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RESEARCH

Modeling Externality Costs and Intermittent Technologies in Generation Expansion Planning Models

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Abstract

The objective of the generation expansion master plan is to determine the necessary capacity and types of power plants for accommodating future load growth. The current software utilized for guiding generation planning primarily relies on the load duration curve (LDC) paradigm, which overlooks the chronological order of events. Additionally, the optimization process does not consider the environmental costs associated with power plants, as these costs are calculated separately once the optimal plan is finalized. This research study focuses on incorporating wind power plant modeling into generation planning models based on the LDC approach. Furthermore, the article emphasizes the integration of environmental costs into the optimization process, enabling researchers and policymakers to make more informed decisions regarding the growth of electricity and energy resources. The paper employs the widely used and reputable Wien Automatic System Planning (WASP) Package, version WASP-IV planning tool to identify the most optimal capacity expansion plans for Oman's Main Interconnected Network (MIS) as a specific case study. In this tool, the load is represented using the LDC approach, while the built-in optimization feature does not account for environmental costs. To overcome this limitation, environmental costs are added to fuel costs so that they become part of the optimization function. The results show that when the opportunity cost of gas and environmental costs are considered in the optimization process, a significant number of wind generators are selected. To guarantee that non-dispatchable renewable technologies are fairly considered by decision-makers, the study suggests including opportunity costs as input data in generation planning models.

Keywords Generation planning · Wind plant modeling · Energy resource planning · Environmental externality cost · Loss-of-load probability · Internalizing externalities

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1 Introduction

In integrated resource planning (IRP), a comprehensive analysis is conducted to assess both energy savings and energy generation options concurrently. The aim is to identify the most suitable combination of resources that achieve the lowest overall cost while also considering environmental and health factors [1, 2]. To illustrate this process, Fig. 1 presents a schematic diagram adapted and expanded from [3]. The diagram highlights various elements, including supply- and demand-side choices, the involvement of prosumers and storage, measures to reduce transmission and distribution (T&D) system losses, and the influence of electricity tariff rates (demand response). These factors collectively contribute to addressing the need for new resources within the IRP framework.

The advent of smart grid technology has empowered users to generate their own electricity, particularly through the installation of renewable energy sources on their premises, and even sell excess energy back to the interconnected electricity grid. Storage devices play a crucial role in load balancing as they store surplus energy and release it when needed, thereby enhancing the overall efficiency and reliability of the system. This modern grid structure is better equipped to accommodate a significant penetration of renewable energy sources [4].

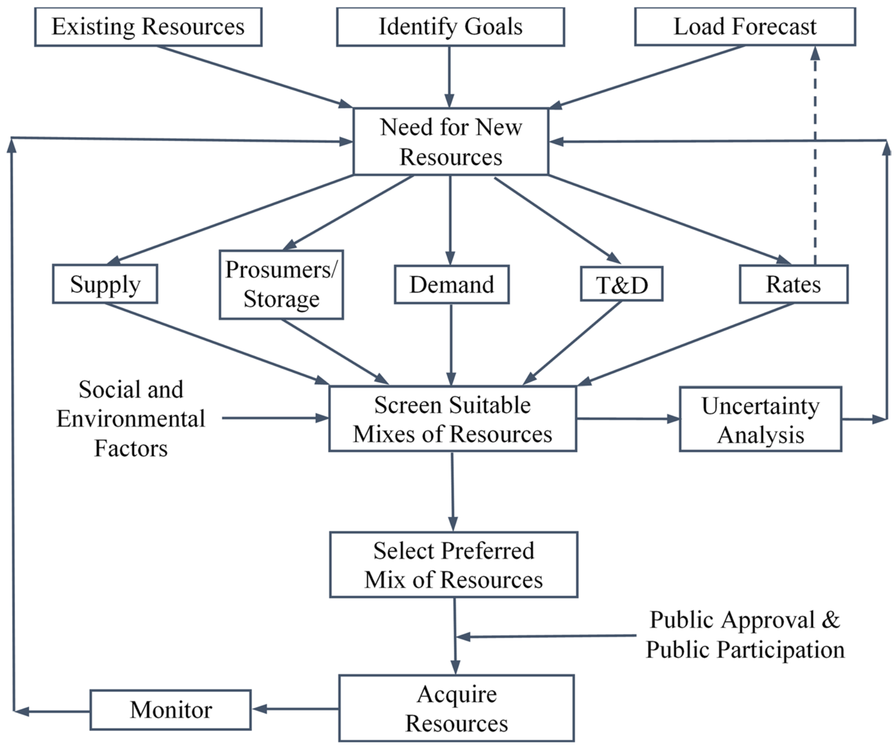

Fig. 1 Integrated resource planning process adapted and expanded from [3]

The selection of an appropriate resource mix considers social and environmental considerations, and uncertainty analysis is employed to determine the most desirable and cost-effective combination of resources. Public participation and approval are essential before acquiring resources, and in case of public dissent, the planning process is revisited.

After adjusting the load forecast to incorporate the aforementioned options (conservation, T&D, rates, etc.), the supply-side options are typically devised. These options are identified through the generation expansion planning (GEP) exercise. The primary objective of GEP is to determine the optimal supply-side resource plan that aligns with the modified load forecast over a specified study period. Several factors are taken into consideration during this process, including achieving low-cost generation (considering both capital and operating costs), ensuring acceptable system reliability, maintaining operational system flexibility, promoting fuel diversity and security, adhering to environmental regulations, and safeguarding the financial health of the utility. The selected plan should ascertain the required capacity to accommodate load growth, determine the timing for incorporating this additional capacity, and ultimately define the types of power plants that will fulfill the demand. The selection of suitable locations for new power plants entails a comprehensive analysis through project planning, encompassing numerous factors such as the presence of transmission corridors, demand centers, fuel and water availability, labor resources, overall infrastructure, and environmental considerations.

Reference [5] provides a comprehensive and updated review of the latest approaches that address current issues concerning the interaction between GEP and other domains. These domains include transmission expansion planning, natural gas systems, short-term operation of power markets, electric vehicles, demand-side management, storage, risk-based decision-making, and applied energy policy, including supply security. GEP is commonly supported by professional software such as GENERATOR X (UPLAN) [6], EGEAS [7], PLEXOS [8], and WASP [9], among others. A strategic evaluation of electricity system models, including WASP, is presented in reference [10]. Additionally, a comprehensive study on expansion planning models and energy policy analysis tools can be found in reference [11].

WASP, one of the oldest and widely used tools for long-term capacity expansion planning, is extensively discussed. Originally developed for the International Atomic Energy Agency (IAEA), WASP has been employed in more than 100 nations, including IAEA members and associate governments, for various academic and development projects related to generation capacity planning. It is recognized as a conventional technique for long-term GEP by institutions like the World Bank and other funding organizations. WASP has a strong track record of accuracy and has been instrumental in validating market models [10].

WASP has demonstrated its versatility and enhanced capabilities by integrating with other models [12, 13]. The authors of reference [12] expanded the functionality of WASP to transform it into a multicriteria planning model, addressing growing concerns related to global warming and nuclear hazards. Similarly, in reference [13], the WASP-IV model was utilized to assess the impact of different scenarios on three key variables: generation cost, environmental cost, and energy dependency. To aid

Israeli decision-makers, supplementary specialized software was incorporated with the WASP-IV model, specifically designed to handle multiple pollutants.

Moreover, WASP has been employed to tackle non-traditional or unique challenges in power system expansion [14, 15]. In the study outlined in reference [14], the WASP-IV tool was utilized to quantify carbon dioxide emissions and assess total energy changes in an electric vehicle rollout project in Ireland. In a recent investigation [15], several methodologies were proposed in three countries (Mauritius, Kosovo, and Montenegro) to overcome specific modeling obstacles encountered in WASP for planning power system expansion. These obstacles encompassed power exports and imports, seasonal dual-fuel plants, IPP contracts, and more.

The utilization of WASP has encompassed the incorporation of environmental expenses within the optimization procedure [16, 17]. In analyzing the expansion of Mexico's electrical generation, the researchers in these studies aimed to minimize both internal and external costs throughout the study period. The external cost was considered as part of the variable component of the operation and maintenance (O&M) cost, effectively contributing to the objective function of WASP. Although this approach of integrating external costs into the objective function appears satisfactory, there is a caveat regarding the reliability of the assessment outcomes. This paper will outline a more precise methodology for integrating externalities into the optimization process.

Due to the importance of WASP and its wide range of use, this paper describes how to model intermittent technologies and environmental costs correctly within the WASP optimization process so that renewable technologies are not treated unfairly [18]. Although WASP is selected as the representative tool, the approach outlined in this paper can be implemented in any optimization model utilizing the load duration curve technique. To showcase the influence of integrating environmental costs in the selection of the generation mix, the Main Interconnected System (MIS) of the Omani power sector is utilized as a case study.

This paper is divided as follows: Section 2 provides a detailed description of the WASP model. Section 3 describes how non-dispatchable technologies can be modeled in WASP, and Section 4 discusses how environmental costs can be included in the WASP optimization process. Section 5 provides generation and load data for the MIS of Oman. Section 6 is about results and discussion, and Section 7 ends the paper with conclusions and policy implications.

2 WASP Model

WASP utilizes various essential inputs, including load data and data pertaining to existing and potential power facilities. The modeling process involves capturing the peak load and energy demand for each period (up to 12 in a year) across multiple years (up to 30), along with their corresponding normalized inverted load duration curves (LDC). The inverted LDC points can be developed based on actual hourly load data from some previous years. The shape of an inverted LDC can also be provided through the coefficients of a fifth-degree polynomial. For existing thermal and nuclear plants in the system, the models incorporate factors such as maximum and minimum capacities, minimum capacity heat rate, incremental heat rate, variable fuel cost, fixed and variable components of O&M costs, scheduled maintenance days, forced outage rate, and percentage spinning reserve.

Expansion candidate plants, including run-of-river, daily peaking, weekly peaking, and seasonal storage projects, are modeled by considering parameters such as installed capacity, reservoir energy storage capacity, inflow energy available per period, and fixed O&M expenses for each current plant. Additionally, information on capital investment costs, construction time, and plant lifespan is required for potential expansion projects. Hydroelectric power plants are assumed to be completely reliable. To account for the stochastic nature of hydrology, hydrological conditions (up to five) are incorporated, each described by its probability of occurrence. For each hydroelectric project, the available capacity and inflow energy are provided for each specific hydrological condition.

Given the provided constraints, WASP is capable of identifying a least-cost generation plan for the next 30 years, aiming to optimize the total costs. The optimal solution is determined based on the lowest discounted total costs. The cost function employed by WASP, as described in [19], is as follows:

$$z_j = \sum_{t=1}^{T} (\overline{\chi_{j,t}} - \overline{\sigma_{j,t}} + \overline{\mu_{j,t}} + \overline{\varphi_{j,t}} + \overline{\upsilon_{j,t}}) \tag{1}$$

where:

z_j is the objective function to be minimized among all j (plans). WASP uses dynamic programming to find the least-cost plan by searching all the combinations of plants (existing and candidate) that can meet the demand for each period/year with the specified reliability criteria.

χ is the capital investment costs (equipment, site installation costs).

σ is the investment costs' salvage value.

μ is the costs of operation and maintenance.

φ is the fuel costs.

υ is the penalty cost related to the energy that is not supplied because of capacity shortage.

t is the time in years (1, 2, …, T).

T is the total number of years in the study period.

All the costs, including salvage value, have to be discounted by a specified discount rate to a base year of the study represented by the bar above the symbols in Eq. (1).

The following relationship must be satisfied:

$$\left[\Gamma_t\right] = \left[\Gamma_{t-1}\right] + \left[\Upsilon_t\right] - \left[\Psi_t\right] + \left[\Omega_t\right] \quad (2)$$

where:

$[\Gamma_t]$ is a vector for an expansion plan, representing the number of all generating units in operation in year *t*.

$\left[\Upsilon_t\right]$ is a vector of committed additions of units in year *t*.

$\left[\Psi_t\right]$ is a vector of committed retirements of units in year *t*.

$\left[\Omega_t\right]$ is a vector of candidate-generating units added to the system in year *t*.

$[\Upsilon_t]$ and $\left[\Psi_t\right]$ are input known data, whereas $\left[\Omega_t\right]$ is the unknown system configuration variable vector to be determined.

Every acceptable configuration should meet the following constraints:

$$(1 + \alpha_t)D_t \geq C(\Gamma_t) \geq \left(1 + \beta_t\right)D_t \quad (3)$$

Equation (3) specifies that the system's installed capacity $C(\Gamma_t)$ of year *t* must be between the given maximum and minimum reserve margins, α_t and β_t respectively, above the peak demand D_t of the year.

The Loss-of-Load Probability (LOLP) index is used by WASP to assess the system configuration's reliability. For each period of the year, this index is calculated in WASP, with the average yearly LOLP equal to the total of the period LOLPs divided by the number of periods.

If LOLP (Γ_t) is the annual LOLP, then any acceptable configuration must meet the pre-defined maximum limit of LOLP as in Eq. (4).

$$LOLP(\Gamma_t) \leq L_t \quad (4)$$

where L_t is the limiting value given as input data by the user.

A more relevant index of loss-of-load expectation (LOLE) can be constructed from LOLP, which is expressed in days per year. In Oman, the LOLE planning guideline is one day each year [20].

WASP-IV, the most recent version, adds new features such as environmental emissions, fuel utilization, and energy limits. Reference [21] contains a more detailed model. In terms of including the externality costs of generation technologies and representing intermittent technologies such as wind or solar energy, WASP has modeling disadvantages. As an important software, it is therefore necessary to discover a means to satisfactorily solve these concerns inside WASP so that decision-makers can use it without jeopardizing their choice of renewable technology. The next sections explore how WASP-IV can address the aforementioned issues.

3 Representation of Non-dispatchable Technologies in WASP

As mentioned earlier, WASP utilizes a load model based on the LDC, which provides information about the percentage of time the load equals or exceeds a specific MW value. The LDC model offers a concise representation of load data, similar to the actual time-varying load curve, providing insights into energy requirements. However, constructing an LDC involves organizing the load values in descending order, resulting in the loss of chronological information. This load model poses simulation challenges for non-dispatchable systems like wind, solar, and other time-dependent technologies that rely on the availability of wind or sunlight.

WASP offers several approaches to model non-dispatchable technologies, each with its own approximations and limitations. In the following discussion, we focus on the presentation of wind turbine models that can be employed in WASP. For the purposes of this discussion, the term “wind plant” refers to either a single wind turbine or a wind park. In WASP, various techniques are available to simulate wind turbines [22]:

1. *Wind plant simulation as a thermal plant with a high forced outage rate:* The simulation of a wind plant in WASP can be accomplished by treating it as a thermal unit characterized by a high failure rate and a fuel cost of zero. In this model, maximum and average incremental heat rates can be artificially assigned since they are only utilized for calculating the energy cost. Given the absence of fuel costs, the energy cost will be zero regardless of the heat rates employed. To account for the intermittent nature of wind power, the wind plant’s forced outage rate (FOR) should be increased to align with its low capacity factor. Due to the economic loading sequence, the wind plant, with its zero fuel costs, will be dispatched as a baseload thermal unit. This approach assumes that the plant operates at full capacity when available and at zero capacity during periods of forced outage. Incorporating wind plants into the optimization process in this manner is preferable, as it ensures a more realistic simulation and treats them as baseload plants. The higher forced outage rate also highlights the necessity for additional backup resources to meet reliability criteria, as is the case with intermittent technologies.
2. *Wind plant simulation as an adjusted down thermal capacity:* The simulation of a wind plant in WASP can be achieved by modeling it as a derated thermal unit with zero fuel costs. The derated thermal capacity is determined based on the wind plant’s capacity factor. To account for potential wind plant failures, a nominal FOR of around 2–4% can be assigned. When specifying the unit’s capital cost per kilowatt (kW) for the simulation, caution must be exercised.

In WASP, the unit's total capital cost is calculated by multiplying the capital cost per kilowatt by the maximum generating capacity in kilowatts. Since the wind-modeled thermal unit's maximum capacity is the derated capacity of the wind plant, the capital cost per kilowatt needs to be adjusted accordingly. For instance, suppose a 100 MW wind farm has a 30% average capacity factor when modeled as a thermal unit. The modeler should input the thermal unit's maximum capacity as 30 MW in the WASP data, but the capital cost per kilowatt must be modified to reflect the actual 100 MW capacity of the wind farm. For example, if the wind farm cost is $1900/kW, the total capacity cost of the 100 MW wind farm would be $190 million. This cost should be accounted for in the wind-modeled thermal unit's unit cost, resulting in a value of $6333.3/kW.

It is important to note that this method of simulating wind plants in WASP, with derated capacity and adjusted capital cost per kilowatt, is not preferable. The increased cost per kilowatt due to the derating factor may lead to wind plants being disregarded in the least-cost optimization process due to the higher capital cost associated with the derated capacity.

3. *Wind plant simulation with adjusted load:* A wind power plant can be represented in WASP as a negative power demand. To incorporate the estimated energy generation from the wind plant, it is subtracted from the original sequential load curve, resulting in the formation of a normalized LDC. It is important to note that the load model in WASP is based on the normalized LDC and peak demands of future years, providing a concise representation of load data for upcoming years.

   To account for the presence of a wind power project starting service in a specific year, the peak load requirement for future years is adjusted. This adjustment involves subtracting the maximum available capacity of the wind power plant at the expected time of peak demand from the peak load requirement. The simulation is then performed without explicitly considering wind turbines, and the discounted capital costs of wind turbines can be added later if necessary, within the optimal solution.

   In this modeling technique, wind power does not directly compete with other technologies and is not included in the objective function of the optimization process. As a result, this approach is not the most preferable way to simulate wind plants since they are not actively considered in the optimization process. However, if wind plants are treated as committed plants, they can be simulated in WASP by introducing a negative load.

4. *Wind plant representation as a hydroelectric power plant:* A wind power project can be simulated in WASP by representing it as a run-of-river hydroelectric power station, where the installed capacity matches the rated capacity of the wind power plant. In the case of simulating wind plants as hydro, WASP requires inflow energy data for hydroelectric plants. Consequently, if a wind plant is treated as hydro, the inflow energy in gigawatt-hours (GWh) represents the energy that the wind plant can generate at the specific site during a given period of the LDC.

   In WASP, there are two types of hydroelectric plants and up to 30 projects can be included for each type. However, it is important to note that WASP does not provide an option for incorporating variable O&M expenses for these two hydro categories. Instead, fixed O&M expenses can be specified for each type. The fixed O&M cost remains consistent for projects within each category, regardless of whether they belong to the existing system or are considered expansion candidates.

From an analytical perspective, modeling wind plants as run-of-river hydro plants, with derated power as baseload plants, is akin to the approach mentioned earlier for modeling derated thermal capacity. However, it should be noted that this method of simulating wind plants as hydro in WASP is not the most preferable approach due to the limitations associated with the representation of hydro in WASP, as mentioned previously.

In the present analysis, a wind power plant is simulated as a high-FOR thermal plant to assess the economic feasibility of wind power plants in light of the preceding discussion. This approach of modeling wind plants in WASP is considered more accurate because the higher forced failure rate effectively compels the WASP model to select a greater number of plants within the network to ensure reliability requirements are met. In practical systems, it becomes crucial to incorporate a significant backup supply to compensate for periods of low or absent wind cycles.

4 Representation of Environmental Costs in WASP

Despite the inclusion of environmental pollution limits for two chemical pollutants (SO_2 and NO_x) in the latest version of WASP, the optimization process does not incorporate the external costs associated with power plant technologies. Numerous studies have been conducted where WASP was utilized to identify the least-cost plan, followed by separate calculations of externalities using expected energy output data [12, 13, 23–25]. Such studies, which fail to integrate externalities into the optimization function, result in an unfair treatment of cleaner technologies and a preference for conventional polluting technologies.

Considering the widespread utilization of WASP by developing countries and its role as a benchmark for institutions like the World Bank and other lending organizations, projects that deviate from the least-cost plan may not be granted funding. This further perpetuates the problem by discouraging the adoption of cleaner technologies.

However, we have come across two studies conducted by the same authors previously mentioned [16, 17] where the environmental costs were incorporated into the variable component of the O&M cost, thus becoming part of the objective function. Although this approach appears to be a straightforward method to include environmental costs in the objective function, it is not the appropriate approach for WASP. Environmental costs are typically specified in terms of thermal energy, such as $/MMBtu, based on the type of fuel, rather than in $/MWh or ¢/kWh.

When environmental costs are included in O&M costs expressed as $/MWh, it implies that the efficiency of converting thermal energy to electrical energy is already accounted for. However, in these papers, we discovered that both simple open-cycle gas turbines (GTs) and combined-cycle gas turbines (CCGTs) were assigned the same environmental cost of 2.59 euro cents/kWh. This is evidently incorrect since, despite both technologies using natural gas as fuel, CCGT is significantly more efficient and should have a lower environmental cost per kilowatt-hour (kWh) compared to GT.

WASP's unit fuel cost data can easily incorporate the externalities associated with various pollutants emitted by different types of fuels. However, it is crucial to maintain consistency in handling the conversion units. The heat rate specific to each generation plant type plays a vital role in determining the amount of pollution generated, whether it be from an open-cycle gas turbine or a combined-cycle power plant. To provide further clarity, an example is presented below using English (Imperial) units.

Example:

1. Fuel cost of gas = 3 \$/MMBtu
2. CO_2 emission factor of gas turbine = 117 lb/MMBtu [26]
3. Externality cost of CO_2 = 0.01134 \$/lb (corresponding to 25 \$/metric ton)
4. Externality cost of CO_2 in terms of heat unit = 117 lb/MMBtu × 0.01134 \$/lb = 1.3268 \$/MMBtu
5. Total cost (fuel + externality) = 4.3268 \$/MMBtu
6. Fuel cost input for WASP corresponding to 4.3268 \$/MMBtu = 1716 ¢/(million kcal)

It is conceivable that the emission factor data for various pollutants, such as in pounds per megawatt-hour (lb/MWh), is available for a specific technology like a gas turbine. This implies that the efficiency of the gas turbine has already been factored into the estimation of the emission factors. In such cases, the emission factors should first be converted to pounds per million British thermal units (lb/MMBtu) for that particular fuel, considering the heat rate of the gas turbine. Subsequently, the conversion process outlined earlier can be applied to include these factors in the unit fuel input cost.

5 Planning Data

5.1 Generation Data

The study period for generation planning spanned from 2017 to 2041. The Main Interconnected System (MIS) comprises multiple interconnected power plants fueled by natural gas, consisting of various producing units such as gas turbines and combined-cycle units of different capacities. Transmission lines with voltages of 132 kV and 220 kV interconnect these power plants. In 2017, the combined capacity of these plants amounted to approximately 7200 MW. The majority of generation data were obtained from [20], with typical values used where specific data were not available. The cost and heat rate data for existing plants can be found in Table 1. The study also considers data from committed units that are expected to be incorporated into the system within the initial years of the study. These committed

Table 1 Existing power plant parameters

Name	No. of sets	Min. load[a] (MW)	Capacity (MW)	Heat rate at minimum (kcal/kWh)	Avg. Incr.[b] heat rate (kcal/kWh)	SPR[c] %	FOR[d] %	Days Sched Maint[e]	O&M fix ($/kW-month)	O&M Var ($/MWh)
ALMA	5	36.8	92	2580	2580	0	2	34	1.63	0.77
GHRU	4	43.2	96	2579	2579	0	5	37	2.07	1.15
GW18	4	7.65	18	4012	3153	9	8.8	27	3.4	0.17
GCC1	1	27.2	68	3287	2428	9	8.3	27	10.37	0.67
GCC2	1	26.8	67	3287	2428	9	8.3	27	10.37	0.67
GHMG	4	10.8	27	3639	2780	9	4	23	5.33	1.4
WJGA	10	12.4	31	3657	2798	9	5	31	2.76	0.16
RR83	6	41.5	83	3636	2777	9	5	37	1.73	2.14
BRK1	1	230.55	435	3389	2530	9	3	27	9.08	0.14
BRK2	1	364.64	688	3099	2240	9	3.2	27	7.07	1.1
BRK3	1	399.62	754	2747	1888	9	3	27	20.05	0.98
SHR1	1	316.41	597	3071	2212	9	3	27	5.84	1.2
SHR2	1	399.62	754	2747	1888	9	3	27	20.05	0.98
SURa	1	601.02	1134	2716	1857	9	3.2	27	13.01	1.96
SURb	1	458.98	866	2794	1935	9	3	27	13.01	1.1

[a]Min. load (MW) is the minimum load required for stable operation of plant

[b]Avg. Incr. heat rate is the average incremental heat rate

[c]SPR is the spinning reserve

[d]FOR is the forced outage rate

[e]Days Sched Maint are the scheduled maintenance days for each year

Table 2 Committed power plant parameters

Name	Addition year	Min. load (MW)	Capacity (MW)	Heat Rate at minimum (kcal/kWh)	Avg. Incr. heat rate (kcal/kWh)	SPR %	FOR %	Days Sched Maint	O&M fix ($/kW-month)	O&M Var ($/MWh)
IBRa	2018	304.25	725	2765	1906	9	3	27	5.84	0.96
IBRb	2018	304.25	725	2765	1906	9	3	27	5.84	0.96
SO3a	2019	450.5	850	2740	1881	9	3	27	13.01	1.1
SO3b	2019	450.5	850	2740	1881	9	3	27	13.01	1.1

Table 3 Candidate power plant parameters

Name	Min. load (MW)	Capacity (MW)	Heat rate at min. (kcal/kWh)	Avg. Incr. heat rate (kcal/kWh)	SPR %	FOR %	Days Sched Maint	O&M fix ($/kW-month)	O&M Var ($/MWh)	Capital cost ($/kW)	Life-time (years)	Construction time (years)
OCGT	112.24	280.6	3013	2154	9	3	27	1.3	2.4	548	25	3
CCG1	222.28	555.7	2295	1436	9	2.5	27	1.3	2	709	30	3
CCG2	175.32	438.3	2295	1436	9	2.5	27	1.3	2	743	30	3
WIND	50	50	–	–	–	73	10	1.46	–	1900	25	1.5

units are detailed in Table 2. Furthermore, candidate units are employed for the system's expansion, selected based on economic and technical suitability. Four types of candidate units are utilized for expanding the generating system: an open-cycle gas turbine (280.6 MW), two types of combined-cycle gas turbines (555.7 MW and 438.3 MW), and a 50 MW wind plant. Table 3 presents the data for these candidate power plants. The wind plant is modeled with zero fuel costs and a high FOR derived from the capacity factor, as mentioned earlier. The FOR is based on Sur's wind conditions [27], since this city is the most efficient area that is directly interconnected to the MIS. The FOR of the wind plant is calculated using the following equation:

$$\text{FOR} = 1 - \text{capacity factor} \tag{5}$$

where:

$$\text{Capacity factor} = \frac{\text{expected annual energy produced (MWh)}}{\text{rated capacity (MW)} \times 8760\ \text{h}} \tag{6}$$

Based on the information provided in [27], a wind farm with a capacity of 20 MW is estimated to produce an annual energy output of 47,387 MWh. This corresponds to a capacity factor of 0.27. Consequently, the FOR for this wind farm is calculated to be 73%. The same FOR value is applied to a wind candidate plant with a capacity of 50 MW. The cost data for wind plants is sourced from [26].

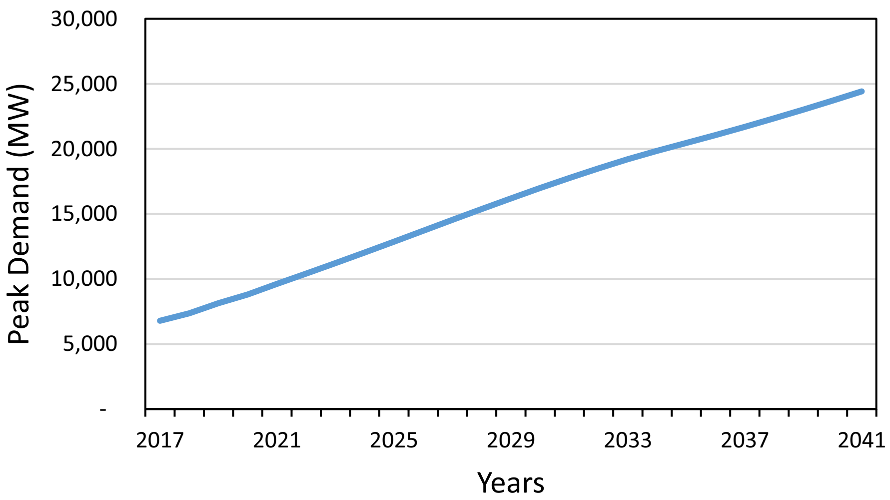

Fig. 2 Annual peak demand forecast

Table 4 Emission factors of gas-fired and combined-cycle plants [23]

Type	CO_2 (kg/MWh)	SO_2 (kg/MWh)	NO_x (kg/MWh)	Particulates (kg/MWh)
Gas-fired	550	0.0998	1.343	0.0635
Combined-cycle	367	0.0665	0.895	0.0423

Table 5 Externality costs of different pollutants [23]

Pollutants	Externality costs in \$/kg (using lower values)
CO_2	0.025
SO_2	7
NO_x	5.5
Particulates	33

5.2 Load Data

Normalized LDCs for the winter and summer seasons are constructed using the annual chronological hourly load curve for the year 2015, as mentioned in [28]. The projected peak load forecast from 2017 to 2041 is illustrated in Fig. 2.

5.3 Economic Data

The study used an 8% discount rate and the cost of unserved energy of 3.2 \$/kWh.

5.4 Externality Costs

Gas-fired and combined-cycle power plants emit various pollutants, including CO_2, SO_2, NO_x, and particulates, which have significant environmental impacts. The emission factors for these pollutants in terms of kilograms per megawatt-hour (kg/MWh) of energy produced can be found in Table 4, as provided in [23]. Furthermore, Table 5 presents the associated externality costs of these pollutants considered in the study [23].

6 Results and Discussion

Table 6 provides a summary of the optimal plans for four different cases considered in the study, spanning a period of 25 years. The first column of the table represents the four cases, while the subsequent five columns present the number of units and the total capacity added to the system for each type of plant during the study period.

Table 6 Summary of results

Cases	Description	Capacity added in the system					Obj. Fn B$	Avg. LOLE days/yr
		Number of units added				Total Cap. MW		
		OCGT	CCG1	CCG2	WIND			
A	Base case, gas cost $3/MMBtu, no EC[a]	6	28	4	0	18996.4	37.68	0.59
B	Gas cost $3/MMBtu with EC	11	26	3	3	18,999.7	52.06	0.63
C	High gas cost $9/MMBtu, no EC	14	23	2	48	19,986.1	45.96	0.93
D	Both high gas cost and with EC	13	14	8	178	23,834	57.95	0.91

[a]Environmental cost

The total cost of the objective function and the average loss-of-load expectation (LOLE) over 25 years are highlighted in the last two columns.

In case A, which serves as the reference, both existing and potential plants utilize a subsidized natural gas supply rate of \$3/MMBtu as the input fuel cost. Environmental costs are not taken into account. Notably, the results reveal that no wind plants are selected.

In case B, environmental expenses associated with various pollutants are incorporated into the fuel cost calculation. As a result, three wind farms are chosen, and the objective function cost significantly increases due to higher environmental costs.

Case C considers an economic fuel cost of \$9/MMBtu for natural gas without considering environmental effects. In this scenario, where the fuel price is three times higher, the results indicate the selection of 48 wind power projects.

The final scenario, case D, incorporates both the environmental costs and opportunity costs of gas. As a result, 178 wind power plants with a combined capacity of 8900 MW are chosen.

Figure 3 illustrates the generation mix and overall expenses for all four cases. Despite the overall generation system capacity increasing by 4800 MW compared to the base case, the average LOLE has also increased due to the unreliability of the wind system. However, the LOLE values satisfy the planning criteria in all four scenarios, remaining below 1 day/year.

The inclusion of the opportunity cost of fuel, environmental cost of generation, or both in the objective function leads to the selection of wind plants, as observed in the cases. Notably, a significant number of wind power facilities are chosen when both the environmental cost of generation and the opportunity cost of fuel are considered.

It is important to note that the study's scope focuses on determining capacity additions, and the technical feasibility of a large number of wind turbines at specific sites is not a concern. Additionally, the wind capacity accounts for 37% of the total generation capacity, which may pose technical challenges in terms of power system reliability and security.

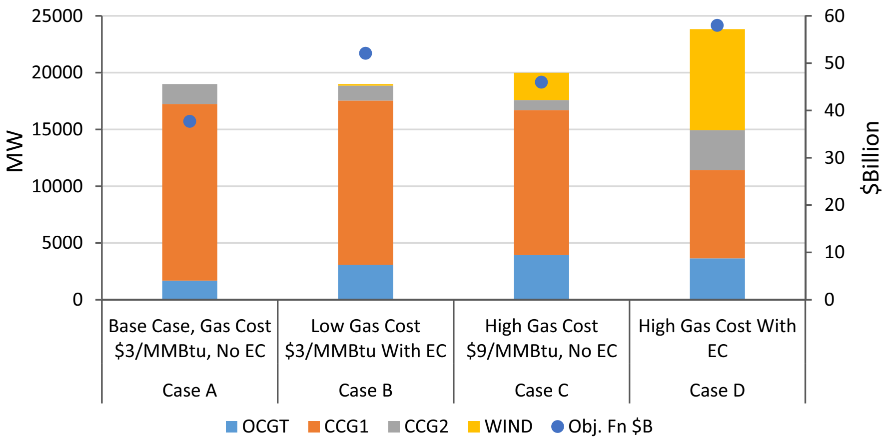

Fig. 3 The generation mix and total cost for the four cases

7 Conclusion and Policy Implications

This paper explores different approaches to modeling non-dispatchable technologies in expansion planning software, focusing on the utilization of a load duration curve model. Specifically, the study employs WASP, a widely used generation expansion planning tool that is freely available for IAEA member countries. Four alternative approaches for incorporating wind power into WASP are outlined, each with its own approximations and limitations. The research also presents a method to integrate environmental considerations into fuel input prices during the optimization process of WASP.

The case study in this paper utilizes Oman's existing load and generation system, selecting four potential plants for system expansion. Three of these plants utilize natural gas as a fuel source, while a 50-MW wind plant is employed to demonstrate the concepts discussed in the study. Based on the expected capacity factor at the site, the wind plant is modeled as a thermal plant with a high forced failure rate. The study considers a 25-year assessment period for development plans and optimizes four potential scenarios.

The first scenario serves as a reference, considering the gas market price while ignoring the environmental costs of the facilities. In the second scenario, the gas retail price is used, but this time, the environmental costs of both existing and candidate generation units are incorporated into the optimization process. The third scenario focuses on the opportunity cost of gas without considering environmental consequences. The fourth scenario integrates both the opportunity cost of gas and the environmental impacts of the plants. Findings indicate that in the base-case scenario, no wind plants are selected. However, wind plants are chosen in the other three scenarios. Notably, the fourth scenario, which incorporates both the opportunity cost of gas and environmental impacts, results in a significant number of wind generators being selected. This highlights the importance of considering actual economic costs, such as fuel opportunity costs and environmental costs, in the planning process to promote the adoption of environmentally friendly technologies.

Based on the study's results, the article recommends incorporating opportunity costs as input data in generation planning models to ensure that non-dispatchable renewable technologies are given fair consideration by decision-makers. By doing so, the planning process can effectively support the adoption of environmentally friendly technologies.

Author Contribution Arif Malik: Conceptualization, Methodology, Software, Data curation, Writing—Reviewing and Editing Aamir Al-Kharusi: Software, Writing-Original draft preparation Ahmed Al-Khathiri: Preparation of Figures and Writing- Original draft preparation Yousuf Al-Mahrouqi: Preparation of tables and Writing-Original draft preparation.

Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical Approval Not Applicable.

Competing Interests The authors declare no competing interests.

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