

In With the New: A 100% Renewable Energy Plan for the City of San Diego

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Abstract— Energy system planning and modeling is a critical step in designing power systems that operate safely and reliably for electricity consumers. The need for developing accurate plans is even more important when considering that many federal, state, and local governments have set aggressive goals for transitioning to high-penetration renewable energy systems over the next 30 years. Thus, there exists the need to create high fidelity models for power system transitions that consider resource availability, grid stability, and system cost, amongst other factors. There are several challenges that must be addressed when considering what a 100% renewable energy system will look like. These include the intermittent nature of wind and solar power, operator regulations that require certain levels of load carrying capability, daily and seasonal changes in load, and predicted changes to the load itself over time. The following report presents the assumptions made and research done for developing a 100% renewable energy system for the City of San Diego. The plan aims to estimate what generator capacities will be required to meet demand and what costs will be associated with such a system while addressing proposed ancillary services, contingencies, and utility rate structures.

Index Terms—Battery Storage, Capacity Expansion Modeling, Demand Response, Effective Load Carrying Capability, Electric Vehicles, Energy Modeling, Geothermal Energy, Renewable Energy, Reserve Margins, Residential Solar, Resource Adequacy, Solar Energy, Time-of-Use Utility Rates, Wind Energy

I. INTRODUCTION

ENERGY systems are expensive, high impact assets that are relevant to nearly every aspect of day-to-day life. As the world continues to rely more on renewable energy resources, there will follow a growing need to build accurate system models that ensure capital investments are worthwhile and provide long-term stability and reliability to power grids. Energy systems are also multifaceted and can take many forms depending on the objective and of the system and the load they serve.

The goal of this project was to create an energy plan for a 100% renewable energy system that can serve a provided load at the lowest cost while maintaining grid reliability. The load provided was time-synchronous, so a secondary objective was to build a time-synchronous model that addressed these goals at each timestep for which there was load data. A scaled-down load profile from San Diego Gas and Electric (SDG&E) at 5-minute intervals was the primary model input. The load profile was from 2012 so weather data from the same year was used to model weather-dependent generators like wind power and solar photovoltaics (PV). The geographic area in question was

constrained to the municipal borders of the City of San Diego and land within 50 miles of those borders in any direction. Only renewable energy generation technologies were considered. A “renewable” energy source was defined as a resource that occurs naturally or would naturally replenish itself with time. This included: wind energy, solar energy, hydroelectric energy, and geothermal energy. Storage technologies such as lithium ion batteries and pumped-hydro storage were also considered renewable if they were charged using renewable technology. It should be noted that biogas and biomass energy was not considered to be renewable. It was also assumed that the power system would utilize existing transmission lines with the only cost incurred being spur costs. The theoretical completion year for the energy system was 2025. It was assumed that there would be no lead times on construction and capital costs of generating plants would reflect projected prices for 2025. It was also assumed that if any existing generating plants were to be utilized, they would be built brand-new and therefore be subject to their full capital cost. ITCs were applied to solar, wind, and geothermal generator costs based on actual federal credit rates in 2022.

To build an accurate model, data on existing conditions was gathered to determine what capacity of renewable energy was already available. Plants in operation, plants under construction, and plants in the planning phase were all considered. Solar and wind resource availability data was gathered based on the locations of existing generator plants. Models of each generator type were created to generate output profiles based on 2012 resource data. Requirements for system generators beyond serving the provided load were also considered. These included projecting changes to load based on EV and residential solar adoption, resource adequacy requirements, n-1 contingency, and reserve margins. Cost data associated with each generator and storage technology was gathered and included capital, fixed O&M, and variable O&M costs. All of the data collected was configured as inputs to a capacity expansion model called GenX [1]. The model was run and used to determine the most cost effective total capacity mix, generation mix at each timestep, and total project costs. Finally, a utility rate structure was created.

II. EXISTING CONDITIONS RESEARCH

To evaluate the existing conditions, data for actual renewable generators within a fifty mile radius of San Diego was gathered using the EIA (Energy Information

Administration) interactive map [2]. This interactive tool has information for all types of generators within a user defined area. Using the filter tool to display only renewable energy and transmission lines within the limits given by project requirements yielded the following map:

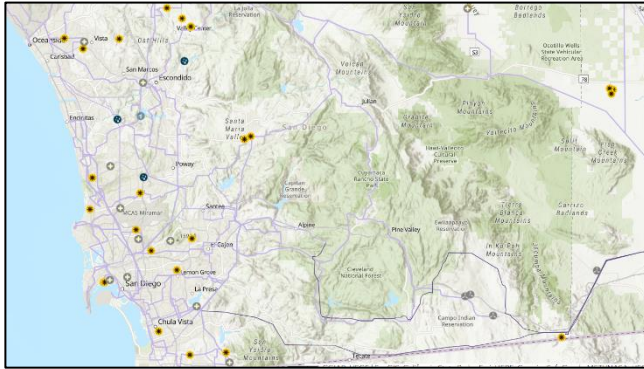


Figure 1. EIA map with filters for renewable energy generators and transmission lines

As part of the research, details such as generating capacity and plant locations were compiled. Capacities were broken down by generator type to derive total generating capacity of assets within the area. Using reasonable assumptions for omitting projects near the end of their lifetime, the following table was created showing total generating capacity per technology.

Generating Resource	Capacity (MW)	% of total
Solar Utility-scale	48.5	5.3%
Battery Storage	361	39.1%
Pumped Storage	42	4.5%
Wind	458.4	49.7%
Hydro Electric	13.3	1.4%
Total Renewable Energy	923.2	

Table 1. Breakdown of generating assets by resource type

The EIA database was also used to gather information on generator monthly energy production. Finding actual monthly data from each facility would be a valuable resource to have for comparison to the generator models and were used to validate accuracy of model predictions. The problem with this was many generators in the area were not operational in 2012 as they were built after this year. This presented a challenge but luckily some facilities did have information dating back to that year. The information that was available was for Kumeyaay Wind, ISH Solar, and Univ. of California San Diego, the monthly production graphs for wind and solar facilities are shown in the figures below.

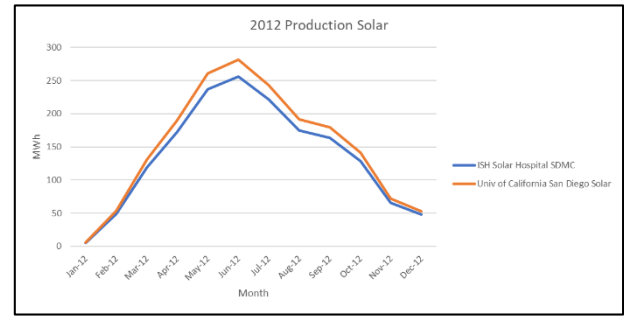


Figure 2. Actual 2012 solar production for (2) generating plants

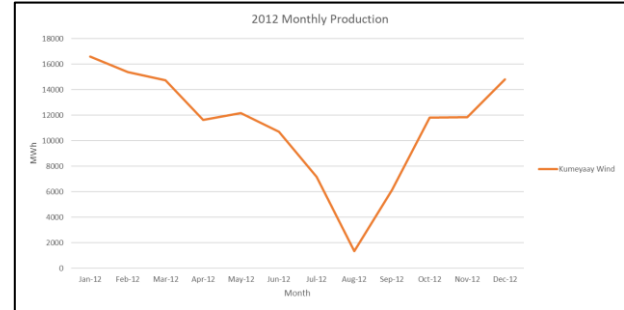


Figure 3. Wind and solar monthly generation reported data for 2012

Another existing condition for which evaluation was required was the provided load profile. This was given in 5-minute time intervals and further dissection was needed to correctly place the load into bins to determine time periods where load requirements were similar. This was accomplished using k-means clustering via an output from the GenX capacity expansion model (discussed further in Section IV) in an effort to effectively evaluate stress on the grid at each time of the year. This process also aided in determining which representative periods required further evaluation. The binned model for the load can be seen in the following graph:

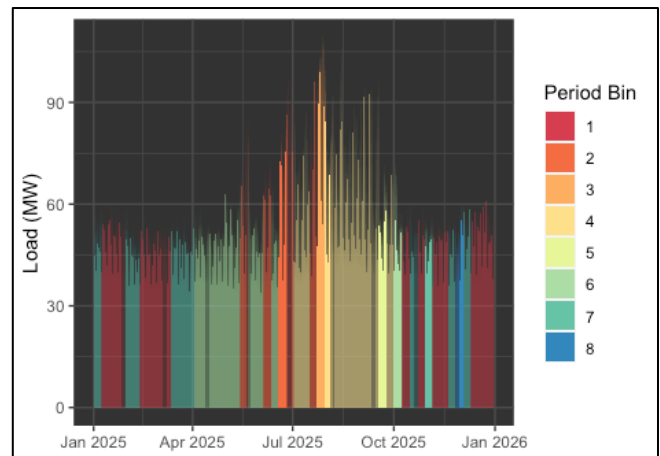


Figure 4. 2012 yearly load profile clustered according to load and generator availability profiles

III. GENERATION REQUIREMENTS

A. Generator Models

To evaluate the potential of each renewable resource, models for each generator type were created. These included a model for utility-scale solar, residential solar, utility-scale wind, utility-scale geothermal, and utility-scale hydropower. The utility-scale solar and wind models were created using PySAM and used existing plant locations and total capacities as iterative inputs, with each plant modeled individually at 30-minute time steps. The power output profiles for each generation type were then aggregated into two time series files, one for wind and one for solar. The solar model was created using a generic PV Watts Power Purchase Agreement SAM model with single-axis tracking, bifacial modules. A 1.3 DC/AC ratio was used with a 96% inverter efficiency. Initial values for soiling and shading losses were 3% and 2% respectively. An azimuth angle of 180° (due south) was used for all models. A utility-solar control model was also generated to validate the assumptions made. This was done by modeling the 2012 outputs for the ISH Solar and Univ. of California San Diego plants and comparing them to their actual output data. This analysis found that total annual modeled energy generation exceeded actual generation by roughly 20%. The shading and soiling losses of the generic model were adjusted to 8% and 5.5% respectively. This brought the modeled output to within a 10% of actual output, an acceptable margin of error. Figure 5 below shows the results of this control analysis. It should be noted that the (2) plants in question were brought online in 2011 and were not operating at full capacity for the first (3) months of 2012. Data from these months were therefore treated as outliers and excluded. The wind model was created using a generic wind Power Purchase Agreement SAM model using spec data from a Vestas V150 4.2 MW turbine. This design had a 150m rotor diameter and hub height of 105m. A shear coefficient of 0.2 was assumed [3].

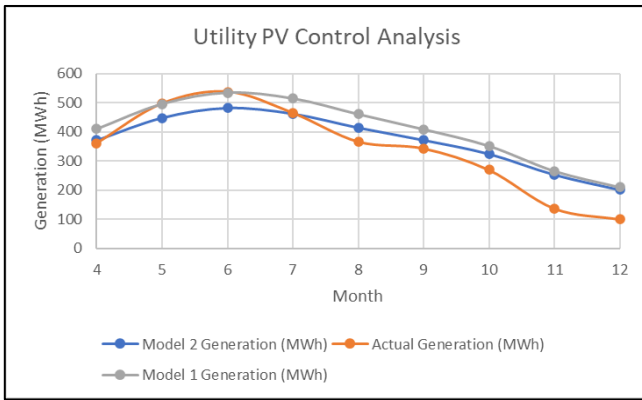


Figure 5. PV model control analysis

The residential solar model was created using a Detailed PV Power Purchase Agreement SAM model. A single location in the center of San Diego was selected for resource data. The module selected was LG Electronics Inc. LG400Q1C-A6 and the inverter selected was SolarEdge Technologies Ltd: SE11400H-US [208V]. Systems were assumed to have a fixed axis, as is typical for residential solar. (3) residential solar

models were generated with azimuth angles of 90°, 180°, and 270°. The total capacity assigned to each model followed the breakdown of actual azimuth angle data from California Distributed Generation Statistics for residential solar panels. The details of this breakdown can be found in Figure 6. A total capacity of 40 MW of residential solar was modeled.

The hydroelectric generator model was created using actual output and capacity factor data from EIA for the (2) plants considered within the area in question: Bear Valley (1.4MW) and Rancho Penasquitos (4.6MW) [4]. The output from these two hydro plants in 2012 was modeled as reservoir inflows in the GenX model, giving these units dispatch flexibility while still respecting energy constraints across longer time spans.

The geothermal model was created using a Geothermal PPA SAM model. The geothermal resource was evaluated based on NREL's U.S. geothermal resource maps [5]. Due to the lack of hydrothermal resources within 50 miles of San Diego, enhanced geothermal plants were selected as the plant design. An area near San Diego with relatively high favorability for enhanced geothermal resources was then identified. Due to lack of data on actual resource temperatures, conservative estimates were made when modeling these generators. Resource temperatures of 190°C at a depth of 3km were chosen based on typical, low-end operating conditions of these plants [6]. A binary-cycle was selected as the heat-converter for these plants due to its favorability for low temperature resources [7].

B. Reserve Capacity Margin

Reserve capacities implemented to meet necessities of a large incursion of VREs (Variable Renewable Energy) is difficult to estimate as there is debate on the correct amount for a 100% renewable energy macro grid. For this project it was decided to use two different reserve strategies [8]. The first is a load following reserve, these are very fast acting resources that fill in the gap during normal operations should weather resources drop such as a large cloud passing a major part of solar generation or wind taking a dip in wind speed. These phenomena will cause fluctuations in frequency which can compromise grid stability negatively. To prevent this the use of Battery Storage as load following reserves will provide needed stability to a 100% renewable energy grid. Load following resources will act as shock absorbers to these momentary conditions of major difference between generation and demand. Examples of these markets are Frequency regulation and Fast Frequency response which will be used in our proposed strategy to keep a reliable and stable grid with a large penetration of VREs.

Secondary reserves will also be required to be able to be dispatched for longer term durations to combat power imbalance or generator failures. These contingency reserves will account for 15% load at any given time and should be dispatched between 2 to 15 mins after an event deems it necessary. These reserves are made to last a longer time than load following reserves and give the system longer term stability. In this project's model a contingency reserve of 15% was selected based on existing grid system operators as well as generator plant sizes in this system [8].

C. Residential Solar Adoption

To better project how the use of energy would change by the year 2025, a baseline understanding of the current customer base was needed. We approximated our rate base as a fixed percentage of the current SDG&E rate base, calculated as the fraction of the total annual energy consumption in the provided load profile divided by the SDG&E's projected "managed consumption" in 2022 [9]. The managed consumption figure includes BTM generation offsetting load. Using this methodology, we estimated our rate base as 1.92% of SDG&E's. To determine the projected amount of distributed solar generation for 2025, some scaling and linear regression techniques were deployed. First, data was collected from the California Distributed Generation Statistics database [10]. This dataset includes information on all interconnected solar projects in the state, including data on SDG&E territory. The SDG&E territory data was filtered to include only projects approved after 2012 (the year that the provided load data correlates to). After this year, a total of 1,674 MW of distributed solar power was installed in the SDG&E territory. Scaling this down with the 1.92% scaling factor produces an estimated 32MW of distributed generation by 2022. A linear regression was then applied to this data to approximate the amount of solar generation by 2025. The data was also divided into three respective cardinal directions to better estimate energy production in the later stages of modeling. A graph depicting this analysis can be seen in Figure 6 below. By 2025, the total distributed solar generation will be 40MW. To model this in GenX, 32MW was treated as existing capacity at zero cost that cannot be curtailed. The additional 8MW by 2025 was modeled as capacity that will be built for zero cost and will be able to be curtailed. To be clear, this is a policy choice on our behalf; we plan to respect the NEM contract of existing customers without the threat of curtailment but reserve the right to curtail generation from any new generation installed starting in 2023.

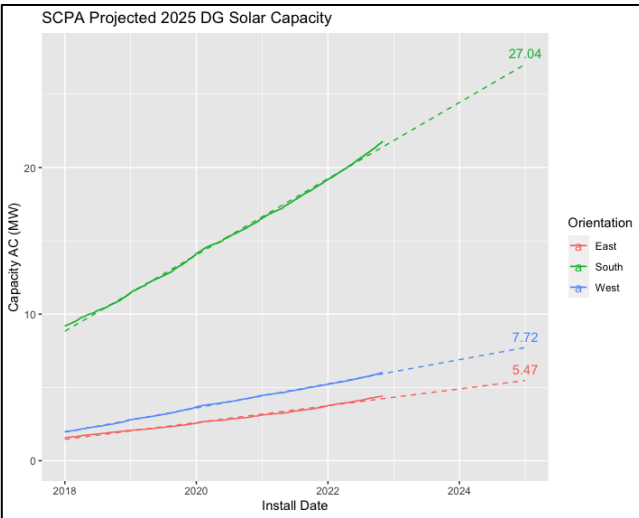


Figure 6. Distributed solar generation in San Diego scaled down. 32MW in 2022, 40MW predicted in 2025. Broken between East facing, South facing, and West facing panels.

D. Electric Vehicle Adoption

A similar approach was employed for estimating the expected electric vehicle load on the system. Due to the availability of data, we used EVs in San Diego County as a proxy for EVs in SDG&E territory (which is essentially just San Diego County with a sliver of Orange County as well). EV adoption trends were gathered from the California Energy Commission [11], and we employed logistic regression to estimate that there will be about 285,000 EVs SDG&E territory in 2025. To create a load profile that accurately portrays this charging load, a software tool called EVI-Pro by NREL was used [12]. The load profile was generated with a 5 minute interval over the course of the day and scaled down using the scaling factor of 1.92% from before. This was then added to each day of the original provided load, increasing it by about 4MW on average. By including this additional load, our model will be able to account for the increasing number of electric vehicles on the road by 2025.

IV. SYSTEM MODELING

A. Financial Inputs

In order to find the optimal generation mix and investment decisions required to satisfy load, the data collected during the generation requirements phase of the project was run through GenX, a capacity expansion modeling software. The objective function of the optimization was cost, with constraints coming from various inputs such as total available generator capacity and ramp rates. Another important input to the model was ELCC factor, discussed in the generator assumptions section below. Financial inputs for annual capital cost (\$ / MW), annual fixed O&M cost (\$ / MW), and variable O&M cost (\$ / MWh) for each generator were also required. Municipal bond rates and ITCs for renewable technologies were also given as inputs. The main financial inputs to the GenX model can be found in Table 2 below. A municipal bond rate of 3% was used in the model to calculate interest rates associated with investments [13]. A demand response program was also factored into GenX. This included an 8% participation rate at \$20-savings / kWh and a 1% participation rate \$5-savings / kWh.

Generator Type	Ann CAPEX (\$/MW/yr)	Fixed O&M (\$/MW/yr)	Variable (\$/MWh)	ITC (%)
Wind	86,241	25,000	0.03	30
Solar (Utility)	39,355	23,000	0.02	30
Solar (BTM)	0	0	0	0
Hydro	97,200	43,205	1.20	0
Geothermal	1,368,421	325,000	46.00	30
Li-ion 4hr	145,594	10,517	3.60	30
Li-ion 8hr	279,758	10,517	3.60	30
Pumped Hydro	349,696	40,113	2.40	0

Table 2. Main Financial Inputs for GenX [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]

B. Generator Inputs

For the generator types selected, several assumptions needed to be made that are required by GenX. Ramps rates are an important consideration for the model to dispatch power appropriately. The maximum ramp rates of wind, solar, and battery storage were assumed to be 100% per minute. A 15% per min ramp rate was chosen for hydro [24] and geothermal power [25]. All generator types have a minimum power output

of 0% except for geothermal at 10% (when committed). To ensure our portfolio met California's resource adequacy standards, we added an RA constraint to our GenX model, which requires a planning reserve margin to be maintained at all periods in the simulation. To model unavailability due to unforced outages or resource unavailability, we used the effective load carrying capability (ELCC) for each resource in our model, as estimated by the CPUC for 2035 in their 30MMT greenhouse gas scenario [26]. While not perfect, the portfolio of the 30MMT scenario should most closely match our portfolio, and therefore the ELCC's should be similar. With more years' worth of load data we would be able to run an ELCC calculation ourselves to improve the accuracy of our model. We note here that this RA requirement drove the bulk of the investment in our portfolio, with shadow prices reaching nearly \$36,000/MWh for a few hours in July.

C. System Model Outputs

After running the GenX model, a portfolio describing the required generating capacity mix was produced. This mix represents the amount of installed generator capacity that is needed to meet our load while also adhering to our various constraints. Figure 7 below shows the complete breakdown of the generation mix.

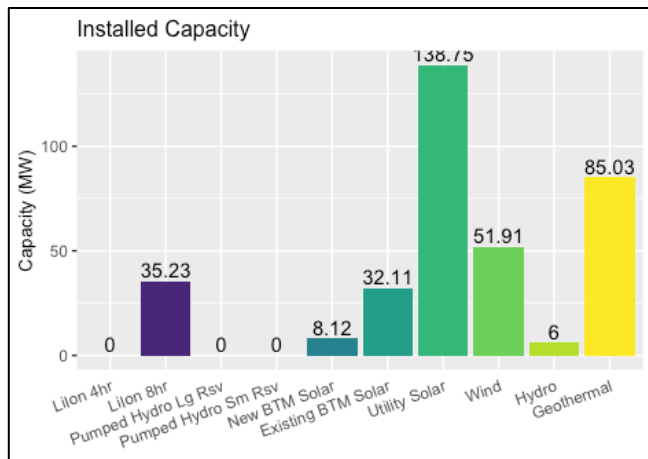


Figure 7. Proposed installed capacity mix. Note that distributed generation is broken into existing and new installations.

There are several items of note with this breakdown. Rather than having any pumped hydro storage, the model deemed that it was more optimal to meet all storage requirements using 35.23MW of 8-hour Li-Ion Batteries. This is only 10% of the current battery power capacity in San Diego. At this power level, 280MWh of batteries are needed. Additionally, the model also calls for nearly three times as much capacity for utility-scale solar compared to what is currently installed in the area surrounding San Diego. But with more than 5kWh/m²/day of global horizontal solar irradiance in the San Diego area, this should not be an issue [27]. The wind capacity that is needed is lower than the current capacity at only 50MW. A small amount of hydropower needs to be used at 6MW alongside 85MW of enhanced geothermal power. The geothermal plants will be built in areas in which the geothermal resource is most plentiful.

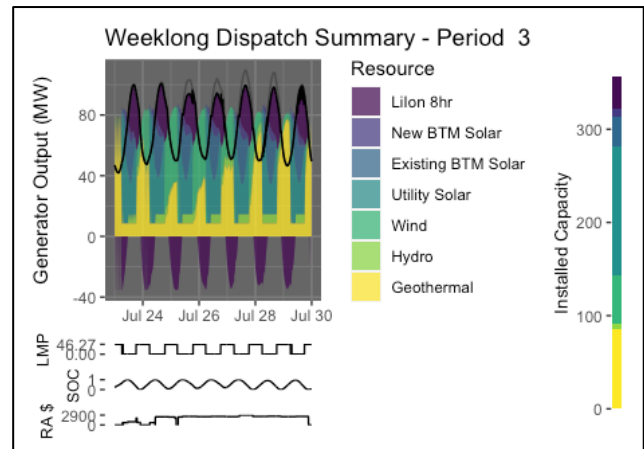


Figure 8. Dispatch stack for week in July when grid is most stressed

A dispatch stack for a week in July is shown above in Figure 8. The time of most stress on the grid occurs when load is high, but the solar resource is relatively low. It should be noted that during this period, the system relies heavily on geothermal energy which causes daily spikes in LMP due to its relatively high variable cost. This demonstrates the value in investment for geothermal energy as a dispatchable generator with high ELCC.

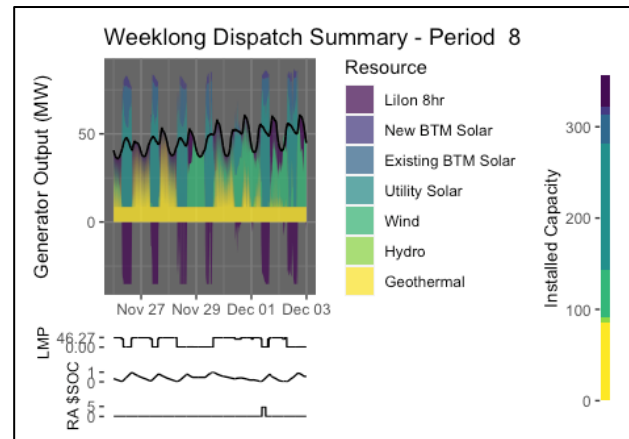


Figure 9. Dispatch stack for week in November when solar resource is lowest

A dispatch stack for a week in November is shown above in Figure 9. During the week of lowest solar resource, the grid is shown to be relying heavily on wind power but also geothermal energy. LMP is also seen to spike when geothermal energy is used or when batteries that were charged using geothermal energy are being discharged.

D. Key Performance Metrics

Achieving a 100% renewable energy grid for San Diego may be achievable but will it meet the current market prices to make it a financially sound investment. The cost assumptions mentioned in previous sections were used to determine the financial metrics obtained from this project.

Annual Capital Costs	\$171MM
Annual Variable Costs	\$4.9MM
Annual Demand Response Payments	\$4.9MM
Annual Net Energy Billing Payments	\$6.11MM
Total Annual Costs	\$186MM
Levelized Cost of Energy	\$0.424/kWh
Current LCOE (supply)	\$0.149/kWh

Table 3. Financial costs compared to current costs of energy [28]

Table 3 above shows the annual costs broken down by services and adjustments. Levelized cost of energy refers to raw price for generating 1 kWh considering all associated costs to produce. This is then broken down to a yearly rate for which each year of the lifetime of the project one unit of energy will cost. Annual Capital Costs are the capital expenses required to purchase and build new generators to meet this model parameters over the lifetime of each generation facility (Geothermal: 30 years, Solar: 25 years, Wind: 20 years, Battery Storage: 10 years) Annual variable costs are costs which are dependent on current market prices, tax credits, O&M costs; demand response payments are payments expected for incentive programs for ratepayers who choose to participate in these programs estimations are based off of 1.92% of current SDG&E population. Annual Energy billing payments are estimated payments for the net energy generated in any given year to the generators. This yielded total annual costs of 186 million dollars yearly cost or Levelized Cost of Energy (LCOE) 0.424/kWh this value is almost triple the current SDG&E LCOE of 0.149\$/kWh.

E. Utility Rate Structure

We are calling for a rate structure that is reflective of how costs are incurred. With a generation mix that has near-zero marginal costs much of the time, but is capacity constrained in a small concentration of hours, incentivizing customers to consume electricity when it is plentiful and conserve when it is scarce will be much more important with our generation mix. We propose passing through the average LMP for each hour of the day, meaning that energy will be virtually free during times with good solar production, and pricing rising towards the marginal cost of geothermal (\$46/MWh) during the evening hours in late summer. We also plan to pass through RA shadow prices (expected to peak at \$34,800/MWh), but spread these costs out over the entire year for each customer so that bills are not an order of magnitude higher in August than in all other months. We plan to inform customers via text when RA periods are expected to facilitate conservation. For T&D costs, we propose keeping rates the same as they are now but are open to the idea of restructuring those rates with coincident peak pricing as well to further incentivize conservation when it is needed most.

V. CONCLUSION

The goal of this project was to develop a 100% renewable energy plan for the City of San Diego given a load profile and geographic constraints. This was done by evaluating the existing conditions of San Diego's grid, building models for

renewable energy generators, and evaluating generator requirements beyond serving the load. The outcomes of this research and analysis were used in a capacity expansion model to determine generator capacity and investment requirements for a proposed energy plan. The outcomes of the model were evaluated and a utility rate structure was then developed based on those outcomes.

The proposed generation portfolio represents the most cost effective portfolio that meets the requirements of 100% renewable energy while maintaining reliability. The model shows that in order to maintain resource adequacy, a large capacity of geothermal power is required. This was the largest driver of total annual costs but was necessary given the resources high ELCC and lack of available hydropower resources. Levelized costs were found to be significantly higher than current SDG&E supply costs, the price of sprinting so quickly to a full 100% renewable mandate. It should be noted that relaxing the constraint to even just 95% renewable would likely lead to a significant reduction in costs given that natural gas plants have lower capital costs than geothermal while providing similar levels of resource adequacy. Enhanced geothermal power is an immature technology that has not yet been adopted at scale. Therefore, the costs associated with the technology are inherently conservative and much higher than traditional renewable generators. Despite this, the need for system reliability outweighed these financial risks, as demonstrated by the model's outcomes. These outcomes further demonstrate the need for continued investment in the research and development of renewable technologies that are also reliable and dispatchable. These in-turn can begin to alleviate the concerns associated with the intermittency and lack of stability of wind and solar resources. Taking a more holistic view, the added costs in electricity due to the 100% renewable requirement is small in comparison to the benefits of leading the nation towards a renewable energy future.

Avenues for future work related to this project include a deeper investigation into the risks associated with enhanced geothermal power, particularly the seismic events they induce. Additionally, a sensitivity analysis should be conducted on the inputs of the GenX model to more accurately evaluate how outcomes change with different cost and generator assumptions. The static inputs model presented here incorporated estimates based on ongoing research and fluctuating economics. As the prices and efficiencies of renewable technologies change, so will the optimal solution for achieving the goals of this project.

REFERENCES

- [1] N. Sepulveda and J. Jenkins, "GenX: Configurable Capacity Expansion Model." MIT Energy Initiative and Princeton University ZERO Lab, May 02, 2022. [Online]. Available: <https://tlo.mit.edu/technologies/genx-configurable-capacity-expansion-model>
- [2] U.S. Energy Information Administration, "EIA Interactive GIS Data Viewer." <https://eia.maps.arcgis.com/apps/webappviewer/index.html?id=5395ae9a72a04064932c1c11efc1db3e&webmap=fccfa2e687784012b9c7b26d5ebe801f¢er=-117.16300,32.71000&level=10>

- [3] Vestas, “V150-4.2 MW,” Vestas, 2022. <https://www.vestas.com/en/products/4-mw-platform/V150-4-2-MW> (accessed Dec. 07, 2022).
- [4] EIA, “Form EIA-411 Data,” Electricity, Nov. 29, 2017. <https://www.eia.gov/electricity/data/eia411/>
- [5] B. J. Roberts, “Geothermal Resources of the United States: Identified Hydrothermal Sites and Favorability of Deep Enhanced Geothermal Systems,” National Renewable Energy Lab, Feb. 22, 2018. [Online]. Available: <https://www.nrel.gov/gis/assets/images/geothermal-identified-hydrothermal-and-egs.jpg>
- [6] D. D. Blackwell, P. T. Negraru, and M. C. Richards, “Assessment of the Enhanced Geothermal System Resource Base of the United States,” Nat. Resour. Res., vol. 15, no. 4, pp. 283–308, Mar. 2007, doi: 10.1007/s11053-007-9028-7.
- [7] I. Lee, J. W. Tester, and F. You, “Systems analysis, design, and optimization of geothermal energy systems for power production and polygeneration: State-of-the-art and future challenges,” Renew. Sustain. Energy Rev., vol. 109, pp. 551–577, Jul. 2019, doi: 10.1016/j.rser.2019.04.058.
- [8] Q. Wang, “Advances of wholesale and retail electricity market development in the context of distributed energy resources,” in New Technologies for Power System Operation and Analysis, H. Jiang, Y. Zhang, and E. Muljadi, Eds. Academic Press, 2021, pp. 99–142. doi: 10.1016/B978-0-12-820168-8.00004-3.
- [9] “Prepared Direct Testimony of Kenneth E. Schiermeyer,” SDG&E, San Diego, May 31, 2022.
- [10] CPUC Energy Division, “Interconnected Applications Data Set.” California Distributed Generation Statistics, Oct. 31, 2022. [Online]. Available: <https://www.californiadgstats.ca.gov/downloads/>
- [11] California Energy Commission, “Light-Duty Vehicle Population in California,” California Energy Commission, 2022. <https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/light-duty-vehicle>
- [12] National Renewable Energy Lab and California Energy Commission, “Electric Vehicle Infrastructure Projection Tool.” [Web]. Available: <https://afdc.energy.gov/evi-pro-lite>
- [13] “5-day Average of GO Yields by State,” Municipal Bonds. https://www.municipalbonds.com/bonds/state_yield_averages/
- [14] National Renewable Energy Lab, “Utility-Scale PV,” Annual Technology Baseline. https://atb.nrel.gov/electricity/2021/utility-scale_pv
- [15] P. Lako, G. Tosato, and IEA ETSAP, “Hydropower,” Energy Technology Systems Analysis Programme, Technology Brief, May 2010. [Online]. Available: https://iea-etsap.org/E-TechDS/PDF/E06-hydropower-GS-gct_ADfina_gs.pdf
- [16] K. Mongird, V. Viswanathan, J. Alam, C. Vartanian, V. Sprenkle, and R. Baxter, “2020 Grid Energy Storage Technology Cost and Performance Assessment,” Technical Report Publication No. DOE/PA-0204, Dec. 2020. [Online]. Available: https://www.pnnl.gov/sites/default/files/media/file/PSH_Methodology_0.pdf
- [17] National Renewable Energy Lab, “Land-Based Wind,” Annual Technology Baseline. https://atb.nrel.gov/electricity/2021/land-based_wind
- [18] J. F. Weaver, “How solar power operations and maintenance costs fell 50%,” PV Magazine USA, Sep. 13, 2019. <https://pv-magazine-usa.com/2019/09/13/how-solar-power-operations-and-maintenance-costs-fell-50-percent/>
- [19] National Renewable Energy Lab, “Geothermal,” Annual Technology Baseline. <https://atb.nrel.gov/electricity/2022/geothermal>
- [20] R. Wiser, M. Bolinger, and Lawrence Berkeley National Laboratory, “Land-Based Wind Market,” Office of Energy Efficiency & Renewable Energy, 2022.
- [21] Vignesh Ramasamy et al., “U.S. Solar Photovoltaic System and Energy Storage Cost Benchmarks, With Minimum Sustainable Price Analysis,” Technical Report NREL/TP-7A40-83586, Sep. 2022.
- [22] Solar Energy Technologies Office, “Guide to the Federal Investment Tax Credit for Commercial Solar Photovoltaics,” U.S. Department of Energy, Jan. 2020. [Online]. Available: [Commercial%20Solar%20PV.pdf#:~:text=Overview%20The%20Solar%20Investment%20Tax%20Credit%20%28ITC%29%20is,during%20the%20tax%20year.1%20%28Other%20types%20of%20ren](https://www.energy.gov/sites/prod/files/2020/01/f70/Guide%20to%20the%20Federal%20Investment%20Tax%20Credit%20for%20Commercial%20Solar%20PV.pdf#:~:text=Overview%20The%20Solar%20Investment%20Tax%20Credit%20%28ITC%29%20is,during%20the%20tax%20year.1%20%28Other%20types%20of%20ren)
- [23] “Production Tax Credit and Investment Tax Credit for Wind Energy,” WINDEXchange. <https://windexchange.energy.gov/projects/tax-credits> (accessed Dec. 08, 2022).
- [24] M. Joshi, S. Rehman, Power System Operation Corporation Limited, and National Renewable Energy Laboratory, “Ramping Up the Ramping Capability: India’s Power System Transition,” Sep. 2020. [Online]. Available: <https://www.nrel.gov/docs/fy20osti/77639.pdf>
- [25] C. Linvill, J. Candelaria, C. Elder, and Aspen Environmental Group, “The Value of Geothermal Energy Generation Attributes,” Geothermal Energy Association, Feb. 2013. [Online]. Available: https://geothermal.org/sites/default/files/2021-02/Values_of_Geothermal_appendix.pdf
- [26] CPUC, “Reliability Filing Requirements for Load Serving Entities’ 2022 Integrated Resource Plans: Results of PRM and ELCC Studies,” Jul. 19, 2022. [Online]. Available: <https://www.cpuc.ca.gov/-/media/cpuc-website/divisions/energy-division/documents/integrated-resource-plan-and-long-term-procurement-plan-irp-ltpp/2022-irp-cycle-events-and-materials/20220729-updated-fr-and-reliability-mag-slides.pdf>
- [27] B. J. Roberts, “U.S. Annual Solar GHI,” National Renewable Energy Lab, Feb. 22, 2018. [Online]. Available: <https://www.nrel.gov/gis/assets/images/solar-annual-ghi-2018-usa-scale-01.jpg>
- [28] SDG&E, “Electric Energy Commodity Cost,” Jun. 01, 2022. [Online]. Available: https://tariff.sdge.com/tm2/pdf/tariffs/ELEC_ELEC-SCHEDS_EECC.pdf