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Renewable Power Systems Transition for New York State using a Multi-Scale Bottom-Up Planning Framework

Ning Zhao, Fengqi You

Cornell University, Ithaca, New York, 14853, USA

ABSTRACT

In this work, we propose a novel multi-scale bottom-up optimization framework to address the decarbonization transition planning for power systems, which incorporates multiple types of information for each existing or new unit in the power systems, including its technology, capacity, and age. To reduce the computational challenge, a novel approach integrating Principal Component Analysis (PCA) with clustering techniques is proposed to obtain representative days. To illustrate the applicability of the proposed framework, a case study for New York State was presented. The proposed approach obtaining representative days using PCA coupled with K-means shows better performance than multiple state-of-the-art clustering approaches. The optimization results indicate that offshore wind, hydro, and utility solar are the main power sources in the state by the end of the planning horizon. To validate the optimization results, we conduct hourly power systems operations simulation for the entire planning horizon, and the result indicate that the error bar using the proposed framework is less than 1.5% in the case study.

Keywords: decarbonization, renewable electricity transition, multi-scale optimization, renewable generation, bottom-up model

1. INTRODUCTION

The Paris Agreement aims to limit the increase in global average temperature to well below 2 °C above the preindustrial levels. To achieve this target, power systems decarbonization has been a priority topic for countries around the world. It facilitates the design of decarbonization transition pathways for power systems to simultaneously optimize the systems changes and simulate the corresponding hourly operations, while considering each individual units in the power systems.

To the best of our knowledge, there is no existing research work on the multi-scale bottom-up renewable electricity transition optimization that incorporates multiple types of information for each individual generator or storage unit, including information about its technology, capacity, and age. Existing multi-scale energy transition optimization models typically includes two time scales on yearly and hourly bases [1]. The yearly time scale accounts for the decisions of systems changes or design decisions, while the systems operations decisions are made on an hourly basis in conjunction with the design decisions [2]. To reduce the computational requirements associated with planning for the energy transition pathways and simulating the hourly systems operations for the entire horizon simultaneously [3], the approach of representative days has been widely applied in multi-scale energy transition optimization studies [4]. Multiple approaches have been used to obtain the representative days, such as rule-based selection, agglomerative hierarchical clustering (AHC), and K-means clustering [5]. On the other hand, most of the existing multi-scale bottom-up energy transition models include only the capacity and technology information of a unit, while including the ages of both existing and future units in the framework is crucial for developing more reliable transition pathways, as existing units with large ages and new units with short technology lifetime may retire during transition period.

In this work, we propose a novel multi-scale bottom-up renewable electricity transition optimization framework, which incorporates two time scales that correspond to the design and the operation of power systems, and it includes multiple types of information for

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both existing and new units in power systems, including technology, capacity, and age. We also propose a novel approach integrating PCA and clustering techniques to obtain representative day and benchmark the approach with state-of-the-art clustering approaches. A case study for the power sector in New York State is presented.

2. PROBLEM STATEMENT AND METHODOLOGY

2.1 Problem Statement

In this work, a bottom-up multi-scale electricity transition framework is proposed to address the optimization of potential renewable transition pathways for the electricity sector. In the framework, the systems transition and operations are interpreted in two time scales, namely the design periods and the operations periods. The design periods have a time interval of a year for making the systems changes decisions, and the operations periods consist of consecutive representative hours for hourly power systems operations in a year. The decision variables can be categorized into design variables and operations variables. The design variables include the annual installation and deactivation for both the electricity generation and storage units, while the operations variables consist of the hourly power outputs from generators, electricity importation or exportation, and the charging and discharging activities of storage units.

The objective of the proposed framework is to determine the optimal decarbonization transition pathway for power systems that minimizes the total electricity transition cost while considering both the annual changes and the hourly operations of the power systems. To apply the proposed framework, the following information is considered to be available and serves as the modeling parameters, including the current formulation of power systems in terms of the capacity, technology, and age of each existing generator or each electricity storage facility, renewable generation goals, greenhouse gas emissions targets, scheduled changes to power systems, availability of variable renewable energy, and a set of power generation and energy storage technologies, as well as their corresponding technological, economic and greenhouse gas emissions data. To ensure the reliability of future highly decarbonized power systems, electricity storage facilities are incorporated into the proposed framework to address the intermittency issues. Note that the electricity demands and supply are balances on an hourly basis for the representative hours in the operations years, considering power generation from each generator, electricity importation and exportation between the region of interest and its neighbors, and the charging and discharging activities of energy storage units. The overview of the proposed multi-scale bottom-up renewable power systems transition model is shown in the next sub-section.

2.2 Multi-scale bottom-up optimization framework

The proposed framework includes two time scales to simultaneously optimize the systems changes and simulate the corresponding hourly operations, and it has a bottom-up structure so that multiple types of information for each existing or new unit in the power systems can be incorporated, such the technology, capacity, and age of a generator.

The temporal overview of the proposed framework is presented in Fig 1. Two time scales are applied in the proposed framework, namely the design periods and the operations periods. In terms of the design periods, the planning horizon is equally partitioned on an annual basis, and the design decisions that include the additions and deactivations of generators and storage units should be determined for each year of the resulting design periods. To ensure the stability of power systems, hourly systems operations during the operations periods are incorporated in the proposed framework, while considering the changes to the electricity sector resulted from the design decisions.

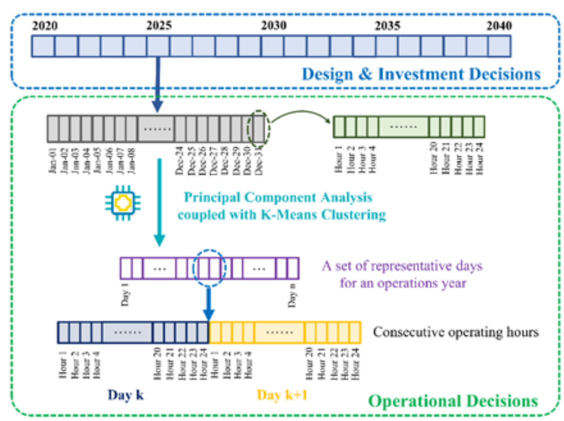

Fig 1 Temporal overview of the multi-scale renewable energy transition framework.

To reduce the computational challenges associated with optimizing the power systems changes and the hourly operations simultaneously for the entire planning horizon, a novel approach is proposed to obtain the representative days by coupling Principal Component Analysis (PCA) with clustering techniques that includes agglomerative hierarchical clustering (AHC), Gaussian mixture model (GMM), Dirichlet process mixture model (DPMM), and K-means clustering. The data being clustered is the 24-dimension hourly power loads for all days in a year, based on which we investigate the performances of using PCA coupled with each clustering approach, as well as the performances using the clustering approaches alone. The clustering performances are evaluated by three metric, namely intra-cluster variance, inter-cluster variance, and the Calinski-Harabasz index.

As for the formulation of the renewable electricity transition model, the objective is to minimize the total discounted energy transition costs, which include the design costs and the operations costs for both power generation and energy storage, subject to energy demand and electricity storage balance constraints, energy availability constraints, power systems scheduling constraints, energy and emission target constraints, transition relationship constraints, transition capacity constraints, economic constraints, non-negativity constraints, and binary constraints.

3. CASE STUDY FOR NEW YORK STATE

3.1 Data and information for the application

To illustrate the applicability of the proposed framework, a case study on the renewable electricity transition for New York State is presented. The renewable electricity requirements as well as the climate targets for New York State are set following the state legislation. The technologies for power generation in the New York State case study include bituminous coal, fuel oil, methane from biogas, refuse of solid waste, utility solar PV, distributed solar PV, nuclear power, hydropower, on-land wind, offshore wind, natural gas combined cycle, natural gas combustion turbine, natural gas steam turbine, natural gas combined cycle with carbon capture and storage [7]. Three electricity storage technologies are included for the case study, namely lithium-ion batteries, flywheels, and pumped storage hydropower, which are current electricity storage technologies in New York State. Note that the proposed renewable electricity transition model has a bottom-up structure that include the individual generators and electricity storage units by technology and operations ages, so it is general enough to apply the proposed framework to other regions of interest. The generation and storage capacity data, the annual electricity generation projections, and the scheduled power systems changes for New York State are obtained based on a report from New York Independent System Operator (NYISO). In addition, the data on generation capacities for existing distributed solar PV in the state are collected following a work of New York State Energy Research and Development Authority (NYSERDA). The technological and economic data projections for the power generation and electricity storage technologies are collected from a study by the National Renewable Energy Laboratory (NREL). The hourly operations data for the state are obtained from NYISO energy market and operation data, while the hourly availability of solar, on-land wind, and offshore wind are retrieved from a database of NREL.

3.2 Obtaining representative days

To obtain the representative days, we investigate the performances of using PCA coupled with multiple clustering approaches, including AHC, GMM, K-means, and DPMM, as well as using the clustering techniques without PCA. Three performance metrics are applied in this work, namely intra-cluster variance, inter-cluster variance, and Calinski-Harabasz index. Lower values of intra-cluster variance are preferred, while higher values of inter-cluster variance and Calinski-Harabasz index indicate better clustering results. The results are shown in Fig 2.

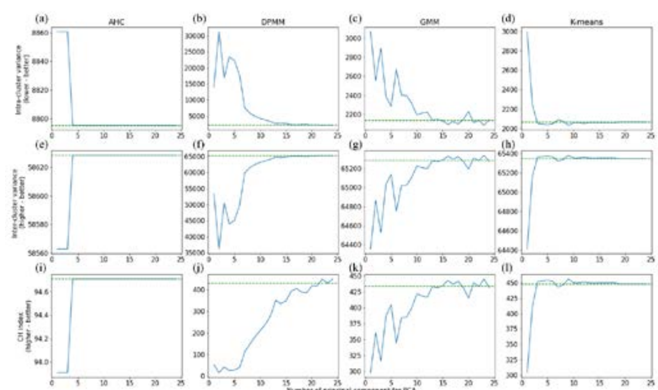

Fig 2 Intra-cluster variance, inter-cluster variance, and Calinski-Harabasz index using PCA coupled with four clustering approaches under different numbers of principal components. Green horizontal lines indicate values of three metrics while applying the clustering techniques directly.

For AHC, all three metrics are not as good as the other types of clustering techniques, regardless of whether it couples with PCA or not, while coupling PCA with other clustering techniques could improve the data grouping performances compared to using these techniques without PCA. This is owing to the effectiveness of PCA in capturing the correlations of the high-dimensional input data. Across all clustering techniques and all performance metrics, an obvious trend is that higher numbers of principal components tend to provide better data grouping results than lower numbers. This is because the projections of data onto few principal components cannot effectively reflect the differences between the original data points. On the other hand, choosing the highest number of principal components does not guarantee the best data grouping results, potentially because of the influences from the values associated with the less effective principal components.

Among all approaches tested, PCA coupled with K-means with 9 principal components shows the best performance across all three metrics, so it is used to obtain the 25 representative days for an operations year.

3.3 Computational optimization results

The optimization programs of the renewable electricity transition problem using the proposed framework are coded in GAMS 27.3 on a PC with an Intel Core i7-8700 @ 3.20 GHz and 32.00 GB RAM, running on a Windows 10 Enterprise, 64-bit operating system. The energy transition planning is solved using CPLEX 12.9.0.0 with an optimality tolerance of 1%.

The problem has 4,889 integer variable, 2,294,943 continuous variables, and 1,596,333 constraints. The optimal objective value is \$ 96,343MM, and the solution process takes 12,294 CPUs. In addition, to validate the optimization results, power systems operations are simulated on an hourly basis for the entire planning horizon, based on the optimal transition pathways. The total transition cost under operations simulation is \$97,729MM, indicating that the error bar of the proposed optimization framework is less than 1.5%. In addition, the simulation time for power systems operations is less than 70 seconds, which is significantly less than the optimization time for the transition optimization using the proposed framework, because the capacities of generators and storage units in each year are fixed the operations simulation. Consequently, the simulations for each year are independent to other years, leading to substantial reduction of computational requirements.

3.4 Renewable electricity transition pathways

The transitions of power generation capacity by source are shown in Fig 3 following the optimization result. offshore wind turbines and utility solar PVs account for the majority of power generation capacity by the end of the planning horizon. Specifically, offshore wind starts to participate in power generation at the year of 2024, and its total generation capacity remains relatively stable during 2025-2030. In the 2030s, the capacity of offshore wind power gradually increases until the end of the planning horizon. As for on-land wind, its total generation capacity gradually increases during the first five years of the transition, because multiple new on-land wind farms are scheduled to be constructed according to NYISO. Its capacity remains stable during 2025-2035, and the capacity of on-land wind power begins to decrease in 2036, owing to both the economic reasons and the lifetime limits of 30 years, as there are on-land wind farms that started operation during the 2000s. In terms of solar PV, the generation capacity of utility solar PV has no significant changes during the beginning years of the planning horizon, and it starts to increase after 2027. This is potentially because the annual electricity consumption in New York State is expected to decrease at the beginning years, owing the efficiency improvements across the state, while in comparison, total annual power load is projected to increase after 2027.

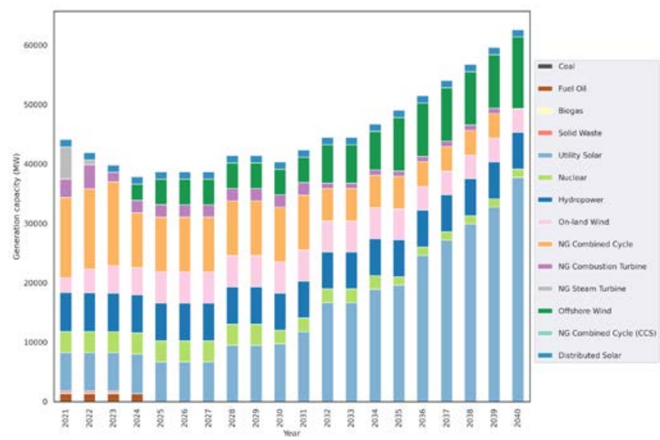

Fig 3 Electricity generation capacity by source during the transition according to the optimal transition pathways.

On the other hand, distributed solar PV has a stable capacity across the planning horizon, which is owing to two reasons. Specifically, the economic efficiency of distributed solar PVs is not as good as utility solar PVs, and it would reduce the total transition costs to install utility solar PVs during generation capacity expansions, as both options have the same energy availability represented by hourly capacity factors. The other reason is that most distributed solar PVs are installed during the 2010s, so the lifetime limits of 30 years would not result in noticeable decreases in the generation capacities, and

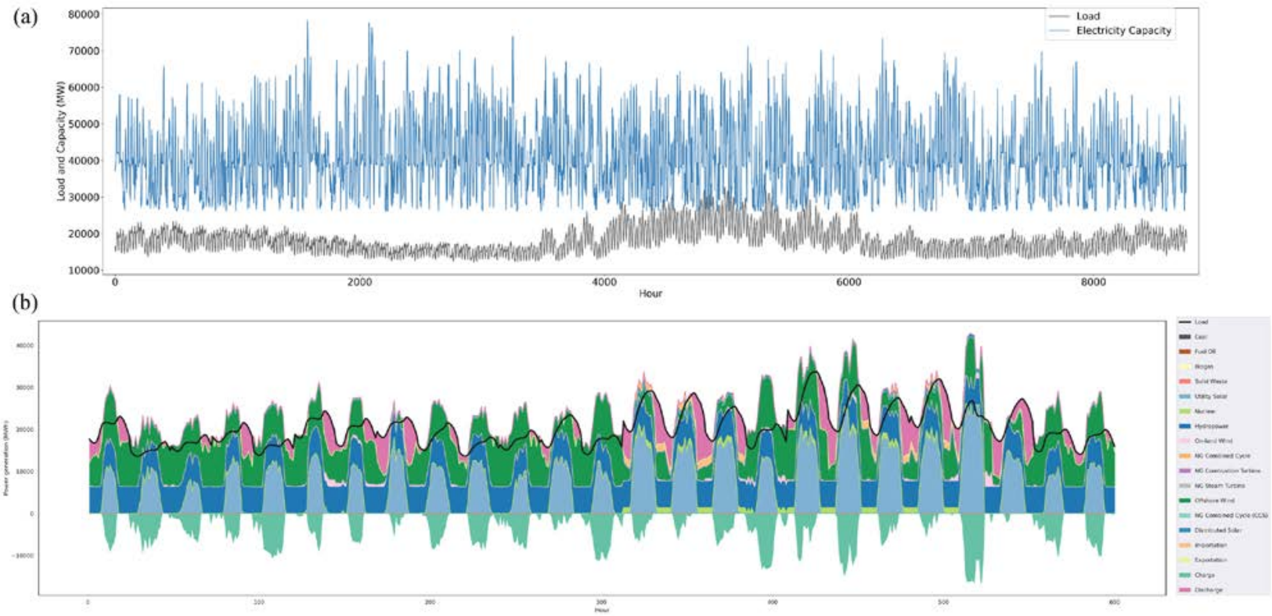

Fig 4 Hourly power demand and supply capacity for the year of 2040 (a), and hourly electricity supply by source during the representative hours in 2040 (b).

it is not economically preferred to replace the existing distributed solar PVs by other types of generators owing to the high installation costs. In addition, a previous study working on the energy transition for both the electric and heating sectors for New York State suggests that offshore wind would be a major source of electricity in 30 years [6], and there are mainly three reasons for the seemingly different transition pathways. The first is reason is that the previous work focuses on the total annual electricity generated by different technologies, while Fig 3 only shows the generation capacity by source. In terms of annual electricity generation, the conclusion of this work is consistent with the previous work, suggesting that offshore wind power would provide more electricity than any other technology owing to its high capacity factor, which is to be illustrated in the later part of this subsection. The second reason is that the previous study involves both the electricity and the heating systems, and the electrification of the heating sector would considerably increase the power demands, which starts to become a significant amount of additional electricity after the year of 2040, namely the end of the planning horizon for this study. The third reason is that the previous work focuses on the annual energy balances, while this work involves hourly power systems operations. In this case, a potential drawback of offshore wind is that its availability can occasionally become much lower than its average, which would require more generation capacity using other technologies, such as utility solar, to compensate.

Based on the optimization results, Fig 4 presents the hourly power demand and supply capacity for the year of 2040, and hourly electricity supply by source during the representative hours in 2040. Note that the fluctuation of electricity supply capacity is significant, owing to the high penetration level of variable renewable energy, such as solar and wind. For the hourly operations during the representative days in 2040, solar PVs show clear periodic power outputs, because of the limited availability of solar energy during the evening. On the other hand, the power outputs from offshore wind show no clear intra-day correlations. In terms of energy storage, the charging and discharging activities are conducted frequently in large-scale, since the resulting power systems have high-level of intermittent generation capacities that require electricity storage operations to shift the power supply.

The annual electricity generation from different technologies, net electricity importation, and energy loss of electricity storage are shown in Fig 5, based on the operations simulation results under the optimal transition pathways. Specifically, offshore wind would generate the most electricity by the end of the planning horizon, which is consistent with the existing literature [6], while hydropower and utility solar PV are the other two main generation technology in 2040. Note that although the total capacity of offshore wind is less than that of utility solar PV in 2040, as shown in Fig 3, offshore wind turbines tend to have much higher average capacity factors than utility solar PV, which enable them to generate more electricity on an annual basis. Hydropower currently accounts for most of the renewable electricity generation in the state, and it continues to provide stable electricity on an annual basis across the planning horizon, owing to its relatively stable total generation capacity over the planning years. The trends of annual electricity generation from utility and distributed solar PVs are consistent with the trends of their capacity changes in Fig 3. The net annual electricity importation gradually decreases over the next two decades, and this is potential because of the increasing penetration of variable renewable energy, such as solar and wind, as the marginal generation cost is zero for technologies based on these energy sources and is more economically favorable than imported electricity that has a price. Furthermore, note that the bars below zero indicate the electricity losses, which are negative values owing to the round-trip efficiencies of storage technologies that are between 80%-90%.

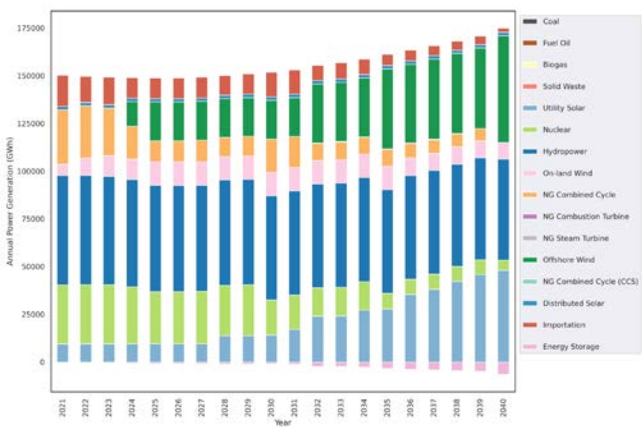

Fig 5 Annual electricity generation by source, electricity loss from energy storage units, and net electricity importation, according to the operations simulation .

In Fig 6, the annual greenhouse gas emissions of the electricity sector decrease almost linearly across the planning horizon, while the reduction rate at the beginning years are slightly higher compared to the later periods, which is potentially attributed to more deactivated fossil-based power generation capacities at the beginning of the planning horizon. Note that the greenhouse gas emissions reach zero in 2040, indicating that the goal of 100% decarbonized power systems is achieved under the optimal transition pathways obtained using the proposed framework. For electricity storage changes, lithium-ion battery has the highest storage capacity by the end of the transition process, owing to its higher economic efficiency compared to the other storage options under a planning horizon of 20 years. The capacity of lithium-ion battery mainly increases during the first 5 years and during the 2030s, because the transitions of fossil-based electricity to generation from variable renewable energy are more significant in these years, which consequently requires more storage capacity to ensure system reliability.

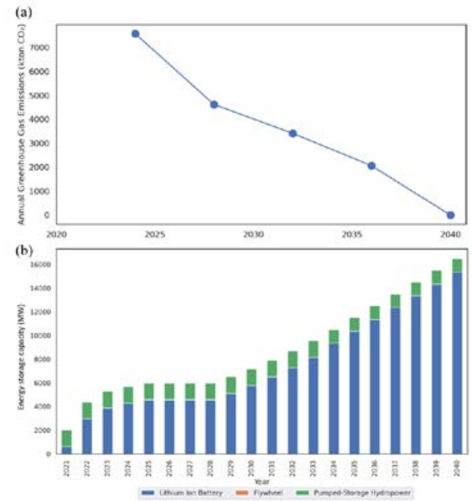

Fig 6 Annual greenhouse gas emissions from electricity generation and electric energy storage capacities.

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