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A spatially and temporally resolved model of the electricity grid – Economic vs environmental dispatch

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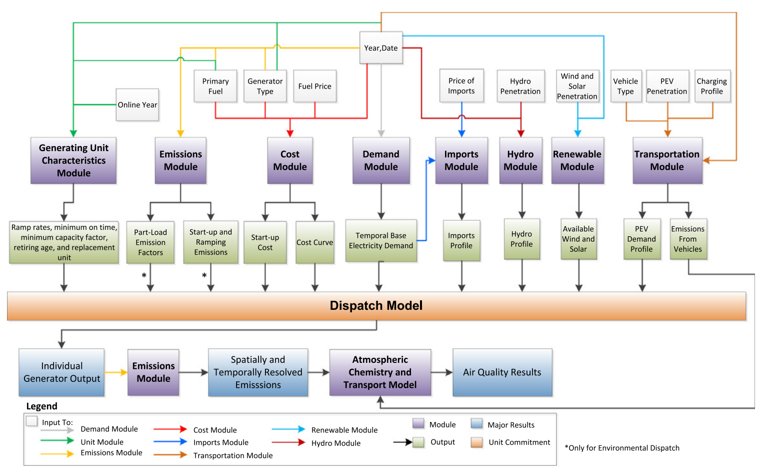
HIGHLIGHTS

- A spatially and temporally resolved dispatch model is developed.
- MCP and average price of electricity are determined for 2050 base case.
- Economic and environmental dispatch strategies are assessed.
- Environmental dispatch results in significant NO_x reduction and higher prices.
- A combination of economic and environmental strategies is the preferred method.

GRAPHICAL ABSTRACT



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ABSTRACT

Substantial changes need to occur in the electricity generation sector in order to address greenhouse gas and urban air quality goals. These goals, combined with increasing energy prices, have led to elevated interest in alternative, low to zero carbon and pollutant emission technologies in this sector. The challenge is to assess the impacts of various technologies, policies, and market practices in order to develop a roadmap to meet energy and environmental goals.

To this end, a spatially and temporally resolved resource dispatch model is developed that simulates an electricity market while taking into account physical constraints associated with various components of an electricity grid. Multiple technology simulation modules are developed to provide inputs to the model.

The model is used to design a market-based grid, and to develop and evaluate different dispatch strategies. To maintain the system cost at acceptable levels and reduce emissions, the results reveal that the best approach is a combination of economic and environmental dispatch strategies. The methodology and the tools developed provide a means to examine various aspects of future scenarios and their impacts on different sectors, and can be used for both decision making and planning.

1. Introduction

Electricity demand in the U.S. increased from 690 kW h per capita in 1930 to 12,158 kW h per capita in 2000. The energy and

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Nomenclature

AB32	Assembly Bill 32
CAISO	California Independent System Operator
FERC	Federal Energy Regulatory Commission
GDP	Gross Domestic Product
LCOE	Levelized Cost of Energy
LP	Linear Programming
LR	Lagrangian Relaxation
MCP	Market Clearing Price
MINLP	Mixed Integer Non-Linear Programming
MIP	Mixed Integer Programming
ND	Net Demand
NERC	North American Electric Reliability Corporation
PEV	Plug-in Electric Vehicle
RPS	Renewable Portfolio Standard
SB32	Senate Bill 32
SC	Scheduling Coordinator
SCED	Security-Constrained Economic Dispatch
SCUC	Security-Constrained Unit Commitment
SoCAB	South Coast Air Basin
UE	Unserved Energy

electricity demand are estimated to increase 44% and 77% from 2006 to 2030, respectively [1], and fossil fuels are projected to remain the number one source of primary energy for years to come. In the United States, coal and natural gas are the major fuels for generating electricity.

Electricity has become an inseparable part of everyday life, essential to power homes, businesses, and industry, and directly impact thereby the quality of life, economy, and gross domestic product (GDP). With increasing concerns about air quality and climate change, inflexibility of the demand side, and increasing requirements for reliability, attention in the electricity sector is focused on exploring strategies to promote a more efficient and environmental-friendly industry, keeping energy prices relatively unchanged, and providing the necessary generation to meet the future demand while ensuring that the grid meets the resiliency needs of the community.

The power generation industry has progressed from the localized distributed generation and monopoly of the *Pearl Street Station* days. Advances in technologies such as high-voltage transmission lines and computer systems facilitate the long-distance transmission of electricity. However, electricity is different from other commodities and energy sources (oil or natural gas for instance) because of its physical characteristics that require matching injection and withdrawal at each point and instant in the system (at least until massive storage becomes economically viable and pervasive for more widespread use). This characteristic makes the scheduling of electricity generation crucial. In the state of California, the California Independent System Operator (CAISO) is the responsible entity for scheduling electricity generation and also ensuring the reliability of the system. Those who wish to sell power in this market have to participate and bid into the CAISO various electricity markets including energy and ancillary services markets. The CAISO processes the bids and announces the schedule while making sure that all system constraints are met at all times.

The model developed in this work mimics the operation of the CAISO market. Not only is the model consistent with business practices and goals of the ISO, the model also has the capability to introduce advanced power generation (e.g. higher market penetration of renewable resources including wind and solar, and distributed generation such as fuel cells) in order to (1) evaluate the future economic and environmental impacts of these technologies, and (2) assess various possibilities and scenarios for the future grid from different perspectives. With California's stringent environmental policies such as Assembly Bill 32 (AB32) that requires reduction in greenhouse gas emissions to 1990 levels by 2020 [2], renewable portfolio standards (RPS) requiring that 33% of electric energy sold in the state come from renewable sources by 2020 [3], and Senate Bill 350 (SB350) that requires 50% of electric energy sold in the state come from renewable sources by 2030 [4], it is inevitable that the penetration of renewable sources of energy will increase in the future. The current model and research can help clarify (1) how the addition of renewable sources can affect the electricity market, and (2) if and how the market procedures should change in order to better accommodate these new technologies.

The model is capable of resolving the spatial and temporal operation of the utility grid network. It is temporally resolved in order to predict the market results with a resolution of down to 5 min. It is spatially resolved in order to include the amount of electricity that each specific generator produces. Resolving the spatial and temporal electricity generation also allows the amount of pollutants emitted from each generator to be established as a function of space and time, thereby providing the opportunity to study air quality impacts associated with various market and generator dispatch strategies [5].

Currently, several ISOs use the Security Constraint Unit Commitment (SCUC) to clear their energy and ancillary services markets and find the corresponding Market Clearing Price (MCP) for these markets. SCUC commits generating units in the day-ahead market and allocates the necessary reserves. In the real-time markets, the Security Constrained Economic Dispatch (SCED) algorithm is used and, for all intents and purposes is the same as the SCUC but with more accurate inputs and network parameters.

The objective of the SCUC is to find a dispatch schedule that minimizes the electricity price (which results in minimizing the social cost in most cases), and also ensure the reliability of the system (and hence the term Security-Constrained). Moreover, the SCUC is subject to several constraints, most of which are associated with the physical characteristics of the generating units and reliability of the electric utility network, while other constraints are due to various regulations and laws (e.g., environmental regulations). The solution of the SCUC problem results in a challenging Mixed-Integer Nonlinear Programming (MINLP) problem.

1.1. Previous related studies

After deregulation and development of competitive markets for electricity, many studies have modeled the restructured electricity market. In competitive markets, each participant in the market tries to maximize profit. Some of the previous studies have focused upon modeling a single firm's profit and determining how they could effectively participate in the market. In these studies, Linear Programming (LP) and MINLP methods are used to obtain the solution. If the price uncertainty is taken into account, the scheduling of each unit of the firm can be treated independently, thus simplifying the problem. This strategy has been used in [6] to optimize self-commitment under uncertain energy and reserves prices, and in [7] for portfolio managent. These sets of problems have been typically solved using backward Dynamic Programming solution strategies.

More sophisticated models take into account the impact of the individual generator unit decision on the market clearing price using the leader-in price model of microeconomic theory [8]. Some efforts aim at optimizing the generation curve, and use algorithms based upon MINLP to determine strategic bidding strategy in deregulated markets [9,10]. Other efforts, focus upon optimizing the demand curve by taking into account, using probability distributions, the uncertain behavior associated with other firms and consumers [11].

Another group of market models focuses on the clearing process of various types of markets in a wholesale electricity market. A handful of these studies focus on the price or supply curves that generating units submit and estimate the impacts on the market results. Cournot equilibrium and Supply Function Equilibrium methods are usually used in such approaches [12,13].

The majority of recent studies focus upon solving the SCUC. Various optimization methods have been applied to the SCUC problem with Lagrangian Relaxation (LR) and Mixed-Integer Programming (MIP) as the two most-widely used and recommended methods [14–16]. (A detailed comparison of the two methods can be found in [17].) The downside of the MIP methods is the large number of binary variables, which adds complexity to the problem. On the other hand, LR involves heuristics to solve the SCUC problem and thus, does not always guarantee an optimal solution.

The LR method is the direct technique to solve the SCUC problem as used in [18,19]. In this approach, if all the transmission constraints are not relaxed, the problem will include a large number of Lagrangian multipliers which make the problem very complicated and nearly impossible to solve. To overcome this problem, Benders decomposition is used to separate the problem into a master problem and several sub-problems. The master problem is the traditional unit commitment problem without the transmission and voltage constraints, and the sub-problems include security-checking routines using the results from the master problem and Benders cuts [20,21]. This method has been used to solve the UC problem with transmission constraints and voltage constraints [22], and with stochastic unit commitment to include higher penetration of wind energy resources [23].

The use of MIP methods has become more common with the introduction of efficient techniques and solvers such as the branch and cut technique. These techniques allow modeling of nonconvex and nondifferentiable costs [24], as well as start-up and shut down power trajectories of generating units [25]. In [26], in order to reduce the computation time, the authors reduce the number of integer variables by fixing unit states and then changing them gradually into committable states if the solution is infeasible. Previously obtained results and Benders are kept and used to accelerate the solution process, and at the end the results are used as initial conditions in an MIP algorithm to assure that the results obtained are indeed the optimal results.

The output of each generating unit is usually approximated by a smooth quadratic and convex curve. In real life, however, units may have prohibited operating zones that make the problem non-convex, solutions to which are available in the literature [27,28].

Other methods have been used to find a solution to the SCUC; including dynamic programming [29,30], particle swarm optimization [31–34], genetic algorithms [35–38], stochastic optimization [39–42], and adaptive optimization [43].

Concerning the applications assessed in previous work, some dispatch models were developed to assess the impacts of plug-in electric vehicles (PEVs) on air quality [5], emissions [44,45], and distribution system [46]. Others assessed integration of intermittent resources [47] such as wind [48] or solar [49], addition of demand response [50], water consumption [51] and climate impacts of the grid [52].

While other dispatch models have been developed, the results are not spatially resolved and thus do not count for transmission constraints [53–55]. Very few studies are spatially resolved and amenable to air quality analyses [5,44,51]. However, most of these do not include a sophisticated dispatch model and use a relatively simple dispatch strategy, such as marginal dispatch [56,57], or average grid mix [58,59] with simplified system constraints [60]. Other studies have been performed that model the electricity market and solution methods primarily for solving the complicated unit commitment problem. However, these studies typically only solved the problem for a small number of generators rather than utility scale modeling, and were not used to assess actual systems, present or future [17,20].

In this work, a comprehensive dispatch model is presented for a specific fictional balancing area (the South Coast Air Basin in southern California, SoCAB) which is both spatially and temporally resolved, includes market operations and physical constraints of the electric utility network in this area. Various dispatch strategies are applied to 2050 base case and the economic and environmental implications are discussed.

While currently applied to this fictional balancing area, it is large enough and thus representative of real balancing areas. Therefore, the methodology can be directly applied to large-scale grid modeling of any area simply by changing the model inputs. Modules developed as components of the methodology provide the capability to study the environmental and economic impacts associated with future scenarios.

2. Methodology

In order to study the air quality impacts of various scenarios, it is necessary to have emissions that are both spatially and temporally resolved. The spatially and temporally resolved dispatch model developed in the present study represents the actual electricity market operation that includes various physical characteristics of electric grid operation that are unique to electricity markets, such as the balance of supply and demand at each instant, in all locations.

To simplify the algorithm, the model is divided into several modules (Fig. 1) and a core optimization algorithm, which is referred to herein as the dispatch model (see Fig. 2). To reduce the number of variables in the optimization, base-loading units, imports, and renewable resources are dispatched first with the renewables treated as "must-take" units. Various modules provide the necessary inputs to the dispatch model. These inputs include the cost curves, base electricity demand, electricity demand of PEVs if required, availability of renewable resources, and characteristics of individual generators such as ramp rates, and emissions factors. Fig. 1 offers a summary of the modules developed for the current methodology and the most important inputs and outputs to these modules. For instance, in the cost module, inputs include the future year under study, type of generator, primary fuel, and fuel price. The module calculates the cost curve (Levelized Cost of Energy (LCOE) vs. capacity factor) and the start-up cost for that specific generator operating in the specified future year.

Significant challenges associated with the development of the modules include collecting the necessary data and forecasting the various metrics for future scenarios. Detailed descriptions of the modules used in this paper are provided in the Appendix A.

2.1. Economic dispatch

The objective of the dispatch model is shown in Eq. (1).

$$\text{Minimize} \sum_{i=1}^{N_g} [C_i(P(i,t))I(i,t) + S(i)I(i,t)\{I(i,t) - I(i,t-1)\}] \quad (1)$$

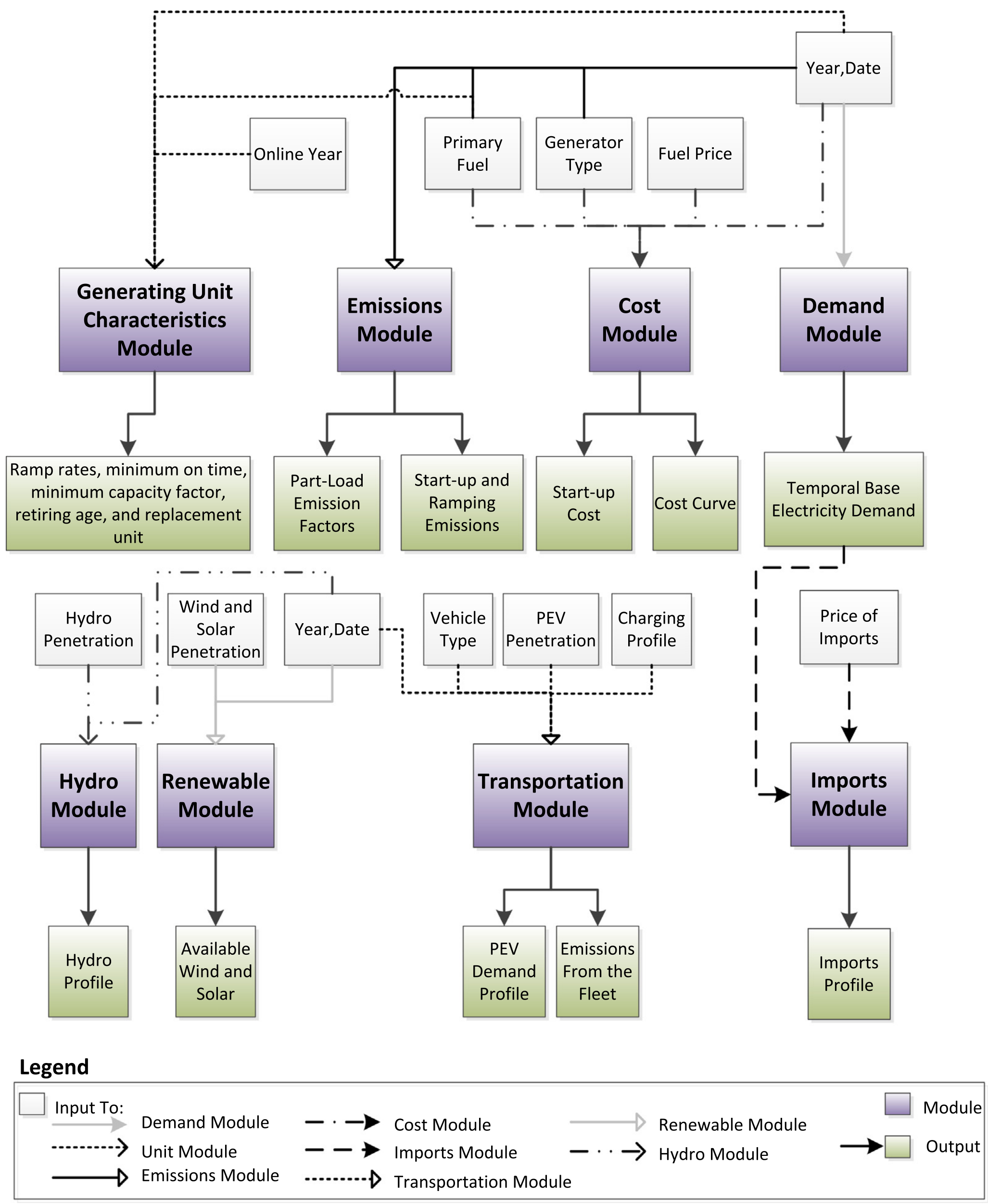

Fig. 1. Modules.

In this equation, N_g is the number of generators participating in the market, C_i is the cost function of generating unit i, $P(i, t)$ is the production (generation) of unit i at time t, $S(i)$ is the start-up cost of unit i, and finally $I(i, t)$ is a binary variable associated with the commitment status of unit i at time t (1 for committed and 0 for uncommitted). Note that the objective function is nonlinear due to the nonlinearity in the cost curves and the start-up costs.

The first term in Eq. (1) is the *production cost* and the second term is the *start-up cost*. To take into account capital and operating costs such as instant costs [61], installed costs, and fixed and variable operation and maintenance costs (O&M), C_i is replaced with the LCOE curves associated with each of the generators (assuming zero start-up) and the start-up cost is calculated based upon the amount of fuel required to start the generator and the cost of the fuel. Note that all of the bids in the current methodology are based upon "actual costs" and do not include gaming and the impact of demand on the bids. Thus the bids include a cost of production (generation) curve as a function of capacity factor and a start-up cost only (i.e., bids are not a function of time of day or electricity demand).

When $I(i, t)$ is zero, $P(i, t)$ *is* zero since generator i is neither committed nor generating at time t. On the other hand, when $I(i, t)$ is equal to one, not only should $P(i, t)$ be greater than zero, it is also less than P_{gmax} and greater than P_{gmin} which are the operating limits of generator i. To ensure that the unit commitment of a generator, $I(i, t)$, and the output of that generator $P(i, t)$ are not independent of each other, a constraint is added that shows the relationship between these variables. Such a constraint is shown in Eq. (2).

$$P(i,t) = 0 \text{ if and only if } I(i,t) = 0 \quad (2)$$

At each time, the output of a generator should be lower than P_{gmax} (Eq. (3)) due to both physical limitations of the system and the reality that the generator never reaches nameplate capacity due to losses. $P_{gmax}(i)$ is derived from the generating unit characteristics module and used as an input here.

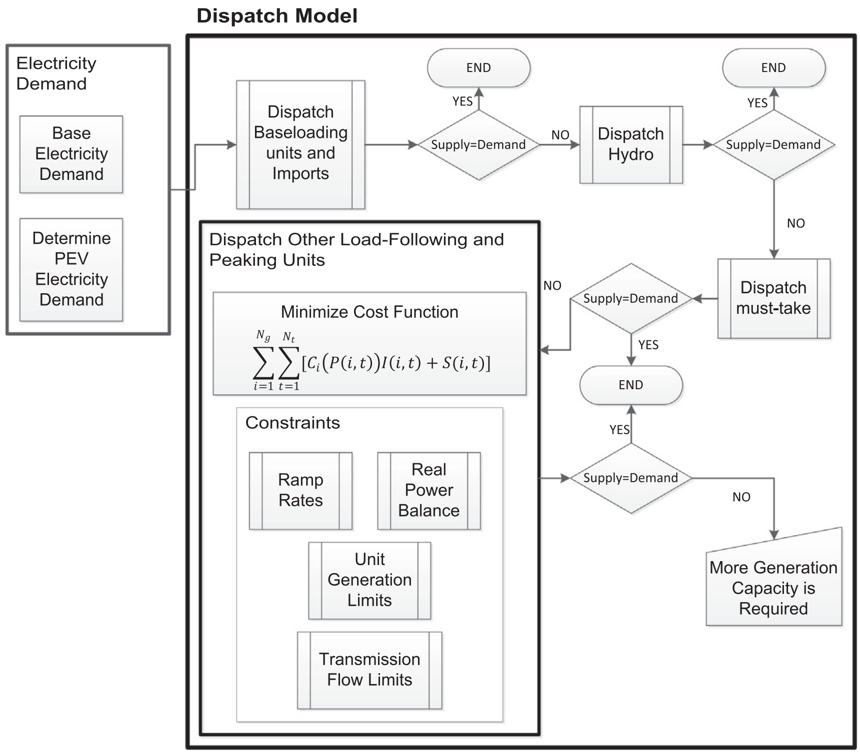

Fig. 2. Dispatch model summary.

$$P(i,t) \leqslant P_{gmax}(i) \tag{3}$$

$P(i, t)$ usually has a lower bound as well which is due to the fact that operation under a specific capacity factor is not economically sound and thus the owner submits a lower bound for generation into the market. Many generators are also constrained to a minimum power output due to requirements of post-combustion nitrogen oxide emissions removal equipment for meeting pollutant emissions regulations. However, $P(i, t)$ can also be zero when generator i is not committed at time t. This constraint is rewritten as in Eq. (4) to include both cases. It must be noted that such a constraint is nonlinear itself.

$$I(i,t)\ P_{gmin}(i) \leqslant P(i,t) \tag{4}$$

The constraint associated with the balance of supply and demand is shown Eq. (5). In this equation, $D(t)$ is the electricity demand at time t.

$$\text{sum}\{i \text{ in } N_g\}I(i,t)P(i,t) = D(t) \tag{5}$$

While it may seem that $I(i, t)$ is not necessary in Eq. (5), this term helps the algorithm run faster. Due to numerical errors, instances may occur where $I(i, t)$ is zero but $P(i, t)$ has a very small value close to zero but not quite zero. In such situations, the $I(i, t)$ term in Eq. (5) helps facilitate the computations.

Another important set of constraints are ramp rates associated with each of the generators. The ramping up or down constraints do not have a lower bound and the lower bound is considered zero. The maximum ramping up constraint and ramping down constraint in this research are assumed equal for a specific generating unit, and thus the ramping up and down constraints are combined together for each generator as shown in Eq. (6) where *abs* stands for absolute value, and $RL(i)$ is the ramping limit associated with generator i. It must be mentioned that the constraint shown in Eq. (6) is nonlinear in nature and can vary for each of the generators (some ramp quickly and others ramp slowly).

$$abs(P(i,t) - P(i,t-1)) \leqslant RL(i) \tag{6}$$

Another constraint taken into account is the minimum on-time of a generating unit (Eq. (7)). It is not economic for a generating unit to be online only for a short amount of time. For peaking units, this minimum on-time has a default value of 2 h and the default value for a combined cycle power plant is 8 h. The minimum off-time is not considered in this research, especially since it doesn't imply any physical limitations and is included in long-term studies to ensure that there is enough down time for scheduled and unscheduled maintenance. The off-time of generating units that is required for maintenance is considered when calculating the annual greenhouse gas emissions but is not considered in the hourly dispatch of the current paper.

$$\sum_{t-T^{on}(i)}^{t} I(i,t) \geqslant I(i,t-1)T^{on}(i) \tag{7}$$

The transmission constraints are also added for transmission lines in locations that have historically been congested. The maximum capacity of the line is considered in these constraints. To fully add the bus-to-bus transmission constraint, it is necessary to solve all the power flows in the system and determine how the power is flowing between supply and demand. Although this is possible for a small area and a limited number of variables, solving for all of the power flows inside of a MINLP optimization is numerically intensive for an actual market size or even for a balancing area like the one considered here. It must be noted that, in the SoCAB, there are around 200 generators (not counting wind, solar, and hydro), each introducing two variables into the model -one for commitment status and one for the amount of generation. Furthermore, the number of the variables increases exponentially if the optimization is conducted for several consecutive time intervals.

The set of equations introduced in this section, make up a mixed-integer (binary here) nonlinear program. In the current study, the AMPL language is used to solve the MINLP problem. AMPL is a comprehensive and powerful algebraic modeling language for linear and nonlinear optimization problems, in discrete or continuous variables. Various solvers such as CPLEX, Gurobi, and KNITRO can be used with AMPL.

Module of the current methodology (Fig. 1) are developed in MATLAB. For each of the scenarios, the outputs of these modules are compiled into a file and used as input to the dispatch algorithm which is developed in AMPL using KNITRO as the solver. The results are then saved and further processed. The results are also used as inputs to some of the modules (such as the emissions module) to calculate the spatially and temporally resolved emissions from individual generators and overall system emissions.

2.2. Environmental dispatch

A dispatch strategy is also developed to minimize the air quality and climate change impacts of the grid by minimizing criteria pollutant or greenhouse gas emissions instead of the cost. Referred to as *environmental dispatch*, the strategy takes into account the environmental impacts of the system before the economics of the dispatch are considered.

For the environmental dispatch, the objective function of the economic dispatch (Eq. (1)) is replaced with the new objective function shown in Eq. (8). In this equation, $EM(i,j)$ is the emissions factor for generator (i) and associated with specific species j. The start-up cost in Eq. (1) is replaced with the start-up emissions for species j, $SE(i,j)$.

$$\text{minimize} \sum_{i=1}^{N_g}[EM(i,j)(P(i,t))I(i,t) + SE(i,j)I(i,t)\{I(i,t) - I(i,t-1)\}] \tag{8}$$

The constraints of the problem remain unchanged from that of the economic dispatch discussed in the previous section. The ramping emissions are not included in Eq. (8) to simplify the problem.

Two environmental dispatch strategies are considered in this paper; one minimizes the emission of nitrogen oxides (NO_x) and the other CO_{2e}. These dispatch strategies are referred to as NO_x *dispatch* and CO_2 *dispatch*, respectively. CO_2 is chosen because of its contribution to climate change and the fact that the state of California has stringent environmental laws mandating significant reduction in greenhouse gas emissions. NO_x is chosen because it is a regulated criteria pollutant, and it is a precursor for ozone and $PM_{2.5}$ impacting urban air quality.

2.3. Future grid design

Since electricity demand is growing, it is most likely that the currently online units will not be sufficient to satisfy the electricity demand of a future scenario. In order to determine how much new generation is required, an algorithm similar to the SCUC was developed. In this new algorithm, the constraint associated with balance of supply and demand is relaxed, and the objective is changed to minimize the amount of *unserved energy* (*UE*).

The first step is to determine a *net demand* (*ND*) which is defined as shown in Eq. (9). This net demand is the sum of electricity demands (base electricity demand and PEV electricity demand (if any) derived from the "electricity demand" and "transportation" modules, respectively) minus the generation from wind, solar, and hydro resources, and imports. In this document, the base case scenario refers to the case in which the penetrations of wind and solar, as well as plug-in electric vehicles are the same as the year 2010 (7% wind, insignificant solar, and 0.1% PEV). The market rules and operation are unchanged meaning that the intermittent resources are treated as must-take. Market clearing is based upon economics and minimizing the social cost in the economic dispatch, and based upon minimizing emissions in environmental dispatch strategy.

$$\begin{aligned} ND(t) = {} & \text{Electricity demand} - \text{wind generation} \\ & - \text{solar generation} - \text{hydro generation} - \text{imports} \end{aligned} \tag{9}$$

To further ensure that sufficient reserves and ancillary services are available, the historical operating reserves in the CAISO are studied together with North American Electric Reliability Corporation (NERC) requirements for various types of ancillary services. Consistent with historical trends in CAISO and in order to have a conservative estimate at each time interval, 10% demand is added to the net demand calculated to account for ancillary services and reserves. The total generation calculated in this manner is referred to as the *required generation* (*RG*). It must be mentioned that hydroelectric units currently being used as spinning reserves and standby units are retained for future scenarios. As a result, the 10% increase provides the required reserves for the *new* load that has been added to the system.

Next, the already installed generating units are assessed. Units are retired based on their age and are replaced with advanced generator of the same type.

As previously mentioned, the objective is to minimize the *unserved energy* (*UE*), which is the difference between the required generation and outputs of all generating units subject to physical constraints previously discussed in Section 2.1 (except for Eq. (5) which corresponds to balance of supply and demand). The objective function is shown is Eq. (10).

$$\text{Minimize } UE(t) = RG(t) - \sum_{i=1}^{N_g}[(P(i,t))I(i,t)] \tag{10}$$

This problem (without the transmission constraints) is a mixed-integer linear programming problem and can be solved using various solvers such as CPLEX. Here, the model and its data are defined separately in the AMPL environment.

Unserved energy greater than zero, indicates that in order to serve the projected electricity demand, it is necessary to install additional generating units.

In the following section, the outcomes of the dispatch model associated with the base case are presented for 2050.

3. Results and discussion

3.1. Model verification

To verify the result, first the model is run for the year 2000–2001 and the results compared to Federal Energy Regulatory Commission (FERC) data [62], the only publicly available database including the hourly electricity production of individual generators. The model produces results for the overall in-basin generation that is within 12% of that reported by the FERC. The error in modeling the output of individual generators, on the other hand, is between 2% and 40% (depending more upon the specific generator than upon the time of the day). There are several reasons for the generator error. First, the current model assumes that generators bid in their actual cost of generation plus a reasonable profit into the market and that the percentage of the profit is uniform amongst all generators. Second, the ownership of the generator has not been taken into account. Owning several generators across the grid can result in better bidding by the scheduling coordinators to maximize their profit. Most importantly, gaming of the system and arbitrage are not taken into account in the dispatch model developed. This is especially important in regards to the FERC data that are used in the verification because the data correspond to the

2000–2001 court case associated with the energy crisis in the state of California, and these data were publicly released because of lawsuits involving Enron corporation [63]. Considering this fact, these data correspond to exceptional situations that may involve significant gaming rather than normal operations. As a result, the verification of the current dispatch model seems reasonable (predicting 2000–2001 data within 12% total, and between 2% and 40% for all generators at all times).

3.2. Air quality analysis

As previously mentioned, the spatial and temporal emissions resulting from the model can be used for air quality analysis. To demonstrate this, the dispatch strategy is applied to the SoCAB grid of 2005. An emissions inventory was generated for the 2007 Air Quality Management Plan by the South Coast Air Quality Management District (AQMD) [64] which includes emissions from both stationary and mobile sources for the year 2005. It includes carbon monoxide (CO), nitrogen oxides (NO_x), sulfur oxides (SO_x), total organic gases (TOG) and total suspended particulates (TSP) emissions from each source for the entire year with the time resolution of one hour. These data are results of a model developed by the California Air Resources Board for an air quality event. Year 2005 is chosen for this section in order to be able to compare the outcomes of the current methodology to those of the emissions inventory developed by the AQMD in order to further verify the results of the model.

A high demand day in August 2005 is selected and the developed model is run for that day. A high demand day in summer is chosen because high emissions from the generating units combined with high temperatures, will likely result in an air quality episode.

The emissions module of the model is then used to develop an emissions inventory from the dispatch model results. NO_x, and other criteria pollutant emissions from the dispatch model, are then used as inputs to the UCI-CIT model [5,65,66] to obtain air quality results.

These results are then compared to the air quality outcomes of the same model using the AQMD emission inventory as shown in Fig. 3. Note that the figure shows the difference between the model results using the emissions from the current methodology from that using the AQMD inventory. The errors in estimating NO_x are less than 8% (maximum error of less than 200 kg/day out of the average of 2000 kg/day) throughout the basin over the time period considered, and $PM_{2.5}$ errors are less than 2.5% (1 μg/m^3 maximum error, the maximum concentration can reach 50 μg/m^3) throughout the spatial domain and temporal period considered. The 8-h ground level ozone nearly matched the ARB's results with a maximum difference of less than 1 ppb (out of a nominal maximum 100 ppb) in very few locations. The 1-h ground-level ozone predictions also agree with ARB inventory (between 20 and 100 ppb) with a maximum difference of 1 ppb mostly at one location. These differences are associated primarily with the difference in dispatching a peaking unit located at Anaheim.

From the results provided, it is shown that the current methodology agrees well with the previously established models and spatially and temporally resolved data that is available for previous years.

3.3. Unserved energy and future grid design

The method described in Section 2.3 is used for future grid design for the year 2050. The results for net demand and unserved energy are shown in Fig. 4a and b, respectively. Negative values in Fig. 4b show the electricity generation still available, and the positive values correspond to the amount of electricity demand that could not be served with the previously installed units, requiring the installation of more generating units in order to satisfy the demand.

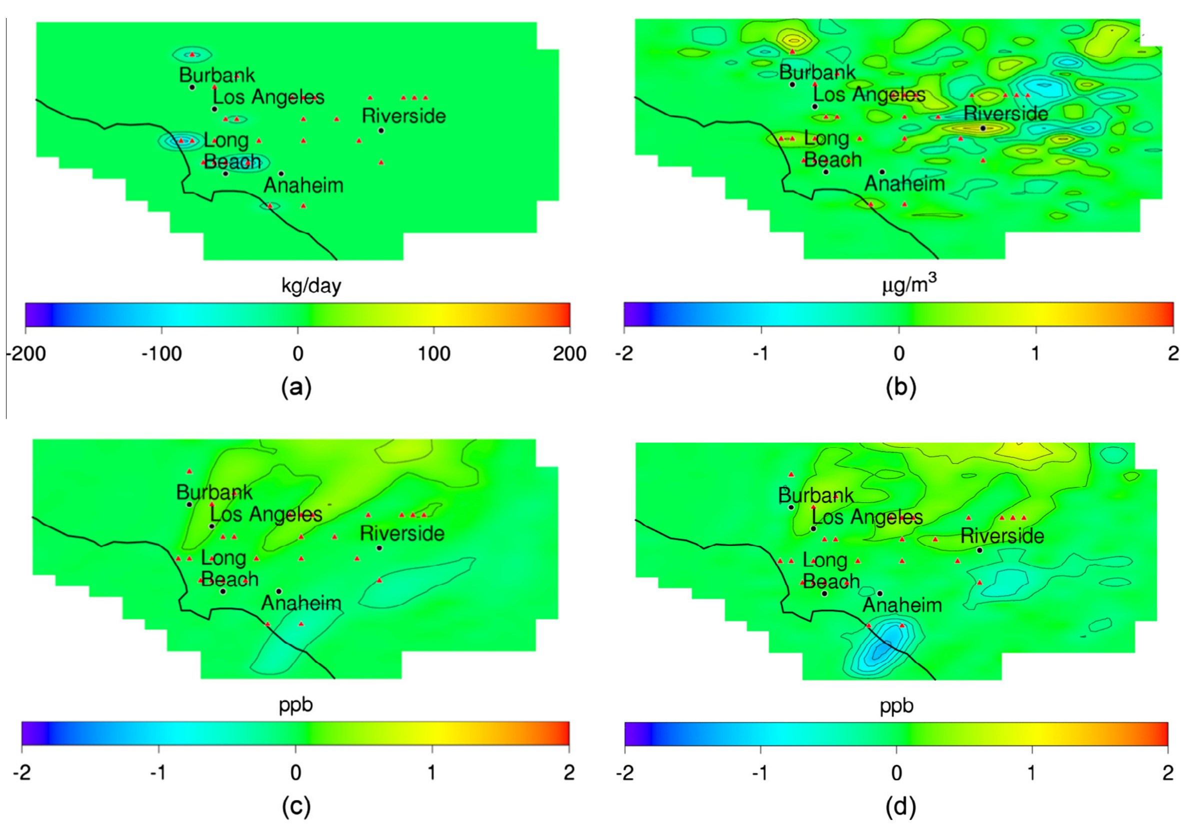

Fig. 3. Difference in (a) NO_x, (b) $PM_{2.5}$, (c) 8-h ozone, and (d) 1-h ozone between the model results and ARB emission inventory.

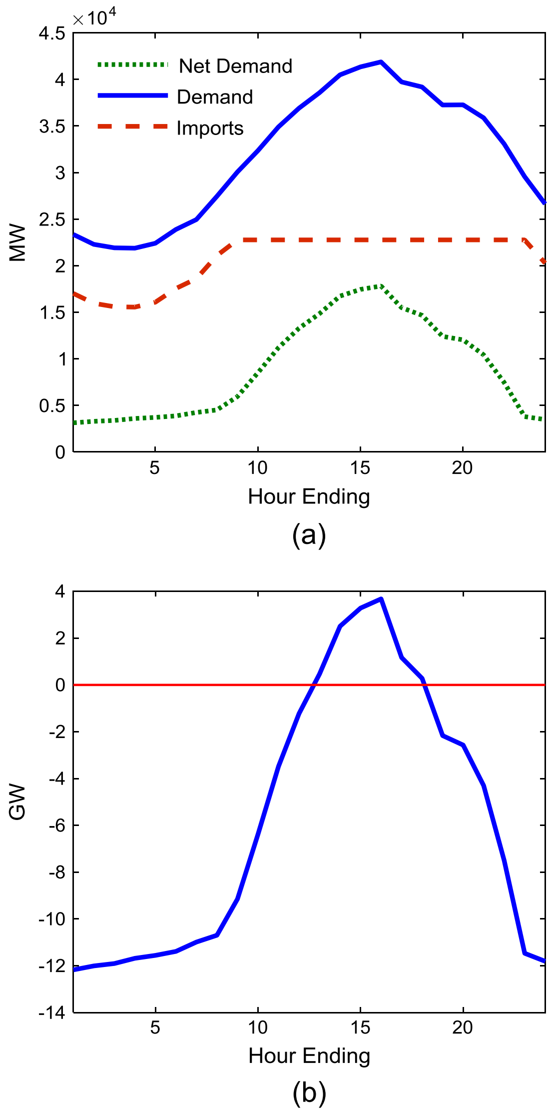

Fig. 4. (a) Net demand, and (b) unserved energy for a typical summer day, Base Case 2050.

As can be seen from Fig. 4b, at least 4.1 GW of new generation is required in 2050 (compared to 2010) assuming that the maximum capacity factor of the units is 0.98. The new power generation units that are selected to meet this demand vary between natural gas combined cycle and simple cycle gas turbine power plants. These technologies are chosen because they provide load-following and also peaking power to the grid, and are amongst the most environmentally-friendly types of *conventional* generation. The other reason is that base-loading units, such as coal and nuclear, are being phased out in the state of California especially because dynamic dispatch is increasingly required as the penetration of renewable resources increases. Finally there is no acceptable location to install base-load power plants inside the balancing area under study (SoCAB) due to various environmental regulations. To allocate the new power generation, various combinations of combined cycles and simple cycle gas turbine power plants with different capacities were added to the lists of generators and to the unit characteristics modules and then iteratively running the algorithm to determine if there is still unserved energy.

The fact that integration of intermittent resources and plug-in vehicles might require more peaking units is also taken into account when determining a combination of load-following and peaking units for the suite of new generating units (strategy described in [5,49] is used to determine PEV demand). Three and a half GW of combined cycles and one GW of simple cycle gas turbine power plants were determined to be required by the final results of the algorithm to meet all demand. The combined cycle plants include four 500 MW units and three 550 MW units. The simple cycle gas turbines include ten 50 MW, three 100 MW, and one 200 MW unit. To locate the new generation, the method in [49] is used to establish the eligible locations based upon land-use and size of the generator that can be accommodated by the footprint and capacity of retired units. In this model, it is assumed that in order to accommodate new generation and avoid congestion, the transmission system capacity will be increased or new transmission lines added.

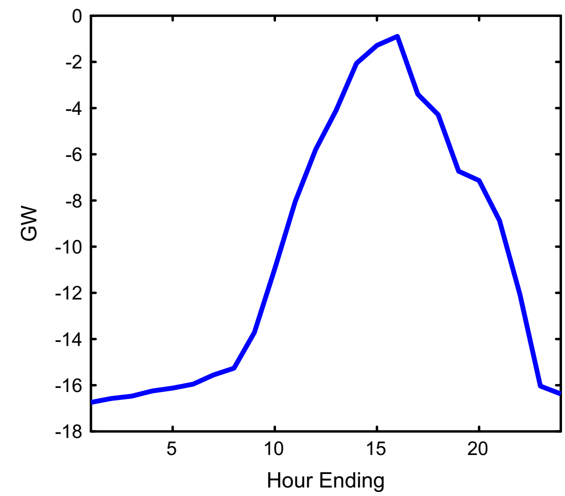

Fig. 5. Unserved energy after adding the new generating units to the model, 2050.

The new generators are added to the model, and appropriate values for ramp rates and cost curves are automatically assigned based upon the type of the generator and fuel specified. These new units are assumed to be of advanced technology with projected characteristics for a future year (2050 in this case) which are specified in the Appendix A.

Now that the new generators are added to the appropriate module, the *unserved* algorithm is run again to ensure that the new capacity installed helps satisfy the demand completely with no unserved energy. The results are shown in Fig. 5. It is evident that the demand is completely met with no unserved energy.

3.4. Dispatch schedule

After the new capacity is added to the model, the characteristics and physical properties of these new generators are determined and added to the dispatch model. The results (by generator type) associated with the 2050 base case are shown in Fig. 6 for the *economic, NO_x*, and CO_2 dispatch strategies. The intermittency of wind is not evident in this figure because of the very low penetration of wind energy in the base case (7%). Since the penetration of hydro and biomass resources remained unchanged form 2010, they contribute very little to the total generation. While the imports are not shown in this figure, they have the same profile presented in Fig. 4a for all dispatch strategies. It must be noted that, in practice, imports are settled ahead of time, and thus in this methodology these energy imports are represented as being dispatched ahead of all in-basin generators.

The use of peaking units is increased in the NO_x dispatch scenario because the steam turbines have significantly higher NO_x

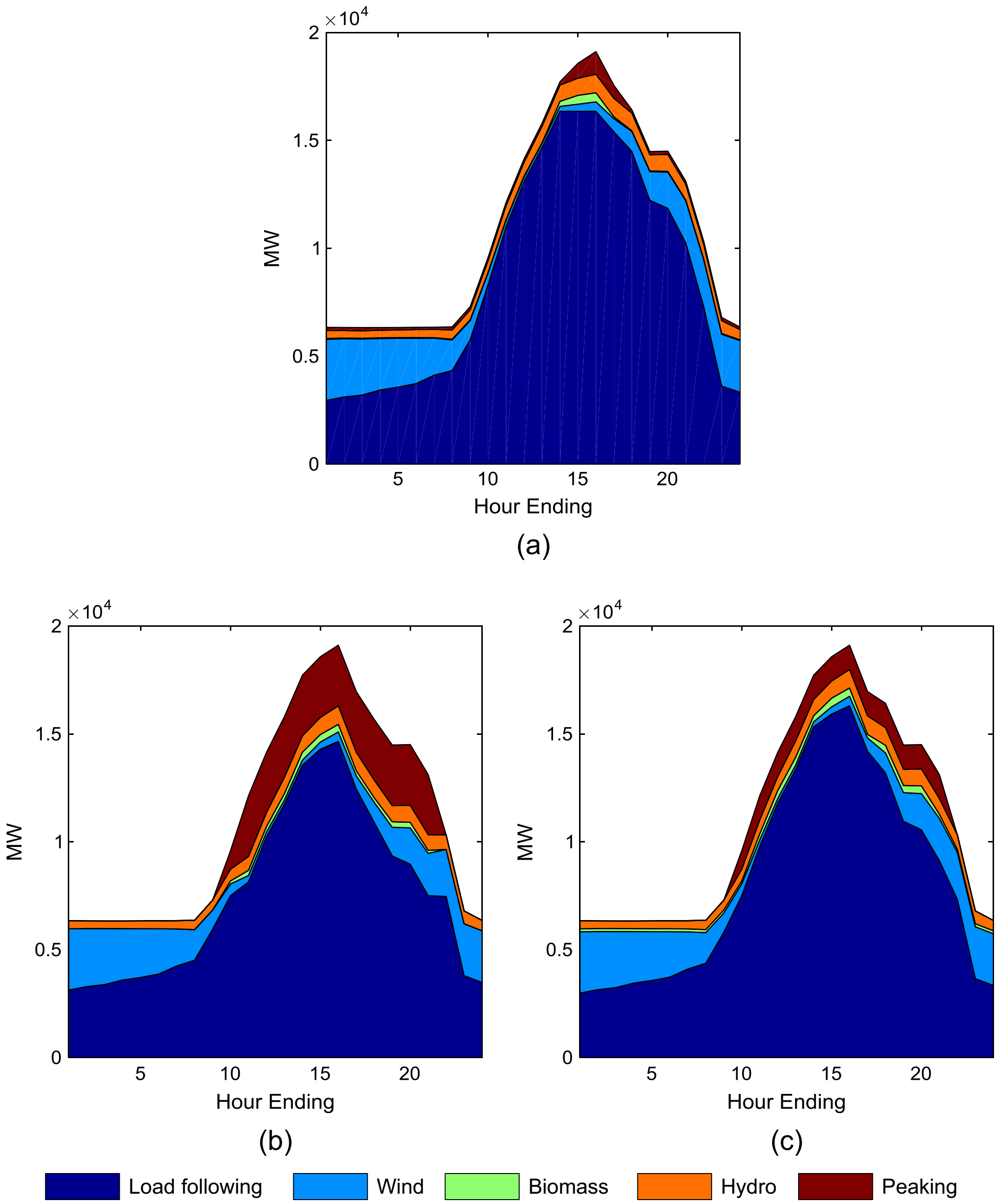

Fig. 6. Electricity generation by type, Base Case 2050. (a) Economic dispatch, (b) NO_x dispatch, and (c) CO_2 dispatch.

emissions factors compared to the gas turbine peaking plants. These units have replaced the retired units of the same type and are very few in numbers in the grid mix. Also at high capacity factors, the advanced peaking gas turbine power plants have lower NO_x emission factors compared to aging combined cycles operating at lower capacity factors. Since peaking unit are, in general, smaller units (50, 100, or 200 MW) compared to combined cycle power plants, for a specific load, they are able to operate at a higher collective capacity factor, and thus the fleet will have a lower average NO_x emission factor.

In the CO_2 dispatch case, the generation from biomass generating units is higher, because their CO_2 emission factor is zero. The use of peaking units is increased but not as much as in the NO_x dispatch case. The reason is that the emission factor associated with older gas turbine power plants is higher than the rest of the generators, while the advanced gas turbines have a CO_2 emissions factors that are lower than that of a steam turbine power plant. To better understand the results, NO_x and CO_2e emissions factors for various technologies operating at nameplate capacity are shown in Table 1. From the emission factors associated with other pollutants, it is evident that the results would have been slightly different if the objective were to minimize other pollutants.

Table 1
Emission factors (kg/MW h) for operation at cf = 1 [67,68].

	NO_x	VOC	CO	SO_x	PM_{10}	CO_2e
Gas turbine	0.127	0.024	0.167	0.006	0.061	528.8
Gas turbine-advanced	0.045	0.014	0.086	0.004	0.028	460.0
Combined cycle	0.033	0.136	0.009	0.004	0.019	391.8
Combined cycle-advanced	0.029	0.008	0.0025	0.002	0.014	354.8
Biomass	0.034	0.004	0.036	0.009	0.091	0
Steam turbine	0.163	0.026	0.361	0.006	0.008	521.5

3.5. Economic metrics

The objective of the dispatch model developed, as described above, is to find a dispatch schedule that minimizes the total cost

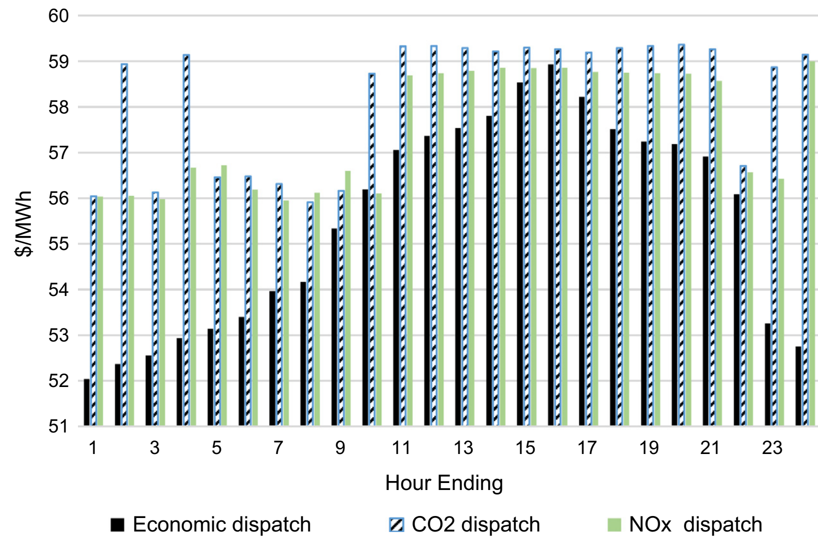

Fig. 7. Average price for in-basin conventional generation, Base Case 2050.

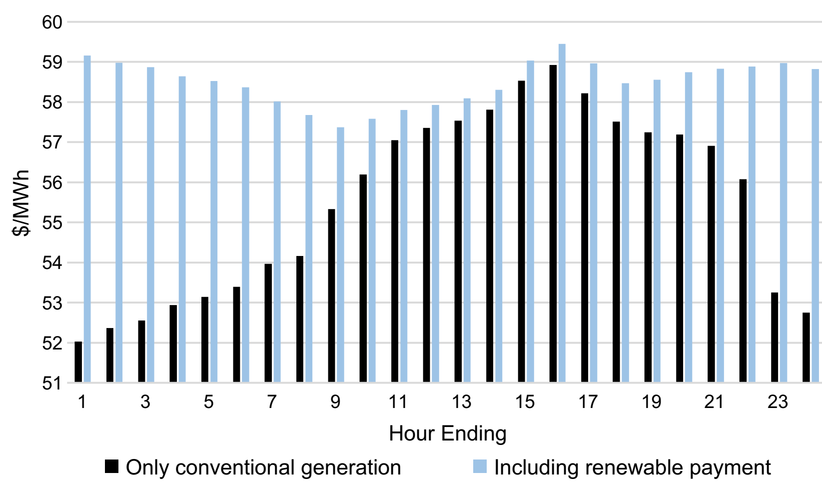

Fig. 8. Average price including payments to renewable resources, Base Case 2050 Economic dispatch.

or environmental impacts of the system. The results of the dispatch model include the total payment of the market operator to the generators. Two methods for compensating generators that are cleared in the market are simulated in this study: (1) pay-as-bid, and (2) market clearing price (MCP). In the first method, each generator gets compensated based upon the bid they had placed, therefore the results are representative of "actual" cost of the system. In the second method, all generators get paid the same \$/MW h according to the MCP. MCP is the price in a market at which the supply equals the demand. All demand customers pay this price, and all supply customers operate at or below this price. In other words, MCP is the price of the last (and the most expensive) generator that is cleared in the market.

The results using pay-as-bid payment method for 2050 base case are shown in Fig. 7 for economic and environmental dispatch strategies. Note that these results also represent the average system cost and include only payments to conventional generation and not to renewable (must-take) generation since none of these scenarios result in curtailment. Therefore, the renewable resources generation profile and associated costs are the same for all three dispatch strategies. The price (including the payment to the renewable resources based on their actual LCOE) is shown in Fig. 8. It is evident that the price at off-peak hours is dominated by the price of wind (a high wind day is shown).

Fig. 7 shows that, as expected, the economic dispatch results in the lowest prices and follows the demand curve showing that, at high demand times, more expensive generators come online to satisfy the demand. The decrease in price after the peak demand hours is slower than the decrease in demand since the expensive generators that come online at peak demand cannot all be turned off at once because of the minimum operation time constraints. Environmental dispatch strategies are slightly more expensive, with the CO_2 dispatch being the most expensive on average mainly because the overall capacity factor of the system is lower. This occurs because in CO_2 dispatch, the number of units that are online is greater compared to NO_x dispatch.

It is interesting to note that, unlike the price of conventional generators which follows the demand curve, the grid price essentially follows the wind profile when including all of the generators (see Fig. 8). At early hours of the day, when wind is available and the less expensive in-basin units are online, the overall production cost is dominated by the price of wind. Under these conditions, the production cost increases compared to in-basin generators because the wind power is more expensive than the online in-basin

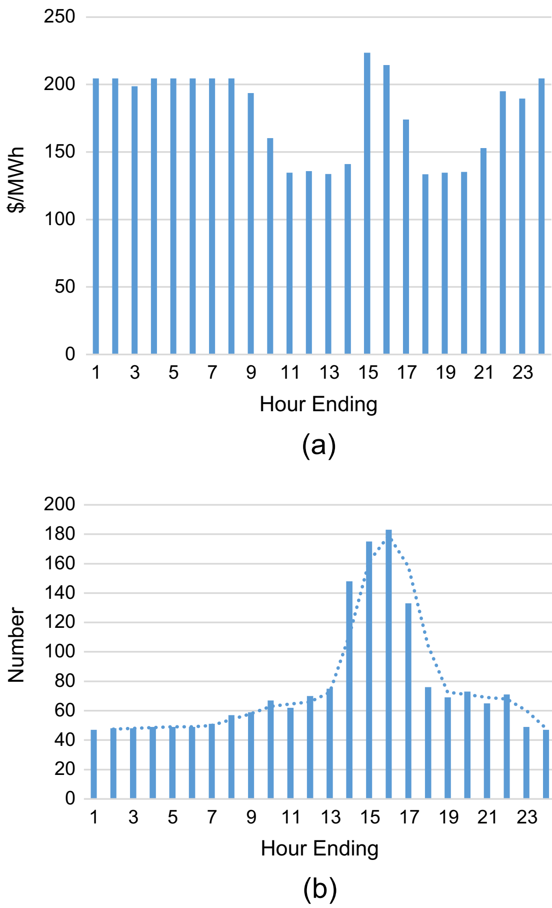

Fig. 9. Base Case 2050 Economic dispatch (a) MCP, and (b) Number of online units.

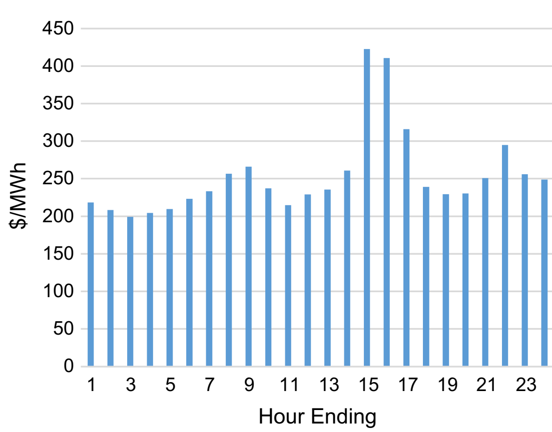

Fig. 10. MCP for Base Case 2050 with economic dispatch and time-dependent bidding.

generators. At peak demand times, the availability of wind energy decreases, and the overall production costs remain virtually unchanged from the case of only considering in-basin generators, and thus the overall price follows the wind profile even at low wind power penetrations such as that included in this base case.

To determine the MCP, the payment a generator should receive is calculated and then divided by the amount of power that each is generating in order to determine the adjusted cost per megawatt hour (MW h) which includes the start-up cost as well. The equation to calculate this adjusted cost is shown in Eq. (11). The

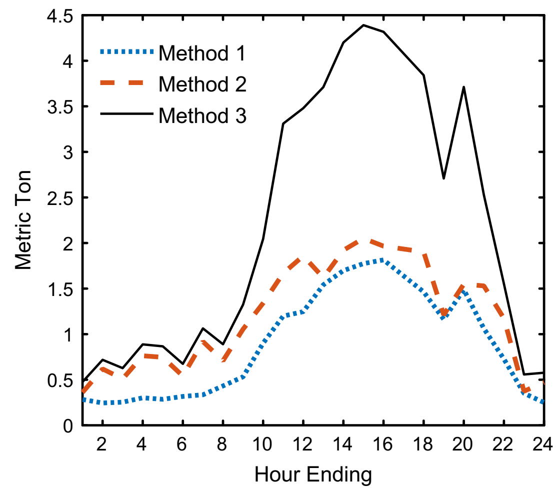

Fig. 11. NO_x emissions from in-basin generating units, Base Case 2050 Economic dispatch.

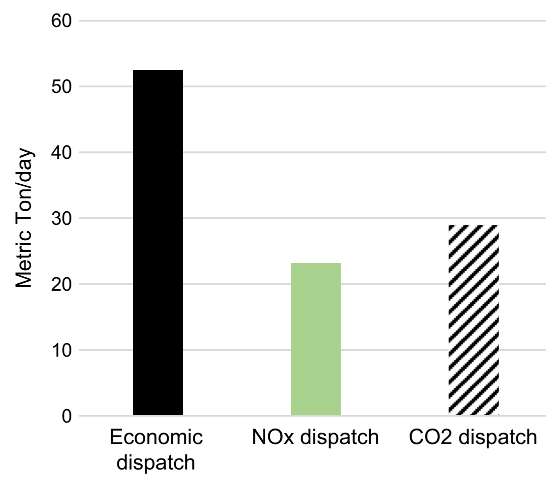

Fig. 12. Average NO_x emission for an average summer day, Base Case 2050.

adjusted cost is calculated for all generators that are cleared in the market. At each time step the generator with the highest adjusted cost determines the MCP.

$$\text{Adjusted Cost} = \frac{\text{Production cost}\left(\frac{\$}{\text{MW h}}\right) * \text{Generation (MW h)} + \text{Start up cost (\$)}}{\text{Generation (MW h)}} \quad (11)$$

The results for the economic dispatch using MCP method for payment are shown in Fig. 9a along with the number of online units (Fig. 9b) to better explain the results.

The MCP is substantially different from the production costs. Note that the start-up costs of wind, solar, and hydro are assumed to be insignificant and, as a result, have little effect on the MCP. The market clearing price is almost uniform throughout the day except for some intervals. From 10 am to 2 pm, although the demand starts increasing, the MCP decreases because very few new generators come online, and those which were online before, operate at higher capacity factors reducing the operation costs and ultimately the MCP. To meet the peak demand, a significant number of generators have to come online to satisfy the demand, increasing the MCP significantly. After 5 pm, the same generators that came online at peak, operate to satisfy the demand but at much higher capacity factors which reduce the MCP due to lower start-up cost and lower production costs. Late at night, the generators operate at low capacity factors, increasing the MCP.

The trend observed in real markets might be different from what is presented so far in this section. In real markets, the price curves depend upon time of day as well as capacity factors because market participants typically adjust their bids based upon the projected demand profile. For example, a peaking unit will most likely submit a higher bid into the market at peak demand times to maximize its revenue, and place a much lower bid during off-peak hours to have the chance of getting cleared in the market. In this research, the cost curves are assumed to be actual operation costs and thus do not vary with time of day. To further demonstrate this point, a case is assessed in which generators' bids in the market follow the demand profile assuming that the bid submitted by a specific generator is never lower than its actual cost of generation. The results for the MCP for this case are shown in Fig. 10.

3.6. Criteria pollutant emissions

The results of the dispatch model are used as inputs to the emissions module (described in the Appendix A) to calculate the hourly emissions from each generator. Emissions from generating units include operating emissions, start-up emissions, and ramping emissions. The operating emissions depend upon the instantaneous capacity factor of the electricity generating unit and increase as the capacity factor is reduced from its ideal value of 1 (part-load emissions). The importance of including part-load, ramping and start-up emissions in the analysis is shown in Fig. 11. In Method 1, average emission factors are used, in Method 2 start-up and ramping emissions are added, and Method 3 includes part-load emissions, start-up emissions, and ramping emissions.

The dispatch model is run for the entire summer for various dispatch strategies, and the daily NO_x emissions for an average summer day are shown in Fig. 12. The emissions calculated include part-load emissions, ramping, and start-up emissions. This figure shows that although NO_x emissions are higher in CO_2 dispatch case compared to NO_x dispatch case, they are still significantly lower than the economic dispatch case. By comparing NO_x emissions from economic and environmental dispatch strategies, it is evident that it is possible to reduce emissions significantly (up to 55%) by just changing the dispatch strategy and without any additional capital investment.

4. Summary and conclusions

In this paper, a spatially and temporally resolved resource dispatch methodology is developed. In addition to a unit commitment algorithm, this methodology includes multiple modules to determine characteristics of electricity and transportation sectors in future scenarios. The methodology is applied to 2050 base case, and economic and environmental implications of various dispatch strategies are assessed. The following are the conclusions of this study:

- A spatially and temporally resolved model is required to correctly capture the electricity market and dispatch of resources. Electricity is different from most other commodities since the storage of electricity is not economic, and electricity is subjected to various physical constraints associated with the generators and the transmission system. Temporal resolution is required to take into account the constraints associated with generators such as ramp rates and minimum operation times. To account for transmission constraints, it is necessary to know the location of generators, requiring spatial resolution. Simplified models can ignore one or more of these important constraints of the system and thereby render results inconsistent with real operations. Furthermore, spatial and temporal resolution is necessary to conduct air quality assessments.
- Better grid management is required in order to take advantage of all available resources.
  In 2050, the electricity demand in the balancing area under study, will be on average 60% higher than 2010. However, using the dispatch model for optimal grid design, it is shown that the installed generation needs to increase by only 25% (ancillary services are treated separately in both cases). This shows that, currently, the resources available are not being used in an optimized fashion. With optimized dispatch and appropriate grid management, future resources will be used to their capacity and moreover, the reliability of the grid will be increased.
- With appropriate planning, congestion in the transmission system can be avoided.
  Planning for transmission infrastructure must occur before new generating units and power plants are put in place. In this research, none of the scenarios studied result in significant increase in transmission system congestion, simply because with each new generator installed, the minimum required transmission capacity was also added to the model, showing the importance of system-wide planning.
- A mix of economic and environmental dispatch portends a successful strategy for reducing emissions while keeping the overall cost of the system at acceptable levels.
  It was shown that it is possible to reduce emissions from the grid significantly by changing the dispatch strategy and without additional investment. While environmental dispatch alone results in lower emissions, the cost of generation is increased. A compromise that takes into account both the cost of generation and the emission factors of generating units by assigning a value (or penalty) for pollutants emitted by generators is suggested by the results. Carbon or other emissions pricing portends a viable option.

Acknowledgments

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Appendix A

A.1. Electricity demand

One of the important constraints of the dispatch model is the balance between demand and supply (Eq. (5)). To make sure that generation procured in the market matches the demand, the electricity demand needs to be included in the model as an input. In order to forecast the future electricity demand, California Energy Commission (CEC) forecasted demands are used and extrapolated up to 2050 [69]. The annual electricity demand growth rates are shown in Table A.1 for various cases studied by the CEC.

The method to calculate and project the electricity load associated with the balancing area under study (the SoCAB) is based on the fact that the electricity consumption per capita has been constant (in some cases even reduced) in the state of California and

Table A.1
Annual growth rate associated with California's electricity demand [69].

	High case	Mid case	Low case
2012–2024	1.56%	1.15%	0.79%

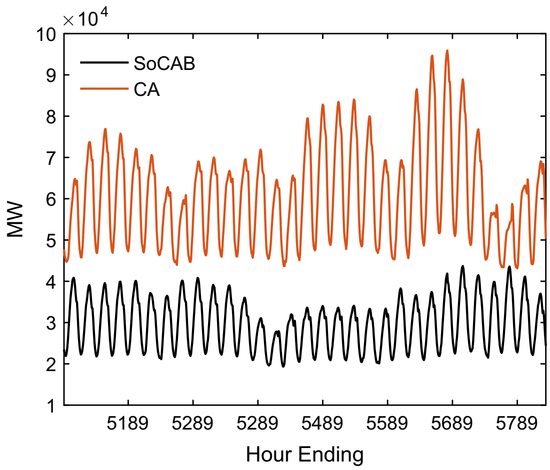

Fig. A.1. Forecasted electricity demand for CA and SoCAB for the month of August in 2050.

is described in detail in Razeghi et al. [44]. In Fig. A.1 the forecasted demand for the state of California is shown for the month of August in 2050, as well as electricity demand of the SoCAB. The demand profile has a time resolution of 5 min and it has been smoothed out using a central moving average to get a more realistic profile.

A.2. Cost module

The objective of a SCUC is to find a schedule that minimizes the social cost of the system which in ideal situations is equal to the operation cost. The operation cost includes production cost and start-up cost. The production cost is defined as:

$$\text{Production cost} = \text{heat rate} \times \text{fuel cost}$$

This approach is very simple but alternative technologies such as wind cannot be compared to conventional generation using this metric. When various technologies with different scales of operation, different investment and operating time periods, are to be compared, Levelized Cost of Energy (LCOE) is used. The LCOE is the cost that, if assigned to every unit of energy produced will equal the total lifecycle cost (TLCC) when discounted back to the base year [70]. In terms of electricity, LCOE is the constant unit cost (\$/MW h) of a payment stream that has the same present value as the total cost of building and operating a generating plant over its life. It is a very useful financial metric in comparing technologies with different operating characteristics.

The LCOE depends on the capital costs, taxes, incentives, operation and maintenance costs, and revenue requirements. Eq. (A.1) shows how the capital recovery factor (CRF) is calculated based on the discount rate (d_r) during the analysis period n which is usually the same as the project life.

$$CRF = \frac{d_r(1+d_r)^n}{(1+d_r)^n - 1} \tag{A.1}$$

If the annual energy generated is assumed to remain constant over time, LCOE can be calculated from Eq. (A.2) in which AE is the annual energy produced by that unit.

$$\text{LCOE} = \frac{\text{TLCC}}{\text{AE}} \times \text{CRF} \tag{A.2}$$

In real-life operations, the annual output of a specific unit decreases each year. When taking this degradation into account the LCOE is calculated from Eq. (A.3). In this equation, l is the project life.

$$\sum_{i=1}^{l} \frac{\text{AE}_i \times \text{LCOE}}{(1+d_r)^i} = \text{TLCC} \tag{A.3}$$

In calculating the LCOE for generating units, the most important factors that must be included are capital cost, fixed O&M cost, variable O&M cost, capacity factor, heat rate, and fuel cost. A simple LCOE (sLCOE) can be calculated from Eq. (A.4) for initial estimate:

$$\text{sLCOE} = \frac{\text{Capital Cost} \times \text{CRF} + \text{Fixed O\&M}}{0.87\ \text{Capacity Factor}} + \text{Fuel Cost} \times \text{Heat Rate} \tag{A.4}$$

A more thorough way to calculate the LCOE is presented in Eq. (A.5).

$$\text{LCOE} = \frac{\text{Capital Cost} \times \text{CRF}}{\text{Capacity} \times \text{Capacity Factor} \times \text{Hours/Year}} + \text{Land Lease Cost} + \text{Levelized O\&M} + \text{Levelized Replacemnt Cost} - \text{Production Tax} \tag{A.5}$$

In this research, it is assumed that the market participants use the LCOE associated with their unit as the bid they submit to the ISO. Thus, the LCOEs associated with each type of technology need to be forecasted. To do this, an extensive literature survey was done to compare projections of capital costs, fixed O&M, variable O&M, unit's lifetime, and other financial metrics that are required to calculate the LCOE. Using these data, the LCOE for each generator type was forecasted. The results for 2050 are shown in Fig. A.2 and are compared to those of 2010. The error bars are used to compare the results of LCOE from this study to those calculated in the literature [68,71–78].

The LCOEs shown in Fig. A.2 are calculated assuming that the generating unit is operating at its expected capacity factor. These capacity factors are shown in Fig. A.3. It must be noted that in the case of a gas turbine, this capacity factor represents the capacity factor of the unit when it is operating and not the annual average capacity factor which is much lower because these units only come online during peak-demand hours. As the capacity factor decreases from the ideal 100%, the heat rate of a thermal unit increases. Therefore, for generating the same amount of electricity, more fuel is required [77,79]. Moreover, the capacity factor affects the annual produced energy and as a result it affects the LCOE. The LCOE for various capacity factors for each type of technology is calculated to determine the cost curve for each generator.

In Fig. A.4, the cost curve projections for 2050 are shown for various technologies. Similar curves are produced for other resources (coal, nuclear, hydro, wind, and solar thermal) as well. These curves are used as the cost curves that generating units submit to the market.

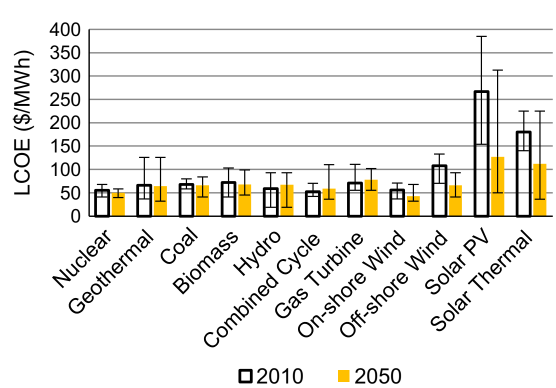

Fig. A.2. Levelized cost of energy for different technologies in 2010 and 2050 projection.

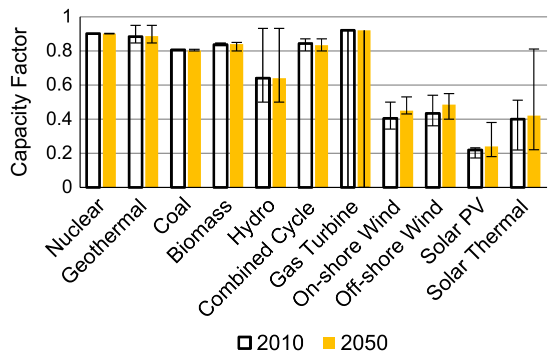

Fig. A.3. Expected capacity factor for different technologies in 2010 and 2050 projection.

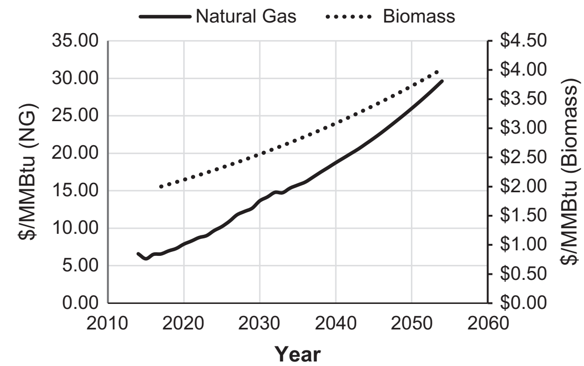

Fig. A.5. Price of natural gas and biomass [77].

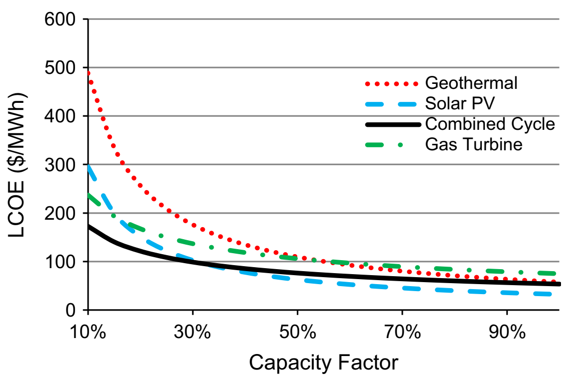

Fig. A.4. Cost curves projections for different types of generators (2050).

Start-up costs are also important especially for combustion (gas) turbines that are being used as peaking units. For combustion turbines and combined cycle units, it is assumed that 2.8 MMBtu (2.95 kJ) of the fuel per MW of capacity is required for each start-up. Using the fuel price projections (Fig. A.5) for natural gas and biomass, the start-up costs for each generator can be calculated.

For generators that provide combined heat and power (CHP) also known as cogeneration (or cogen), the LCOE is adjusted to reflect that some of the heat output is being used. EPA's eGRID database includes the ratio of electricity to heat for individual CHP units. From this ratio, the amount of fuel that needs to be burnt in a boiler with 75% efficiency to produce the same amount of heat, is calculated. The cost of this amount of fuel is calculated and deducted from the fuel cost used in the LCOE calculations.

A.3. Imports

In Fig. A.6, the sources of California's electricity are presented for August 2010. It is evident that the imports, more or less, follow the same profile as the demand. This is shown in Fig. A.7 where the California's electricity demand and imports are shown for three consecutive days in August 2010. For the state of California, it is assumed that the capacity for imports increases with the demand. This results in 60% increase in imports capacity from 2010 to 2050. It must be mentioned that this requires extensive upgrade of the transmission system especially since the import lines at southwest and southern California, and Humboldt region in the northwest of the state, are historically major areas that experience congestion.

In the current study, "imports" only refer to non-renewable imports. Imports are settled ahead of the real-time dispatch. For the following reasons, it is assumed that the imports vary linearly with the demand until the capacity is reached, and transmission capacity to outside SoCAB remains unchanged:

- Obtaining licenses required for building transmission lines takes a long time,

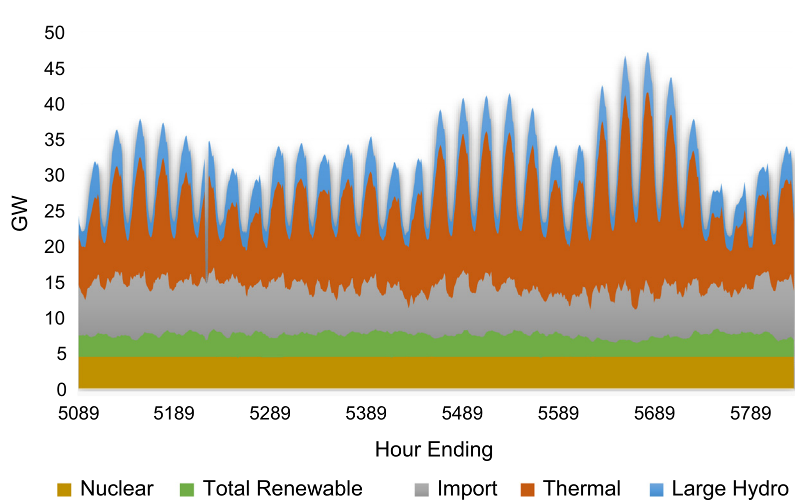

Fig. A.6. Electricity generation in California by resource type, August 2010 [80].

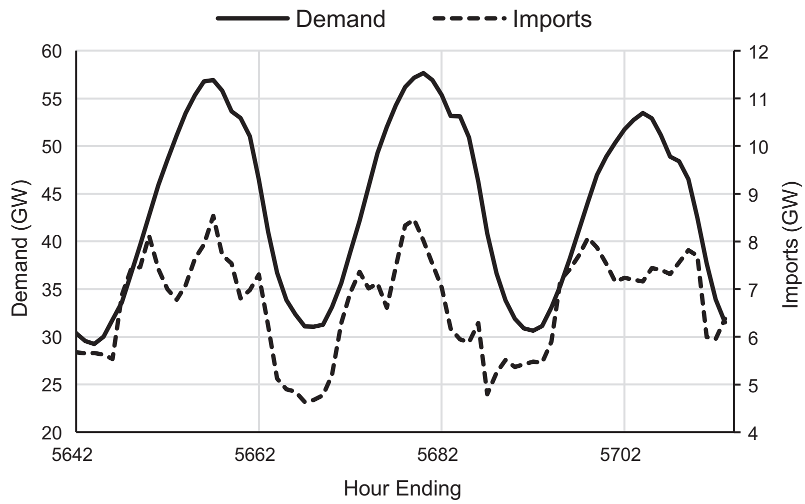

Fig. A.7. CA's demand and imports during August 2010 [81].

- Environmental concerns, and
- Assessing an air quality episode in the basin requires a high generation inside the basin. (This capacity is determined using historical data as mentioned in Razeghi et al. [44].)

During off-peak hours, it is assumed that the imports are provided by load-following units with an average of expected capacity factor (Fig. A.3), and during peak hours, the extra import is assumed to be provided by peaking (and more expensive) units. In all cases, a 5% transmission loss in assumed for the imports [82]. When the amount of imports is less than 10% of the total import capacity, it is assumed that the generators providing the imports are operating at minimum allowable capacity factor, resulting in increase in the price of imports per MW h.

A.4. Generating unit characteristics

This module combines all the data gathered for individual generators into an organized database ready to be used in the optimization process. For each generating unit, this module includes the name, nameplate capacity, type, fuel, minimum and maximum capacity factors, and ramp rates associated with that unit. This module also includes the location of the generators (latitude, longitude) since the dispatch model is both spatially and temporarily resolved. Moreover, major transmission infrastructure components between generators are added to take into account the transmission constraints.

In this module, the age of a generating unit is calculated based on the year it first came online. Units older than 40 years (or less, based on the type of generator), are automatically retired and replaced with new generators of the same type and nameplate capacity but with improved operating characteristic (lower heat rate and emission factors).

A.5. Emissions module

This module includes the emission factors for individual generators for criteria pollutants such as NO_x, SO_x, and CO, and also greenhouse gas emissions. The annual average emission factors are derived from EPA's eGRID2012 [83] for each generator. For generators missing from the database or the newly installed units, generic values presented in Table 1 of the paper are used.

Emission factors also depend on the capacity factor. The adjustments to emissions as a function of capacity factor (power output) are done mainly using the results of the Western Wind and Solar Integration Study (WWSIS) [79]. Ramping also affects the amount of pollutants that a generator emits. The ramping and start-up penalties taken into account in this study are shown in Tables A.2 and A.3.

Table A.2
Start-up emissions penalty (hours of equivalent full-load operation) [79].

	CO_2	NO_x
Combined cycle	0.3	6.1
Gas turbine	0.4	1.8
Steam turbine	0.9	0

Table A.3
Start-up emissions penalty (hours of equivalent full-load operation per ramp) [79].

	CO_2	NO_x
Combined cycle	0.01	0.08
Gas turbine	0.01	0.01
Steam turbine	0.01	0.08

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