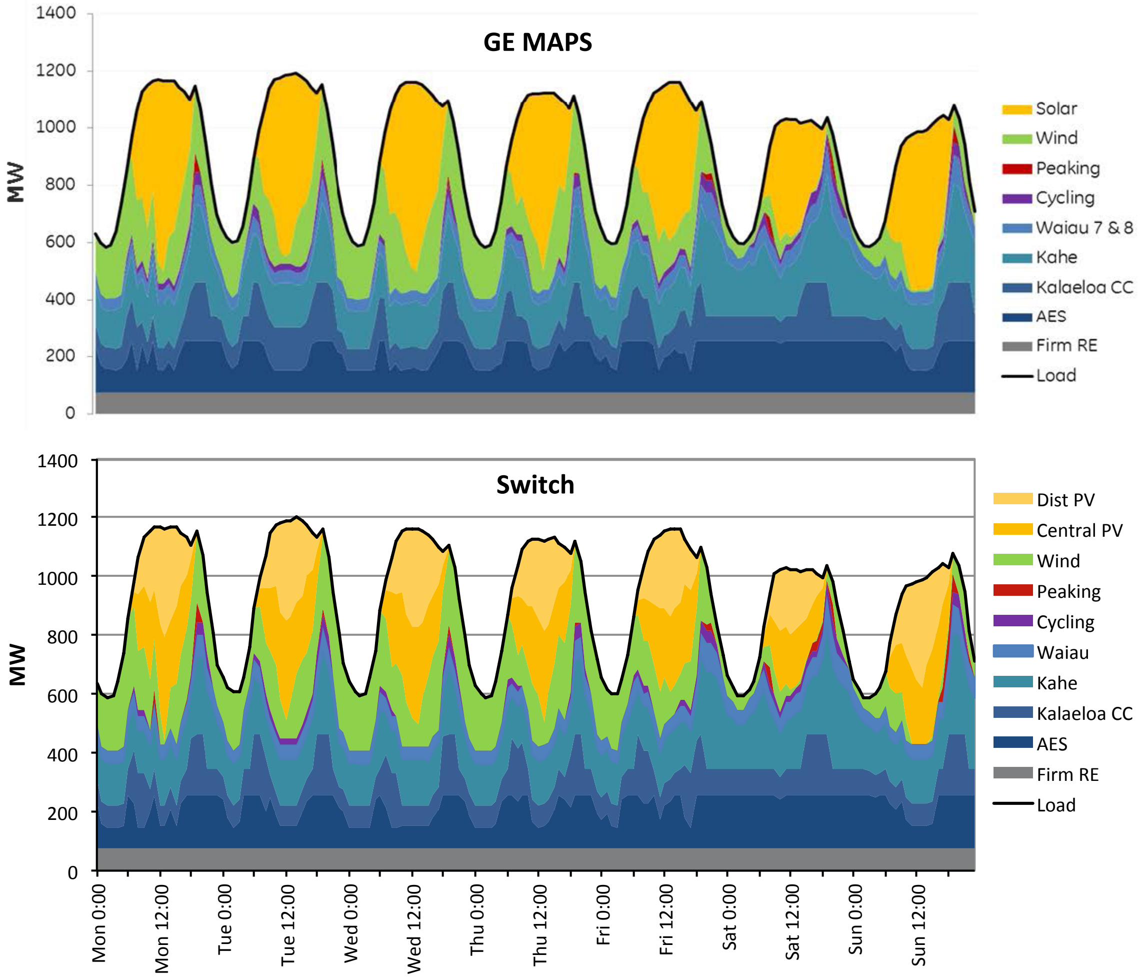

Figure 5. Hourly power production in Scenario 16 during the week of June 22–28, calculated by GE MAPS and Switch with standard model settings (plot begins on a Monday)

Conclusion

The commercial GE MAPS production cost model is widely used for renewable energy integration studies, including the recent *Hawaii Renewable Portfolio Standards Study* (RPS Study) [48]. The goal of this model intercomparison was to test whether similar results could be obtained from the open-source Switch model when studying the same high-renewable power systems. Switch is primarily designed as a capacity expansion model, which means that it selects which assets to build in order to minimize costs while meeting policy objectives. Embedded within this are unit-commitment and dispatch algorithms that decide which plants to turn on each hour and how much power to provide from those plants. GE MAPS is a production-cost model, which means that it focuses on unit-commitment and dispatch, using pre-specified portfolios of power system assets. Consequently, this model intercomparison focuses only on a subset of Switch's capabilities. However, this is a critical subset, which encompasses some of the most important interactions between renewable power, thermal power plants and electricity demand.

We found that when Switch was configured similarly to MAPS, it produced results that were very close to MAPS, at least for the 17 scenarios evaluated here. Although the models agree closely, the agreement is not exact. The largest differences between the models are in the selection among different thermal power plants to provide power each hour. As noted in the Methods and Supplementary Information, there are a number of areas where Switch's configuration may have differed from MAPS, possibly contributing to these differences. These areas include generator outages, calculation of down-reserve targets, allocation of reserve targets between islands, commitment order for Oahu and Maui power plants, commitment rules, treatment of

doi:10.20944/preprints201808.0545.v1

the inter-island cable during unit commitment and dispatch, operating rules for Maui's Maalaea combined-cycle plants, and variable cost of the Kalaeloa plant.

We are not able to judge which of these are the largest contributors, because the complete MAPS inputs and model are not available to the public. However, based on the qualitative similarity in findings between the models, we conclude that it is possible to configure Switch to obtain substantially similar results to MAPS, at least for the types of analysis reviewed here. Nevertheless, when using either model, researchers should be careful to ensure that their model assumptions match local practices.

Future work is needed to compare additional open-source and commercial power system models, and to evaluate performance in larger power systems or power systems with different operating rules.

Methods

Switch normally uses mixed-integer optimization methods for unit commitment and dispatch. MAPS uses linear optimization methods for unit commitment, with heuristic rules to enforce integer decision variables. For the RPS Study [48], MAPS was specially configured to match the Hawaiian Electric Companies' heuristic unit commitment rules. The RPS Study report included a substantial body of information about how MAPS was configured, and GE was generous in providing additional data and answers to inquiries. However, the goal of the RPS Study was to evaluate different pathways of renewable integration in Hawaii, rather than to document modeling methods or data, which are constantly evolving. Consequently, we inferred some operational details from the figures and results presented in the RPS Study, and in some cases made assumptions that may have differed from ones that GE MAPS used. The model configuration and inputs used for this study are described below. Switch 2.0 is available from [37]. The data and code used for this model intercomparison are available from [57].

Switch model setup

The Switch model is primarily used as a power system capacity expansion model (co-optimizing selection of new assets and operational decisions), but it uses a flexible, modular software framework that allows it to be customized and run as a production cost model (optimizing operational decisions only).

For this intercomparison, we used standard Switch modules for time sampling; financial calculations; generator construction, commitment and dispatch; transmission construction and operation (in flowgate mode); operating reserve balancing areas; and fuel cost calculations. We also used a module for Kalaeloa unit commitment that is shared with other Switch-Hawaii models. We also added a custom module to implement heuristic unit commitment rules similar to the Hawaiian Electric rules, as used in MAPS.

To conduct the analyses reported here, we divided the 2020 study year into 12 months, solved the individual models, and then aggregated the results. This resulted in 204 production cost models to solve. These were solved in about 10 minutes via parallel processing on the University of Hawaii high performance computing system. Total compute time for the 17 scenarios on a single four-core desktop computer would be about four hours. The run-time for GE MAPS was reported to be under 30 minutes [58].

Thermal generator properties

Operating costs

Details for modeling operation of utility-owned thermal power plants were taken from [48]. For each plant, these include retirement status, operating mode, type of fuel, heat rate (efficiency) curves, operation and maintenance costs, forced outage rates, minimum up- and down-time constraints, and energy required to startup plants. We modeled independent waste-to-energy plants (H-Power and Honua) as having a take-or-pay contract following a fixed schedule, as reported separately by GE [59], and we modeled the independent AES and Kalaeloa plants using representative heat-rate (efficiency) curves as described in [26]. For AES, we used a variable operation and maintenance (O&M) rate of \$2 per MWh, as reported in [60]. For Kalaeloa, we set the variable O&M to \$8.59/MWh, which resulted in the same full-load operating cost as reported in Figure 30 of the RPS Study [48].

Fixed operating schedules

We configured Switch to follow the same commitment and dispatch schedules as GE described for their model runs [27, 48, 59, 61, 62]. As a general rule, plants identified in the RPS Study as baseload or firm renewable ("firm RE") were committed (turned on) at all times that they were not out for maintenance. Cycling and peaking plants were committed as needed, based on the day-ahead renewable energy forecast.

Commitment for peaking plants was further adjusted based on real-time conditions. Firm RE plants also had fixed dispatch (production) schedules [59]. A few plants followed commitment and dispatch schedules that did not fit this general pattern; they are discussed in the supplementary document.

Operating modes for combined-cycle plants

Kalaeloa power plant. The Kalaeloa combined cycle power plant consists of two combustion turbines, one steam turbine powered by waste heat from the combustion turbines. GE modeled these as three units: Kalaeloa 1 and 2 each consisted of one combustion turbine and half of the steam turbine, and Kalaeloa 3 represented additional peaking capacity available if operating in dual-train combined cycle mode [26, 46, 58, 59]. GE also reported that Kalaeloa 3 could operate in quick-start mode if Kalaeloa 1 and 2 were producing at their rated power level. We configured Switch to match this logic, i.e., only allowing Kalaeloa 3 to produce power if Kalaeloa 1 and 2 were at maximum output.

Maalaea combined cycle plants. We modeled each of the Maalaea combined-cycle power plants as two single-train combined cycle generators (a total of four units). Each of these plants consists of two combustion turbines and one steam turbine. Based on GE's reporting, we believed that MAPS modeled these plants as four single-train units. However, GE reported properties for each of these plants on an aggregate basis in the RPS Study report [27]. So we split these properties in such a way that each pair of units would perform the same as the original aggregated plant, if both units were dispatched in tandem.

Minimum Load and Part-Load Heat Rates for Peaking Plants

We modeled peaking plants with no minimum load (meaning they can operate anywhere between 0 and 100% of their rated load), and with a single incremental heat rate for all operating levels, following information reported separately by GE [59].

Generator Maintenance and Forced Outages

The RPS Study [48] showed Hawaiian Electric's maintenance schedules, but MAPS used different schedules to avoid interfering with normal operation and reserve margins each week [58]. We inferred the dates of full maintenance outages for most thermal power plants in Oahu by inspection of hourly production data for Oahu plants in Scenarios 2 and 16, which GE provided separately [63]. We assumed that baseload plants were on maintenance or forced outage on all days when they produced zero power. We assumed cycling plants were out of service when they produced no power while lower-priority peaking plants produced some power.

We were not able to identify forced outages for peaking plants or Maui plants by this technique. For these plants, we applied the utility's maintenance schedules shown in the RPS Study [48] and then added random 3-day outages until each plant's forced outage rate was 2.5% higher than the level shown in Table 7 of the RPS Study [48]. The 2.5% adder was used because we found that outage rates for the Oahu baseload and cycling plants in MAPS were an average of 2.5% higher than the sum of the maintenance schedules and forced outage rates shown in the RPS Study [48].

This technique was also unable to identify partial outages at power plants (e.g., times when they could only run at 35% or 50% of normal output). By inspection of the hourly production data [63], we noted that there were a number of times when partial outages occurred; however we were not able to identify these systematically, so we omitted them from the Switch modeling. This is likely to introduce a bias toward baseload production rather than cycling or peaking production in all scenarios. It may also introduce a bias toward Oahu baseload over Maui baseload in the gen-tie scenarios (simply because there is more Oahu baseload capacity).

Fuel Costs

We used fuel costs reported for Oahu and Maui in the RPS Study [48].

Transmission Network

GE MAPS models transmission using an AC power flow, with DC variations with each commitment and dispatch decision [58, 64]. Switch is normally run with a flowgate-based transmission model, or it can be run with (experimental) security-constrained AC power flow. Since no network information is available publicly for Oahu and Maui, we ran Switch in flowgate mode, with no congestion or losses within each island, and finite transmission capacity between islands (in grid-tie scenarios). We assumed that all power flows over the grid-tie line incurred losses of 3.8%, based on an analysis of total production values reported for grid-tie and non-grid-tie scenarios in the RPS Study.

Hourly Loads and Renewable Power Production

We used hourly timeseries of renewable production potential, day-ahead forecasts and electricity loads for Oahu and Maui which were provided by GE [56]. Gen-tie wind potential was increased by 5% before applying 5% transmission losses, to achieve consistency with values in the RPS Study.

Spinning Reserve Targets and Allocation

Power systems must keep extra generating capacity committed (turned on) at all times in order to compensate for unforeseeable variations in operating conditions. These reserves can be divided into two main "product" categories: contingency reserves, which can compensate for rare events such as loss of a large generator or load; and regulating or operating reserves, which compensate for routine events such as misforecast of loads or renewable power. Reserves can also be divided into "up" and "down" directions (available to increase or decrease production). In Hawaiian power systems, all reserves are usually provided by "spinning" power plants (online and synced to the grid).

Up Reserves

We configured Switch to use the same pre-calculated contingency and regulating reserve targets as MAPS [56]. In the grid-tie scenarios, we divided the regulating reserve target between the two power systems proportional to their hourly load levels; we were not able to identify how MAPS divided this target. We assumed the inter-island grid-tie cable could provide firm power transfers but could not directly provide spinning reserves.

It is not clear from the RPS Study report which power plants were designated to provide up reserves. Based on analysis of several sources [47, 48, 62, 65], we allowed all baseload and cycling units to provide up reserves. Details of our inferences are given in the Supplementary Information. Switch, like MAPS [65], was configured to optimize production levels for individual plants to minimize production cost while respecting the overall reserve target.

In the grid-tie scenarios, we configured Switch to divide the regulating reserve target between the Oahu and Maui power systems proportional to their hourly load levels. It is likely that GE used a different method to divide this target, but we were unable to find any documentation of this.

Down reserves

"Down" reserves are provided by power plants that are producing power above their minimum stable or permitted level and are able to reduce production on short notice. We set a contingency down reserve target of 10% of hourly load for Oahu, no regulating down reserve target for Oahu, and no down reserve target of either type for Maui, based on analysis of the RPS Study report [48].

Based on analysis of several sources [26, 27, 48, 65], we divided the down reserve target between renewable and thermal generators based on their available capacity, and then among individual generators proportional to their committed capacity, as discussed in the Supplementary Information.

Generator Unit Commitment

"Unit commitment" refers to the process of selecting which power plants will be online during a particular time period. This is different from "dispatch," which is the decision about how much power to produce from each committed plant. Switch and MAPS normally optimize unit commitment directly in order to provide enough capacity for energy and reserves, while respecting minimum up- and down-time limits for power plants. However, Hawaiian Electric instead uses a priority queue to specify the order in which thermal power plants will be committed. For the RPS Study, MAPS was configured to perform a linearized optimization of unit commitment, subject to this ordering, with additional heuristics to ensure integer constraints are satisfied (i.e., units must be fully committed or not at all)[58, 61]. MAPS used two rounds of unit commitment, one based on the day-ahead forecast, and one at real-time, using real-time conditions. All available plants were scheduled in the day-ahead unit commitment, but then peaking plants could be turned on or off as needed in real time [62]. For this study, we configured Switch with a custom commitment algorithm that followed this general approach. In the Supplementary Information we report the assumptions we made about the order of plants in the commitment queues, and the rules that were followed by this commitment algorithm.

Generator Dispatch

For this study, Switch used its standard dispatch methods to choose how much power and reserves to produce from each committed power plant, in order to minimize cost while satisfying the balancing area's requirements for power and reserves, and respecting constraints on the operation of individual plants (e.g., down-reserve quotas).

Declarations

Availability of data and materials

All datasets, code and configuration files used for the current study, as well as installation instructions, are available in a public Github repository at https://github.com/switch-hawaii/ge_validation.

Competing interests

The author declares no competing interests.

Funding

This work was funded under a subaward to the Hawaii Natural Energy Institute, University of Hawaii at Manoa, from the Florida Solar Energy Center, University of Central Florida, through a grant from the US Department of Transportation's University Transportation Centers Program, Research and Innovative Technology Administration. The funding bodies reviewed the design of the study and findings, but did not design or conduct the analysis or interpretation.

Author's contributions

M.F. conceived the study, conducted the study, analyzed the results and wrote the manuscript. The author read and approved the final manuscript.

Acknowledgements

The author is grateful to staff at the Hawaii Natural Energy Institute and the Florida Solar Center, especially Katherine McKenzie, Kevin Davies and John Cole, for assistance in obtaining data and for providing valuable suggestions to help clarify the manuscript. Thanks also to Derek Stenclik at GE Energy Consulting for clarifying the approaches taken in the RPS Study. Any errors remain the author's own.

Author's information

M.F. is an Assistant Professor of Electrical Engineering at the University of Hawaii at Manoa, specializing in optimal design of power systems with large shares of renewable energy, storage and demand response. He is the lead author of the open-source Switch power system software.

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