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Optimal Design of the Power Generation Network in California: Moving towards 100% Renewable Electricity by 2045

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***Abstract*—**To fight against climate change, California government issued the Senate Bill No. 100 (SB-100) in 2018 September, which aims at achieving a target of 100% renewable electricity by the end of 2045. A capacity expansion problem is solved in this case study using a binary quadratic programming model. The optimal locations and capacities of the potential renewable power plants (i.e., solar, wind, biomass, geothermal and hydropower), the phase-out schedule of existing fossil-based (nature gas) power plants and the transmission of electricity across the entire network are determined with the minimal total annualized cost measured by net present value (NPV). The results show that the renewable electricity contribution could increase to 85.9% by 2030 and reach 100% by 2035. Fossil-based power plants will be totally phased out around 2035 and solar and wind will finally become the most dominant renewable energy resource in California electricity mix.

***Keywords*—**100% renewable electricity, California, capacity expansion, binary quadratic programming.

I. Introduction

WITH the socio-economic development, carbon dioxide emissions have increased tremendously due to burning fossil fuels for energy. The Intergovernmental Panel on Climate Change (IPCC) has released a report in 2018 [1] indicating that the world is on track to exceed its carbon budget in the next 12 years. As being a home of 10% population and 13% of U.S. gross domestic product, California ranks on the top of greenhouse gas (GHG) emitters among all the largest economic entities worldwide [2]. To reduce the GHG emissions, California has launched the Renewable Portfolio Standard (RPS) Program, and phase in renewable power into the grid from 2002 [3]. By the end of 2017, the renewables have contributed ~30% of the electricity mix of California (Fig. 1). In September 2018, a more ambitious target, which aims at reaching 100% renewable electricity by 2045, was announced by the California government: Senate Bill 100 (SB-100) [4]. To achieve this ultimate goal, some interim targets were set by the government, i.e., 33% by 2020, 40% by 2024, 45% by 2027 and 50% by 2030 [4].

Many researchers have generated models to analyze the feasibility and economics of long-term GHG emission reduction from renewable power system in the state. The SWITCH designed by Fripp [5] is a multi-period stochastic linear programming model, which provides optimal renewable portfolios and satisfies the constraints at the lowest cost. The model is used to measure the cost of reducing GHG emissions from California power system by deploying large scale solar and wind power. Short et al. [6] introduced the Regional Energy Deployment System (ReEDS) to achieve the least-cost mix of technologies. By simulating exceptional spatial details, the model optimizes the installation of wind farm, solar energy and fossil fuel generation in the Northern America. The above two models have either fine spatial details or temporal details. In contrast, MacDonald et al. [7] proposed the National Electricity with Weather System (NEWS) model that has both fine spatial details (13 km) and temporal details (60 min). The model integrates complex weather data over geography to find the optimal distributions of wind and solar generators in the U.S.

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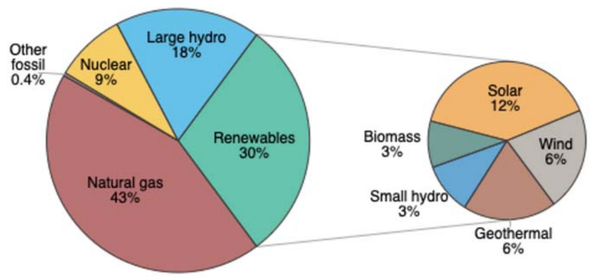

Fig. 1 California electricity profile in 2017

This paper presents a streamlined capacity expansion model named CA2045 to analyze the feasibility of SB-100 and optimize the budget. The model is capable of studying specific load zones, e.g. PG&E North, PG&E South, etc., by summing nodes up. Since the model has a one-year time resolution, it does not consider the instantaneous renewable power generation. For instance, solar and wind power are sensitive to weather conditions. The model hence uses potential renewable energy capacity data [8]-[10] to set up upper bound, and assume constant capacity factors (Fig. 2) to model the power generation.

One of the challenges involved in this study is large-scale geospatial and time-series data. Thus, to save computational power, the time resolution is set to be yearly and the geo-spatial resolution is at county level. The model takes each county of

California as a node, thus 58 nodes in total. Besides, the paper introduces a binary variable to separate decision variable into two categories and assigns different coefficients for them. The optimal results of this project can be used to provide instructions and recommendations for the policymakers in California on the design of the potential power network and help California achieve the 100% renewable electricity target.

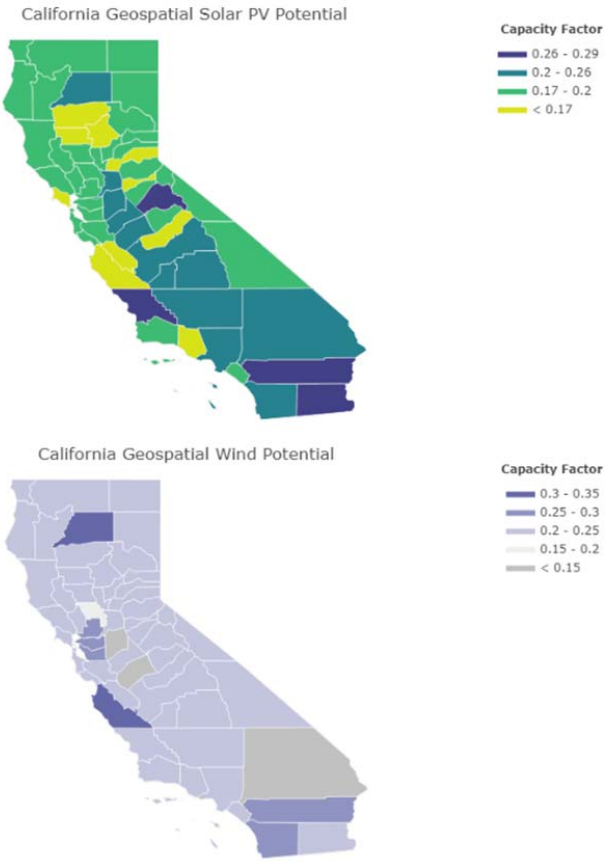

Fig. 2 California geospatial solar and wind capacity factor

II. Description of Problem

The author has developed two case studies with two different optimization models to minimize the total annualized cost measured in NPV of the power system from 2019 to 2045 in California. Case 1 is an ideal case, assuming that 58 counties are fully connected with each other by power transmission lines and transmission capacity is infinite. Case 2 is a practical case, using the existing power transmission connections and limited capacity. Both cases were optimized by using binary quadratic model. The binary variable is used to decide either constructing new renewable power plants or decommissioning the old ones at a certain node and the cost factors for these two operations are different. The following decisions are made: (1) the locations and capacities of the potential renewable power plants; (2) the delivery of electricity across the entire network; (3) the amount of power imported from other states; (4) the phase-out schedule of existing fossil-based power plants; (5) the decommissioning of existing renewable power plants. The detailed mathematical models of these two cases are described in next section; Optimization Model.

III. Optimization Model

A. Model Notation

TABLE I
Notation Definitions

Sets	
F	Set of fossil-based power plants, i.e., natural gas, indexed by f
R	Set of renewable power plants, i.e., geothermal, hydro, biomass, solar, wind, indexed by r
I,J	Set of all nodes, indexed by i,j
T	Set of years, indexed by t
Decision variables	
xf_{ift}	Capacity of fossil-based power plant f at node i at time t [MW]
xr_{ift}	Capacity of renewable power plant r at node i at time t [MW]
e_{ijt}	Amount of electricity transported from node i to node j at time t [MWh]
ip_{it}	Amount of electricity imported at node i at time t [MWh]
Intermediate variables	
tol	Tolerance, 10^{-9}[N/A]
up	Upper limit, arbitrary variable [MW]
low	Lower limit, arbitrary variable [MW]
bn	Selection, binary variable [N/A]
Input parameters	
$Demc_f$	Decommissioning capital cost of fossil power plant f [\$/MW]
$Capc_r$	Capital cost of constructing renewable power plant r [\$/MW]
$FOMf_f$	Fixed operating and maintenance (O&M) cost of fossil power plant f
$FOMr_r$	Fixed O &M cost of renewable power plant r [\$/MW-yr]
$VOMf_f$	Variable O&M cost of fossil power plant f
$VOMr_r$	Variable O&M cost of renewable power plant r
Tc	Electricity transportation cost [\$/MWh-km]
D_{it}	Power demand at node i at time t [MWh/yr]
Pf_{if}	Power production from fossil power plant f at node i at initial time [MWh/yr]
Pr_{ir}	Power production from renewable power plant r at node i at initial time [MWh/yr]
$Dist_{ij}$	Distance between node i and node j [km]
Tr_{ij}	Transmission line connectivity between node i and node j, binary
$TrVolt_{ij}$	Transmission line voltage between node i and node j, [kV]
$TrCap_{ij}$	Transmission line capacity between node i and node j, [MWh]
TrR_{ij}	Transmission line resistivity, [Ω]
βf_{if}	Capacity factor at node i for fossil power plant f [%], assumed to be 0.8
βr_{ir}	Capacity factor at node i for renewable power plant r [%]
TAR_t	Target of renewable power generation at time t
Q_{ir}^{max}	Primary energy potential for renewable power plant r at node i [MW]
η_r	Power conversion efficiency for renewable power plant r [%]
Cr_{ir}^{max}	Maximum capacity of renewable power plant r at node i, $Cr_{ir}^{max} = Q_{ir}^{max}\eta_r$ [MW]
Ef_f	life-cycle GHG emissions of fossil power plant f [tonne CO_2-eq/MWh]
Er_r	life-cycle GHG emissions of renewable power plant r [tonne CO_2-eq/MWh]
CT_t	Carbon tax at time t [\$/tonne CO_2-eq], assumed to be \$30/tonne CO_2-eq with 10% increase per year
IR	Interest rate [%], assumed to be 10%
ABT	Abandon rate [%], assumed to be 10%
U	Unit conversion factor 1 MW = 8760 MWh/yr
$Caprate$	Max capacity increase rate of renewable plant, assumed to be 100 MW, defined as the ratio between the capacity at year t+1 to capacity at year t
$Impr_{it}$	Import power price at node i at time t, assumed to be \$200/MWh

B. Objective Function

The objective of the optimization model is to minimize the total annualized cost in NPV of the entire power system of California, including the costs for construction and decommissioning of power plants, generation and transmission of electricity and purchasing electricity from other states and carbon cost. The objective function is presented in (1), which includes the capital cost (CAPEX), the fixed and variable operating and maintenance cost (FOM and VOM), the import electricity cost (IEC) and carbon tax (CT).

$$Min\ Cost = CAPEX + FOM + VOM + IEC + CT \tag{1}$$

where,

$$\begin{aligned} CAPEX = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T}\frac{Demc_f\left(xf_{ift}-xf_{if(t+1)}\right)}{(1+IR)^t} \\ & +\sum_{i\in I}\sum_{r\in R}\sum_{t\in T}\frac{Capc_r * bn_{irt}\left(xr_{ir(t+1)}-xr_{irt}\right)}{(1+IR)^t} \\ & -\sum_{i\in I}\sum_{r\in R}\sum_{t\in T}\frac{Capc_r * ABT(1-bn_{irt})(xr_{ir(t+1)}-xr_{irt})}{(1+IR)^t} \end{aligned} \tag{2}$$

$$\begin{aligned} FOM = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T}\frac{FOMf_f(xf_{ift})(IR)(1+IR)^t}{(1+IR)^t-1} \\ & +\sum_{i\in I}\sum_{r\in R}\sum_{t\in T}\frac{FOMr_r(xr_{irt})(IR)(1+IR)^t}{(1+IR)^t-1} \end{aligned} \tag{3}$$

$$\begin{aligned} VOM = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T}\frac{U(VOMf_f)(xf_{ift})(IR)(1+IR)^t}{(1+IR)^t-1} \\ & +\sum_{i\in I}\sum_{r\in R}\sum_{t\in T}\frac{U(VOMr_r)(xr_{irt})(IR)(1+IR)^t}{(1+IR)^t-1} + \\ & +\sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\frac{Tc(Dist_{ij})(e_{ijt})(IR)(1+IR)^t}{(1+IR)^t-1} \end{aligned} \tag{4}$$

$$IEC = \sum_{i\in I}\sum_{t\in T}\frac{Impr_{it}(ip_{it})(IR)(1+IR)^t}{(1+IR)^t-1} \tag{5}$$

$$\begin{aligned} CT = & \sum_{i\in I}\sum_{f\in F}\sum_{t\in T}\frac{U(xf_{ift})(\beta f_{if})(Ef_f)(CT_t)(IR)(1+IR)^t}{(1+IR)^t-1} \\ & +\sum_{i\in I}\sum_{r\in R}\sum_{t\in T}\frac{U(xr_{irt})(\beta r_{ir})(Er_r)(CT_t)(IR)(1+IR)^t}{(1+IR)^t-1} \end{aligned} \tag{6}$$

C. Constraints

Power Plant Capacity

Initial fossil power plant capacity:

$$U\left(xf_{if(t=1)}\right)\left(\beta f_{if}\right) = Pf_{if}, \forall i \in I, \forall f \in F \tag{7}$$

Initial renewable power plants capacity:

$$U\left(xr_{ir(t=1)}\right)(\beta r_{ir}) = Pr_{ir}, \forall i \in I, \forall r \in R \tag{8}$$

Construction capacity limitation of renewable power plants:

$$xr_{ir(t+1)} \le xr_{irt} \times Caprate, \forall i \in I, \forall r \in R, \forall t \in T \tag{9}$$

Note t can only be 1 to $(T_{max} - 1)$

The total capacity of renewable power plants at a node should not exceed the maximum capacity:

$$xr_{irt} \le Cr_{ir}^{max}, \forall i \in I, \forall r \in R, \forall t \in T \tag{10}$$

Construction and Phase Out of Power Plants

Phase out of fossil power plants:

$$xf_{if(t+1)} \le xf_{ift}, \forall i \in I, \forall f \in F, \forall t \in T \tag{11}$$

Note t can only be 1 to $(T_{max} - 1)$

Group Renewable Power Plants

$$bn_{irt} * \left(xr_{ir(t+1)} - xr_{irt}\right) - up_{irt} \ge tol, \forall i \in I, \forall f \in F, \forall t \in T \tag{12}$$

$$(1 - bn_{irt}) * \left(xr_{ir(t+1)} - xr_{irt}\right) - low_{irt} \le tol, \forall i \in I, \forall f \in F, \forall t \in T \tag{13}$$

Note t can only be 1 to $(T_{max} - 1)$

Energy Generation and Demand

The energy flow balance of each node:

$$\sum_{j\in J} e_{jit} + \sum_{f\in F} U(xf_{ift})(\beta f_{if}) + \sum_{r\in R} U(xr_{irt})(\beta r_{ir}) + ip_{it} = D_{it} + \sum_{j\in J} e_{ijt}, \forall i \in I, \forall t \in T \tag{15}$$

The total power generation should meet the total demand:

$$\sum_{i\in I}\sum_{f\in F} U(xf_{ift})(\beta f_{if}) + \sum_{i\in I}\sum_{r\in r} U(xr_{irt})(\beta r_{ir}) + \sum_{i\in I} ip_{it} \ge \sum_{i\in I} D_{it}, \forall t \in T \tag{16}$$

Renewable Electricity Generation Target

The total renewable electricity generation should meet the target:

$$\sum_{i\in I}\sum_{r\in r}(xr_{irt})(\beta r_{ir}) \ge \left(\sum_{i\in I}\sum_{f\in F}(xf_{ift})(\beta f_{if}) + \sum_{i\in I}\sum_{r\in r}(xr_{irt})(\beta r_{ir})\right)TAR_t, \forall t \in T \tag{17}$$

Transmission Line Capacity (For Case 2)

$$TrCap_{ij} = \frac{\left(TrVolt_{ij}\right)^2}{TrR_{ij}} * U, \forall i \in I, \forall j \in I \tag{18}$$

where

$$TrR_{ij} = \left(0.0051 * TrVolt_{ij} + 0.17857\right) * Dist_{ij} \tag{19}$$

Note: the correlation between transmission line resistivity and distance is shown in Result and Discussion Section.

Non-negativity

$$xf_{ift} \ge 0, \forall i \in I, \forall f \in F, \forall t \in T \tag{20}$$

$$xr_{irt} \ge 0, \forall i \in I, \forall r \in R, \forall t \in T \tag{21}$$

$$e_{ijt} \ge 0, \forall i \in I, \forall j \in J, \forall t \in T \tag{22}$$

$$ip_{it} \ge 0, \forall i \in I, \forall t \in T \tag{23}$$

IV. Results and Discussions

For better presentation of the results, the paper groups the state counties into 10 regions based on the population density [11] (see Table II). Therefore, the renewable energy potential is also grouped into these 10 regions. Fig. 3 shows that solar and wind potentials are larger than the other renewable resources and both Region 6 & 7 have the largest potential of wind and solar. In contrast, the summation of geothermal, hydropower

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and biomass potential occupies about 1% ~ 5% of total energy potential.

A. Case 1

Fig. 4 delineates the optimal path to achieve 100% clean electricity goal for Case 1 for different energy resources. In most of regions, geothermal, hydro and biomass slightly increase or stay unchanged during the studied time horizon (see Figs. 4 (a)-(c)). It should be noted that the geothermal capacity in Region 10 deceases about 34% after the first year, indicating that the current deployment is not optimal. The model suggests that in the future, wind and solar capacity will replace geothermal to reduce the overall cost in this region.

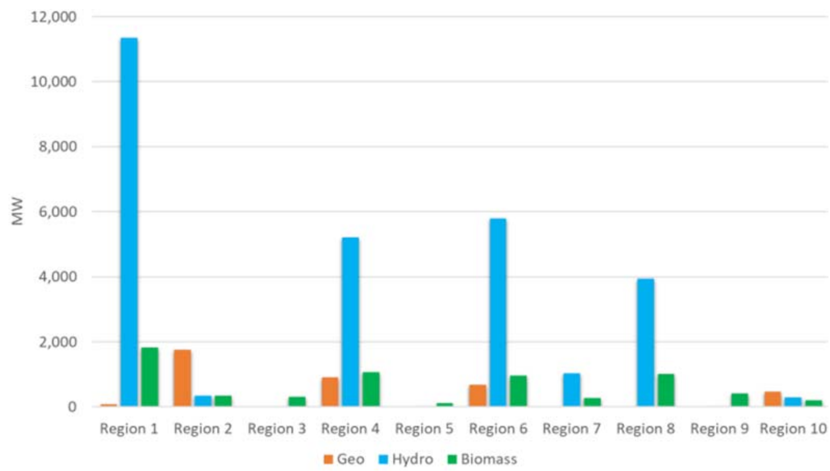
Wind and solar resources (see Figs. 4 (d) and (e)) are sensitive to weather and geospatial variation, but the fully connected transmission line assumption in Case 1 allows the generation of electricity in one of the cheapest locations and transferring the electricity out. Region 10 has the largest solar capacity factor and the result shows that after the termination of fossil-based power plants around 2035, it escalates the solar capacity to satisfy the demand in the state.

Currently, natural gas (see Fig. 4 (f)) has a much cheaper overall cost than the other types of renewable energy resources. However, due to the emission constraint and carbon tax, the fossil fuel energy becomes less and less competitive. The model indicates that the fossil fuel electricity generation will continue until 2035, which is the boundary that fossil fuel becomes less cost-effective or even overpriced. All the regions shut down fossil fuel generators by 2035.

TABLE II
CALIFORNIA REGION

Region#	Counties
1	Butte, Colusa, El Dorado, Glenn, Lassen, Modoc, Nevada, Placer, Plumas, Sacramento, Shasta, Sierra, Siskiyou, Sutter, Tehama, Yolo, Yuba
2	Del Norte, Humboldt, Lake, Mendocino, Napa, Sonoma, Trinity
3	Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara, Solano
4	Alpine, Amador, Calaveras, Madera, Mariposa, Merced, Mono, San Joaquin, Stanislaus, Tuolumne
5	Monterey, San Benito, San Luis Obispo, Santa Barbara, Santa Cruz, Ventura
6	Fresno, Inyo, Kern, Kings, Tulare
7	Riverside, San Bernardino
8	Los Angeles
9	Orange
10	Imperial, San Diego

Note that the above 10 regions are grouped based on the population density [11].



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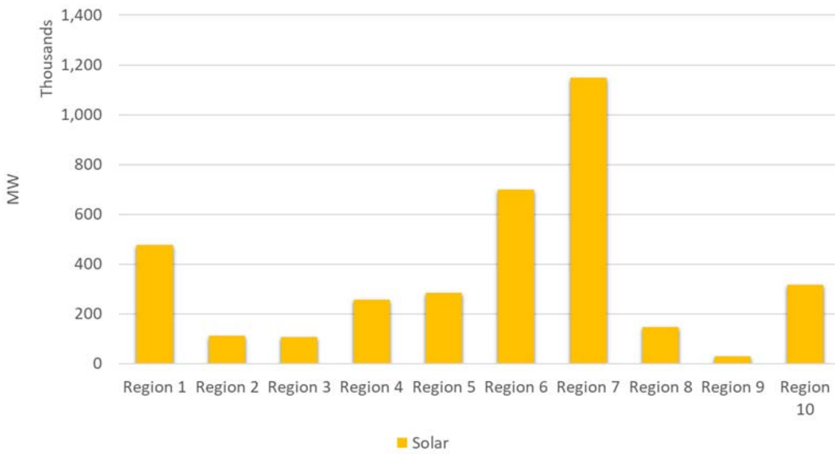

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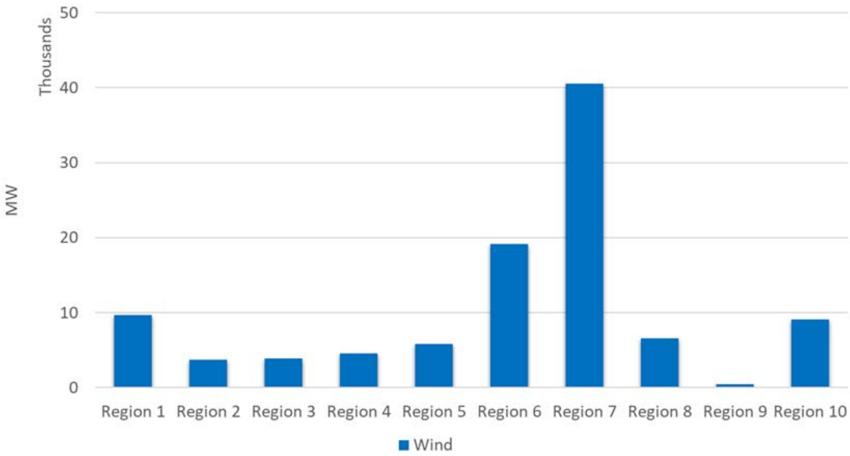
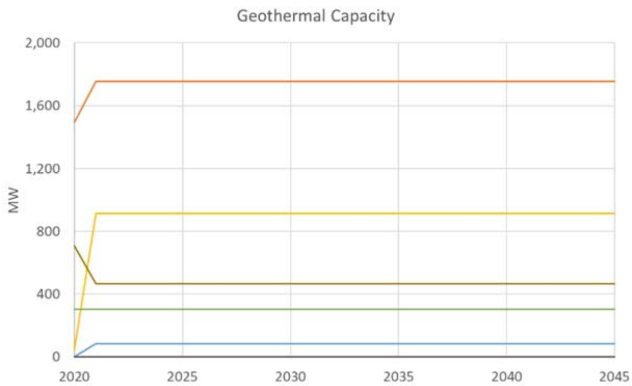


(c)

Fig. 3 California renewable potential for each region

Fig. 5 compares the capacity portfolio of each node in the 2020 and 2045. Kern county, yielding 111 billion cubic nature gas annually [12], transfers from 45% natural gas power to almost 100% wind and solar. The Los Angeles County, locating in the high-density population region, replaces all natural gas turbines with wind generators. California replaces all the natural gas capacity after 2035 with the combination of different renewable power, dominated by solar (41%) and wind (46%).



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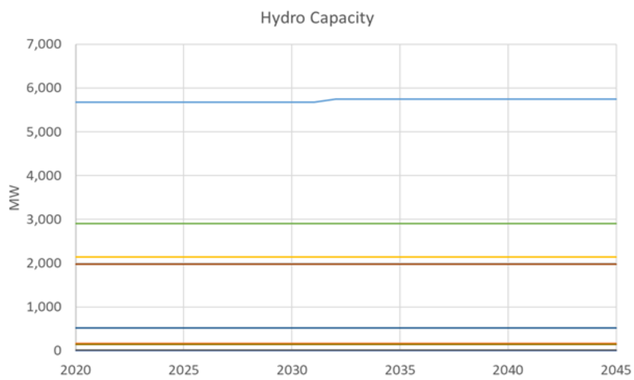

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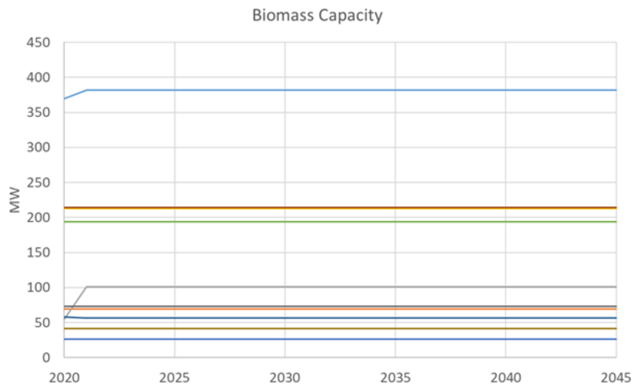

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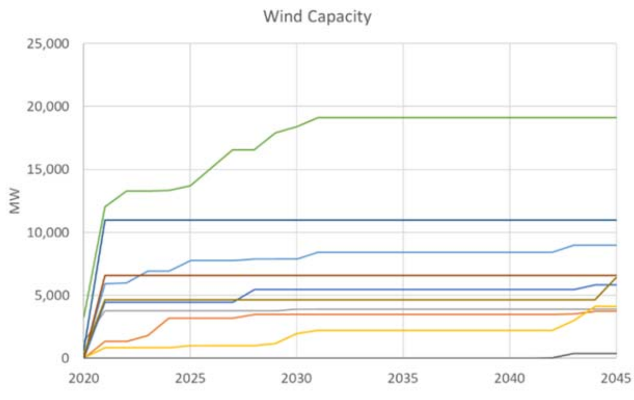

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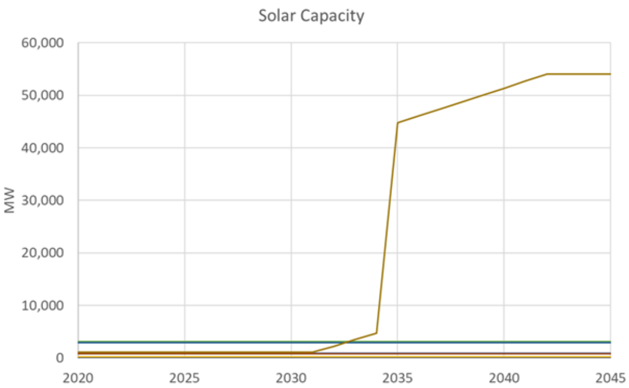

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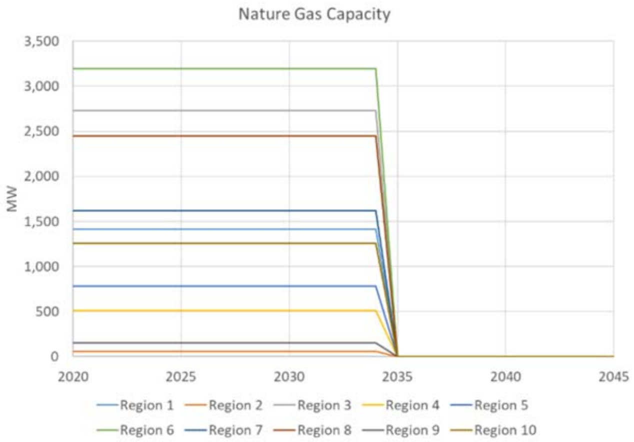
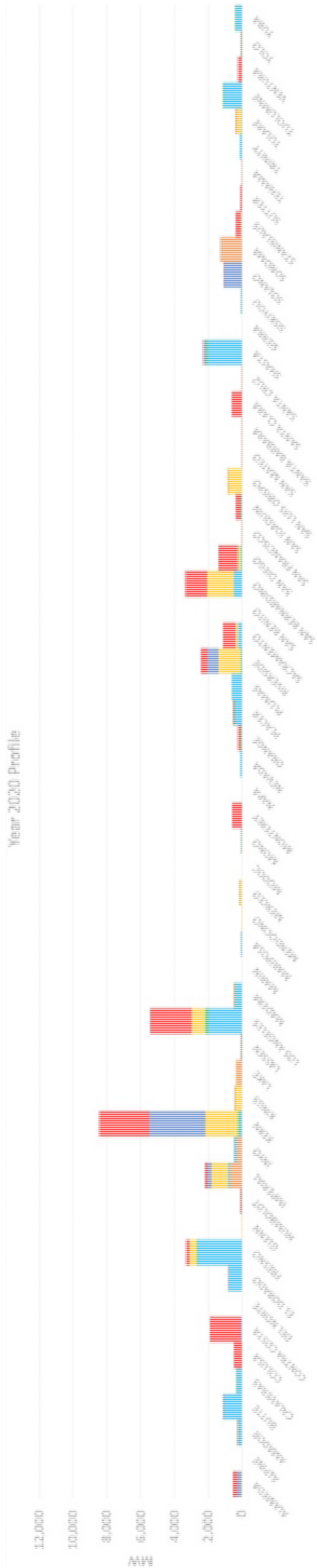


(f)

Fig. 4 Renewable and fossil fuel capacity variation from 2020 to 2045 (Case 1)

B. Case 2

Case 2 introduces the existing transmission topology and capacity into the optimization model. California Energy Commission posted high-resolution transmission line and substation GIS map on the official website. Fig. 6 elaborates the real connections for electricity transmission in California at present. The opacity represents the magnitude of transmission capacity for each connection. From the plot, the current power transmission is mainly between Northwest and Southeast.



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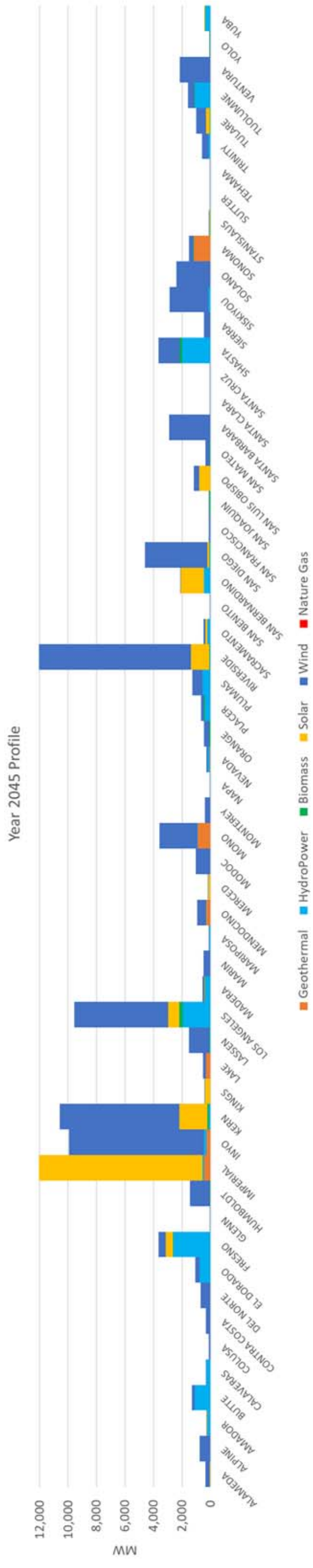

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Fig. 5 Year 2020 (a) and 2045 (b) capacity profile (Case 1)

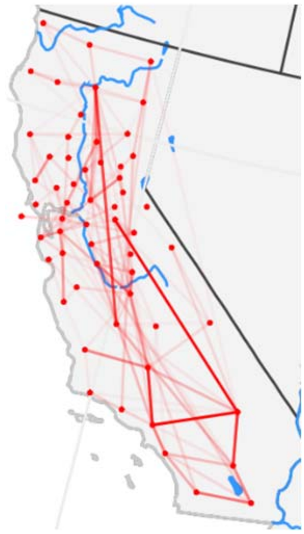
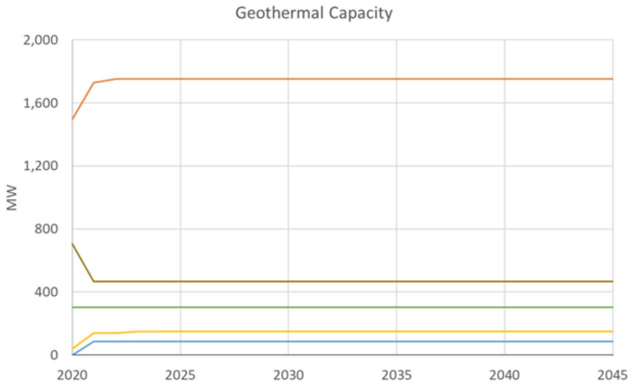


Fig. 6 The existing transmission line between 58 nodes in California

The geothermal and hydropower capacity of Case 2 resembles the behavior of Case 1. The two cases both suggest decreasing the geothermal capacity of Region 10 after the first year and increasing the capacity of other renewable resources. Because of the limitation of transmission lines, the deployment of biomass, wind and solar is significantly different from Case 1. Fig. 7 (c) shows that biomass capacity in most regions in Case 2 grows faster, while wind capacity grows slower. One of the explanations is that wind and solar potential is not evenly distributed in the state. The connection between nodes of large wind power generation and nodes with high energy demand may not be available in the real case or the transmission capacity is limited. Fig. 7 (e) illustrates the trend of solar power capacity in different regions for Case 2. The largest capacity installment in Case 2 (Region 7) is about 30,000 MW that is only 50% comparing to that of in Case 1 (Region 10). The solar and wind also are major resources in the real case, but solar capacity is distributed evenly in each region rather than only Region 10 in Case 1. In several regions, the termination of nature gas power has one-year delay. This is mainly because the cost of building renewable capacity and power transmission are greater than operating the natural gas plants.

Fig. 8 shows county-level portfolio in Case 2. Under the current transmission infrastructure, Los Angeles, Riverside, Sacramental, San Mateo and Stanislaus construct more solar capacity than wind. The total capacity expansion of Case 1 and 2 is shown on Fig. 9. In 2045, Case 1 shows the equivalent importance of solar and wind. However, Case 2 model selects solar as dominant resources over wind. Additionally, with the construction of transmission lines in the future, the results comparison between Case 1 and 2 indicates combined solar and wind are the primary and economical resources to help achieve clean electricity goal in California. Fig. 10 compares the renewable percentage in these two scenarios. Both cases achieve 100% goal before 2040, and Case 2 is two years slower due to the transmission constraint.



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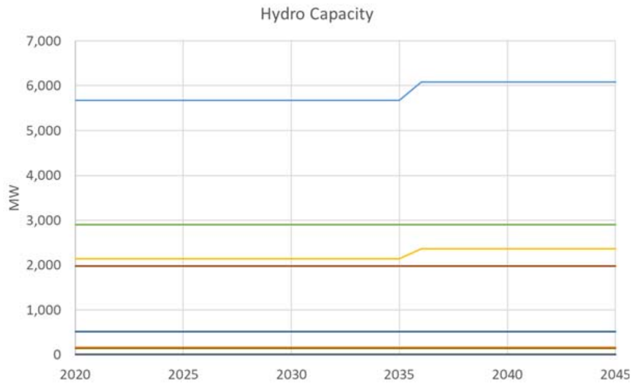

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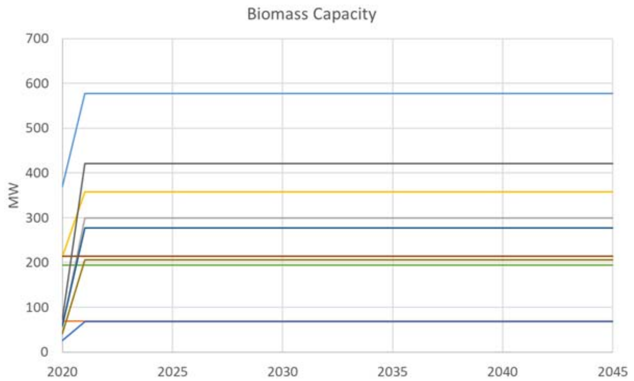

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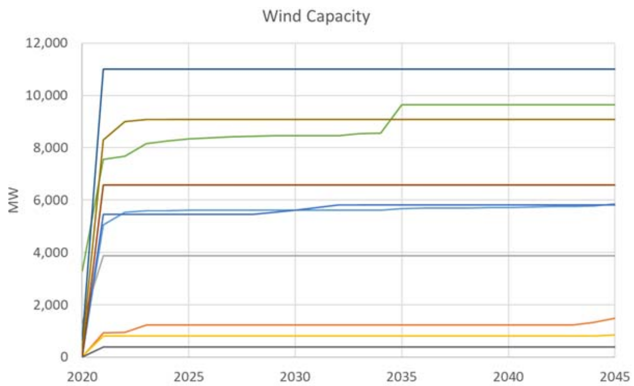

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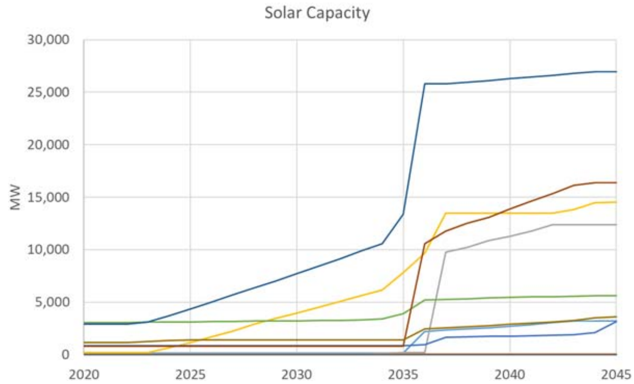

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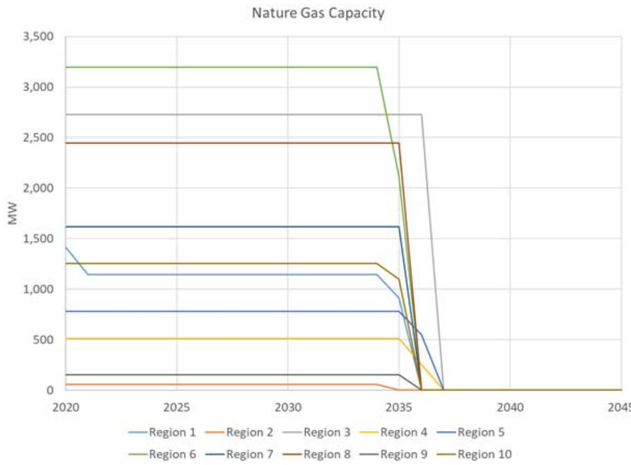


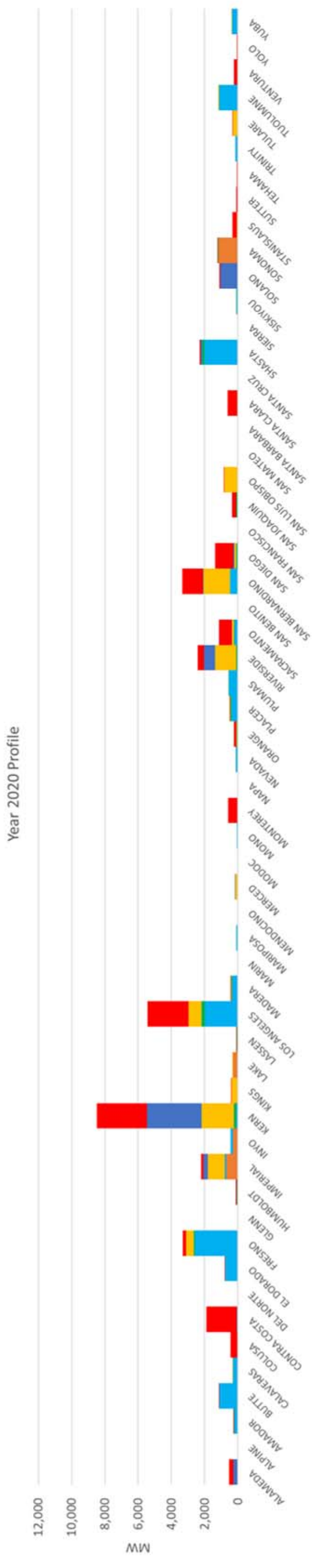
(f)

Fig. 7 Renewable and fossil fuel capacity variation from 2020 to 2045 (Case 2)

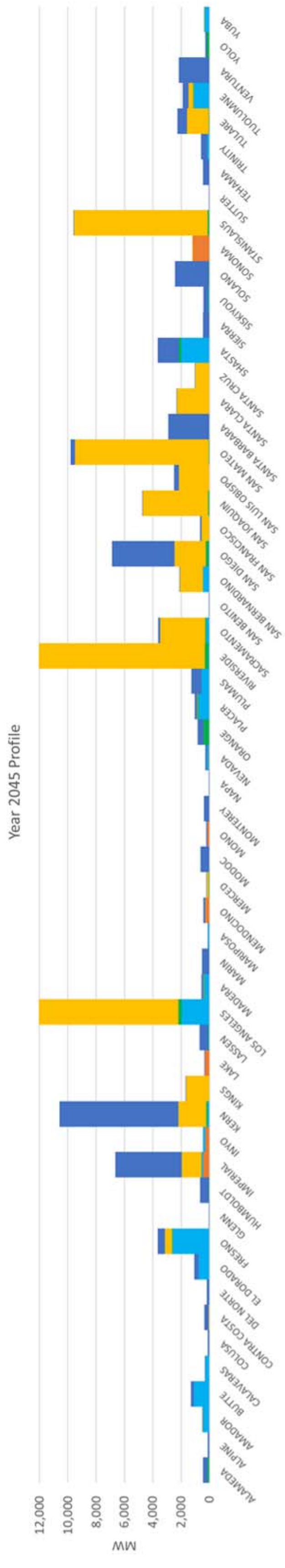
V. Conclusions

The optimization model of Case 1 and Case 2 returns the minimal total cost (measured by NPV) of 174 billion US dollars and 178 billion US dollars, respectively. Both cases attain an agreement that wind and solar will be the most important renewable resources to achieve the SB-100 goals, and other types of renewable resources are trivial. The case study also demonstrates that natural gas power plants will still play an irreplaceable role in the next 15 years. Furthermore, the comparison of two cases illustrates that if the government expands the transmission infrastructure in the future, the wind will become more and more crucial, and finally, the solar and wind are of equivalent importance in the California.

Both cases precede the bill's schedule 5 years. Resting on the case study, it is convincing that the accomplishment of this ultimate goal is possible with reasonable cost. The paper provides good recommendations and reference for relevant researchers, government decision makers and investors.



(a)



(b)

Fig. 8 Year 2020 (a) and 2045 (b) capacity profile (Case 2)

Fig. 9 Total capacity expansion in California (dash line for Case 1, solid line for Case 2)

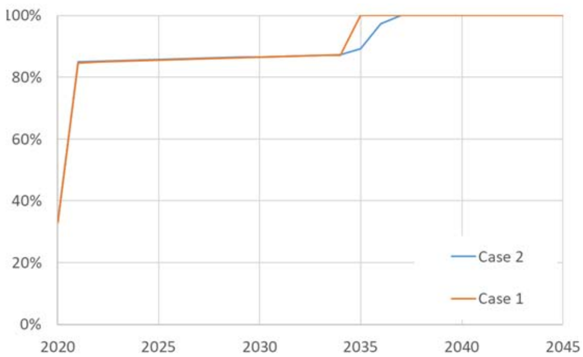


Fig. 10 Renewable capacity percentage versus time

APPENDIX

The transmission line capacity is a direct function of transmission voltage and resistivity. The voltage of each individual transmission line is obtained from published data from California Energy Commission [13]. Nevertheless, the resistivity is not included. The paper assumes that the material to manufacture transmission line in the state is the same, and introduces a linear correlation between resistivity, voltage and distance (Fig. 11). Besides, the rate of change in resistivity is also a linear function of voltage (Fig. 12).

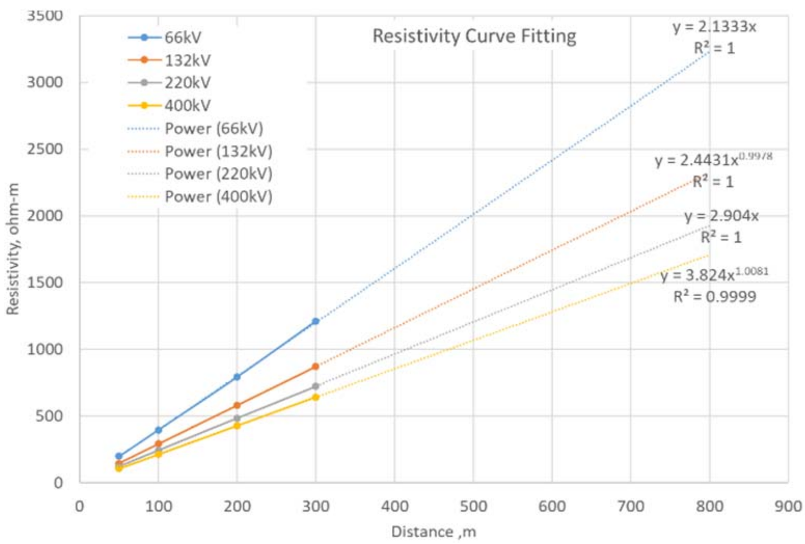


Fig. 11 Resistivity changes with voltage and distance

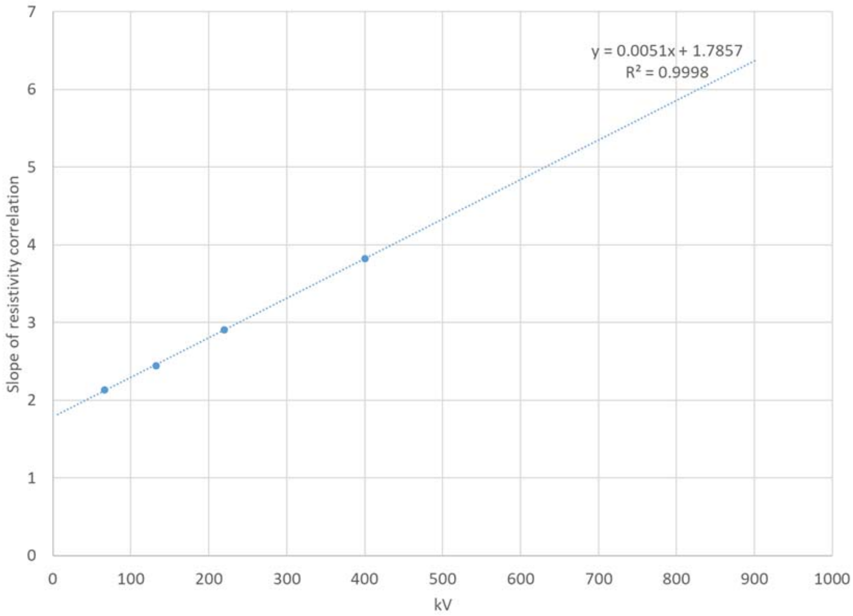


Fig. 12 The rate of change in resistivity versus voltage

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