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A modeling and optimization framework for power systems design with operational flexibility and resilience against extreme heat waves and drought events

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Abstract

Operational flexibility is an important attribute for the design of sustainable power systems with a high share of intermittent renewable energy sources (IRES). Resilience against extreme weather is also becoming an important concern. In this study, a modeling and optimization framework for power systems planning, which considers both operational flexibility and resilience against extreme weather events, is proposed. In particular, a set of piece-wise linear models are developed to capture the impact of extreme heat waves and drought events on the performance of the power generation units and on the system load. A method is also proposed to incorporate the impact models within a modified optimal power system planning problem that can adequately accommodate high shares of IRES. The framework is applied to a case study based on real future climate projections from the Coupled Model Intercomparison Project phase 5 (CMIP5) under different levels of IRES penetration (up to 50\%) and severity of the extreme weather events. A sensitivity analysis is conducted for planning under different Representative Concentration Pathways (RCPs) that cover the impact of different trajectories of greenhouse gas concentration on future climate. In particular, RCPs with increase in radiative forcing of +8.5 Wm\textsuperscript{-2}, +4.5 Wm\textsuperscript{-2} and +2.6

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Wm$^{-2}$ of the pre-industrial levels are considered. The results demonstrate that significant improvements in terms of load supply under an extreme heat wave and drought events can be achieved following the resilient planning framework proposed, compared to conventional planning methods. It is also shown how renewable generation units can improve the system performance against those extreme climate events. Moreover, the quantitative assessment indicates an important interaction between the resilience of the system and its flexibility, and the compound impact of failing to consider either aspect in the power system design phase.

**Highlights**

- A quantitative modeling framework for extreme heat wave and drought events
- An optimization model for resilient power system design against extreme weather impact
- High shares of renewables improve the system resilience against extreme heat wave events
- Investigation of the interaction between the flexibility and resilience of power systems

**Keywords**

Power system design; renewable energy penetration; operational flexibility; extreme weather events; power system resilience

**Nomenclature**

*Indexes:*

- $i$: index of power plant technology cluster
- $j$: index of sub-periods (hours)
- $y$: index of planning year
Sets:

$I$ set of power plant per technology  
$I^{new}$ subset of new power plants available  
$I^{res}$ subset of renewable energy power plants  
$I^{th}$ subset of thermal and nuclear power plants  
$J$ set of hourly sub-periods  
$Y$ set of years in the planning horizon

Parameters:

$\alpha$ share of waste heat released into the air  
$\beta$ efficiency degrading rate when $T_{in, w}$ is in the range of $[T_{health}, T_{risk}]$  
$\rho$ efficiency degrading rate when $T_{i,j}$ is higher than $T_{health, air}$  
$A_{i,j}$ hourly availability of intake cooling flow at plant $(i)$, time $(t)$  
$C^{inv}_i$ investment cost of power plants of technology $(i)$  
$C^{lons}$ cost of load not served  
$C^{marg}_{i,y}$ marginal cost of power plants of technology $(i)$ including the variable O&M and $(CO_2)$ costs, considering inflation  
$C^{OM}_i$ fixed O&M costs of power plants of technology $(i)$  
$C^{stup}_i$ start-up cost of power plants of technology $(i)$  
$Cap_{i}^{max}$ maximum capacity of power plants of technology $(i)$  
$CF_{i,y,j}$ capacity factor of renewable energy sources $(i \in I^{res})$ during hourly sub-period $(j)$ of year $(y)$  
$DR_y$ discount rate for year $(y)$  
$EFOR_i$ Expected forced outage rate of power plants of technology $(i)$  
$Load_{y,j}$ system load at hour $(j)$ of year $(y)$  
$LS^{max}$ maximum allowable load shedding  
$Maxbudget_y$ maximum budget available for investment in generation expansion for year $(y)$  
$M_{i}^{ap}$ minimum up-time for power plants of technology $(i \in I^{th})$  
$M_{i}^{dn}$ minimum down-time of power plants of technology $(i \in I^{th})$
\( P_{i}^{\text{min}} \) minimum stable power output of power plants of technology \((i \in I^{th})\) (MW/h)

\( \text{Penlevel} \) renewable penetration level requirement (%)

\( P_{\text{wr}_i}^{\text{start}} \) maximum output of power plants of technology \((i \in I^{th})\) when started (MW)

\( R_{\text{res}_i}^{\text{min}} \) minimum planning reserve margin (MW)

\( R_{\text{mp}_i}^{\text{Dn}} \) maximum downwards ramping capability of power plants of technology \((i \in I^{th})\) (MW/h)

\( R_{\text{mp}_i}^{\text{Up}} \) maximum upwards ramping capability of power plants of technology \((i \in I^{th})\) (MW/h)

\( t_{\text{min}} \) minimum water stream temperature \((^\circ\text{C})\)

\( t_{\text{max}} \) maximum water stream temperature \((^\circ\text{C})\)

\( t_{\text{ip}} \) air temperature at the inflection point \((^\circ\text{C})\)

\( \Delta T \) permissible temperature increase of the cooling water \((^\circ\text{C})\)

\( \Delta T_{\text{max}} \) regulated maximum permissible temperature increase of the cooling water \((^\circ\text{C})\)

\( t_{\text{as}} \) air temperature at surface \((^\circ\text{C})\)

\( T_{\text{cell}} \) solar-pv cell temperature \((^\circ\text{C})\)

\( T_{\text{health}} \) temperature when the maximum discharge of waste heat is in normal operating range \((^\circ\text{C})\)

\( T_{\text{risk}} \) temperature when the actual maximum discharge of waste heat is equal to the designed value \((^\circ\text{C})\)

\( T_{in,c} \) temperature of cooling water circulated back to the condenser \((^\circ\text{C})\)

\( T_{in,w} \) power plant intake water temperature \((^\circ\text{C})\)

\( T_{\text{out}_{\text{max}}} \) regulated maximum permissible temperature of the discharged cooling water \((^\circ\text{C})\)

\( T_j \) geographical aerage values of the projected air temperature at time \((j)\) \((^\circ\text{C})\)

\( T_{\text{ref}}^j \) historical reference air temperature at time \((j)\) \((^\circ\text{C})\)

\( T_i^{\text{life}} \) expected life-time of new power plant of technology \((i)\) (Years)

\( T_i^{\text{const}} \) construction time of power plant of technology \((i)\) (Years)

\( V_0 \) cut-out velocity of the wind turbine (m/s)
\( V_l \)  
- cut-in velocity of the wind turbine  (m/s)

\( V_H \)  
- wind speed at wind turbine height  (m/s)

\( V_R \)  
- rated velocity of the wind turbine  (m/s)

\( V_{10m} \)  
- near-surface wind speeds at 10 meters height  (m/s)

\( V_{req} \)  
- required volume of cooling water for operating a thermal power plant at its maximum capacity  (m³)

\( V_{i,\text{empty}} \)  
- cooling water extraction capacity of plant \((i)\)  (m³/s)

\( V_{i,\text{src}} \)  
- permissible amount of water flow that can be taken from the water source for plant \((i)\) at time \((j)\)  (m³/s)

\( z_{i,y,j}^{ewe} \)  
- power supply efficiency of power plant of technology \((i)\) at time \((j)\) of year \((y)\) during the extreme weather event  (%)

**Continuous Variables:**

\( lns_{y,j} \)  
- load not served at hourly sub-period \((j)\) of year \((y)\)  (MWh)

\( L_{y,s,j}^{ewe} \)  
- load not served during extreme weather event \((ewe)\) at hourly sub-period \((j)\) of year \((y)\)  (MWh)

\( \text{pwrgen}_{i,y,j} \)  
- energy output of power plant of technology \((i)\) at hourly sub-period \((j)\) of year \((y)\)  (MWh)

**Discrete Variables:**

\( \text{avail}_{unt}_{i,y} \)  
- availability (commissioning) state of power plant of technology \((i)\) in year \((y)\)  \(\in\mathbb{Z_+}\)

\( \text{inv}_{i,y} \)  
- commissioning decision of power plant of technology \((i)\) in year \((y)\)  \(\in\mathbb{Z_+}\)

\( \text{unt}_{cmt}_{i,y,j} \)  
- commitment status of power plant of technology \((i)\) during hourly sub-period \((j)\) of year \((y)\)  \(\in\mathbb{Z_+}\)

\( \text{strtup}_{i,y,j} \)  
- start-up decision of power plant of technology \((i)\) during hourly sub-period \((j)\) of year \((y)\)  \(\in\mathbb{Z_+}\)

\( \text{shtdn}_{i,y,j} \)  
- shut-down decision of power plant of technology \((i)\) during hourly sub-period \((j)\) of year \((y)\)  \(\in\mathbb{Z_+}\)
1. Introduction

Reliability and security of supply are central considerations for power systems design, and are key to regional and global energy-related policies [1]. Methods for power systems planning have typically ensured key reliability aspects under normal operating conditions and in response to anticipated demand variability and supply disruptions, e.g. due to errors in load forecasts and to unexpected generation units outages. Solutions have been commonly built on capacity adequacy and operating reserves requirements.

Recent objectives of environmental sustainability and the threats coming from severe weather events are challenging in various ways the reliability requirements of power systems design:

- On one hand, low carbon power systems with a high share of intermittent renewable energy sources (IRES) are characterized by a sharp increase in inter-temporal net-load variability.
The associated difficulty in anticipating short-term variations brings the need to consider operational flexibility as a critical design concern of future power systems [2]. Power systems operational flexibility under a large share of IRES penetration have received attention in recent years. Various studies proposed flexibility metrics [3–6] and planning models [7–11].

- On another hand, increasingly frequent and extreme weather events, such as heat waves, droughts, floods and storms, significantly affect the operational status of power systems. Evidence of power generation disruptions due to such events highlights the fragility of the existing systems. This leads to the need of considering resilience in the planning of future power systems [12], most notably with respect to events such as extreme heat waves, which affect both power load and generation units. Heat waves are among the most worrying weather extremes, due to the expected increase in their frequency and severity in the 21st century [13, 14]. For example, France was particularly impacted by the 2003 summer heat wave, which caused an excess of about 15,000 deaths from 4th to 18th August directly attributable to the heat [15]. By combining peaks of extreme temperature and severe soil and hydrological droughts, this event can also significantly affect the energy production sector via the cooling process of thermal power plants [16]. These last years, numerous regions of the world experienced severe heat waves with comparable effects: Russia in 2010, Texas in 2011, Australia in 2012, India and Southern Pakistan in 2015. Therefore, it is of great importance to design the ability of the energy systems for coping with heat waves in the future.

Recent research has been dedicated to studying the impacts of extreme weather events on power systems. Rocchetta et al. [17] presents a multi-objective optimization of distributed power generation systems considering extreme wind and lightning events. Panteli et al. [18] proposes a probabilistic methodology to assess the resilience degradation of transmission networks subject to extreme wind events. In Cadini et al. [19], an extreme weather stochastic model is applied to a realistic cascading failure simulator of power grids, accounting for the operating conditions that a repair crew may encounter during an extreme weather event. The impacts of water availability on the generation capacity expansion planning is investigated in Cohen et al. [20], and the electricity sector growth is compared under different scenarios of water rights. Shao et al. [21] proposes an integrated electricity and natural gas planning model taking into consideration the power grid resilience against storms, earthquakes and floods. Ke et al. [22] studies the potential impacts of
heat waves on power grid operation, by quantifying the capacity of thermal power plants as a function of ambient temperature. Whereas most of those studies focus on evaluating the impact of extreme weather threats on the operation of power systems, there exist very few studies that incorporate resilience within the power system design problem itself.

With regards to the above, sustainable and resilient power system design calls for 1) developing integrated flexibility and resilience frameworks for future investment planning on power systems with a high share of IRES penetration and 2) assessing different strategies to mitigate the natural threats and improve system performance. With this perspective, in this work a previously proposed integrated framework for flexible power systems planning [11] is extended to include resilience against extreme weather events. In particular, extreme heat waves and droughts events are considered, and systematic methods for assessing their impact on the design and operation of the system are proposed. The main contributions of this work are:

- Proposing adequate models to describe the impact of different scenarios of extreme heat waves and water availability on the derating of thermal power units operation, renewable generation production and system load. Since the impact of the extreme weather events is nonlinear and is dynamically dependent on the state variables and parameters, a piece-wise linear approximation is applied to reduce the computational burden while preserving the main features of the impact with the desired accuracy.

- Explicitly incorporating the extreme weather impact in a modified mixed integer linear programming (MILP) power system planning model to derive adequate system investment decisions.

- Extending our previously proposed quantitative framework for operational flexibility assessment of power systems with a high share of IRES penetration (presented in [11]) to also include their resilience against extreme heat waves and drought events.

- Applying the framework to a practical sized power system planning problem with realistic future climate projections, for demonstrating the relevance of the proposed planning approach in terms of system costs and technology choices.

The rest of the paper is organized as follows. In Section (2), the piece-wise linear model for describing the impact of extreme heat waves and drought events is described and incorporated into
the power system planning problem. A practical size case study generically based on the southern French power system is presented under different climate projections and IRES penetration levels in Section (3). The results shown in Section (4) quantify the impact of the climate change events from the viewpoints of system costs, flexibility and resilience of energy supply. Section (5) presents concluding remarks.

2. Methodology

Extreme heat waves affect thermal power plants by reducing their efficiency, due to the derating of their cooling capabilities during the events. Load is sensitive to heat waves as it can significantly increase during periods of high temperatures, due to increased air conditioning usage. Indeed, the impact of an extreme heat wave or drought event is nonlinear, and depends on the state variables and parameters. For example, the increase of cooling water temperature does not translate linearly to a decrease in thermal units efficiency, as the latter depends sensibly on the temperature range in question. A linear approximation, therefore, would be an inaccurate approximation, whereas a non-linear model would be computationally burdensome. For this reason, a good trade-off is to resort to piece-wise linear approximations, where the impact is assumed to be linear within specific ranges and with different trends in the different ranges. The following section describes the set of piece-wise linear models used to describe these impacts and integrate them in the power system design problem.

2.1. Piece-wise linear models of the impact of extreme weather events (high temperature and water availability)

2.1.1. Basic model of thermal power plant cooling systems

Different cooling technologies exist for thermal power generation units. In the event of extreme heat waves, the impact on the different technologies can be different. Since in a power systems planning model the choice among the different cooling systems is a decision variable, it is important to model the specific attributes of each technology separately. In this study, two main cooling technologies are considered:

- Once-through Cooling (OTC) system: the heated cooling water is returned to the water source. A large volume of water from the water source is required.
Closed-loop cooling (CLC) system: water is circulated in the cooling loop including a cooling tower, where a small portion of cooling water evaporates and is released to atmosphere. Only a small volume of water has to be withdrawn from the water source.

The required volume of cooling water $V_{\text{req}}$ for operating a thermal power plant at its maximum capacity $P_{\text{max}}$ is proportional to $P_{\text{max}}$ and inversely proportional to the increase of the temperature in the cooling water $\Delta T$ [23–25], as follows:

$$V_{\text{req}} \propto \frac{P_{\text{max}}(1-\alpha)}{\Delta T}$$ \hspace{1cm} (1)

$$\Delta T = \max \left( \min \left( T_{\text{out},\text{max}} - T_{\text{in,w}}, \Delta T_{\text{max}} \right), 0 \right)$$ \hspace{1cm} (2)

where $\alpha$ is the share of waste heat released into air [%]; this share is small for OTC systems ($\alpha \to 0$) whereas it is large for CLC ones ($\alpha \to 1$). The permissible temperature increase of the cooling water $\Delta T$ is limited by: 1) the regulated maximum permissible temperature increase of the cooling water $\Delta T_{\text{max}}$, and 2) the regulated maximum permissible temperature of the discharged cooling water $T_{\text{out},\text{max}}$ [23], where $T_{\text{in,w}}$ is the power plant intake water temperature.

It can be seen that when $T_{\text{in,w}} \leq T_{\text{out,} \text{max}} - \Delta T_{\text{max}}$, the maximum permissible temperature increase of the cooling water is only limited by $\Delta T_{\text{max}}$, and the required volume of cooling water $V_{\text{req}}$ is, thus, a constant value ($V_{\text{req}} = V^*$) for $\Delta T = \Delta T_{\text{max}}$. However, a high value of $T_{\text{in,w}}$ generally leads to an increase in $V_{\text{req}}$ for operating the plant at its maximum capacity. This increase is significant for OTC systems, whereas it is moderate for CLC ones.

For thermal power plants with CLC systems, it is acceptable to assume that such plants are robust to water shortages and are independent from water availability [23, 24]. Also, the dependency to source water temperature can be neglected since any rise in the water temperature can be compensated by increasing the volume of cooling water $V_{\text{req}}$ [24]. Instead, CLC systems are mainly affected by the temperature of cooling water circulated back to the condenser, $T_{\text{in,c}}$, which can be assumed to be close to air temperature [24].

2.1.2. Extreme weather event impact model

Extreme heat waves and drought events during summer time (JJAS, 21 June-20 September) may force thermal power plants to reduce production owing to scarcity and high temperature of
the cooling water. The intensity of the extreme weather event (ewe) of heat wave and drought is modeled by the parameters:

\[
ewe = [T_{i,j}, A_{i,j}], \forall i \in I, j \in J
\]  

(3)

where \(T_{i,j}\) is the air temperature at plant \(i\) and hour \(j\), from which the related stream temperature \(T_{i,j}^{\text{in,w}}\) can be calculated based on air-water interaction as follows [25]:

\[
T_{i,j}^{\text{in,w}} = t_{\text{min}} + \frac{t_{\text{max}} - t_{\text{min}}}{1 + e^{\gamma(t_{\text{ip}} - T_{i,j})}}
\]  

(4)

The parameters for the air/water temperature relationship are derived from the literature [23, 26, 27]: the minimum stream temperature is assessed to be \(t_{\text{min}} = 0^\circ\text{C}\), the maximum stream temperature to be \(t_{\text{max}} = 30.4^\circ\text{C}\), the steepest slope of the regression to be \(\gamma = 0.14\) and the air temperature at the inflection point to be \(t_{\text{ip}} = 16.5^\circ\text{C}\) [28].

The drought event is modeled by the parameter \(A_{i,j}\) which represents the cooling water availability level (in percentage of the total) for power plant \(i\) at time \(j\), and is defined by:

\[
A_{i,j} = \min\left(\frac{V_{i,j}^{\text{src}}}{V_i^{\text{cpty}}}, \frac{V_i^{\text{cpty}}}{V_i^{\ast}}\right)
\]  

(5)

where \(V_{i,j}^{\text{src}}\) is the permissible amount of water flow that can be taken from the water source at power plant \(i\) and time \(j\), \(V_i^{\text{cpty}}\) is the water extraction capacity of the power plant and \(V_i^{\ast}\) is the constant amount of the required volume of cooling water intake for power plant \(i\) when the water intake temperature \(T_{i,j}^{\text{in,w}} \leq T_{\text{out,max}}^{\text{out}} - \Delta T_{\text{max}}\), as previously explained in Section (2.1.1). Then, to calculate the different water availability scenarios, the parameter \(A_{i,j}\) can take the values:

\[
A_{i,j} = \begin{cases} 
1, & \text{Normal water availability} \\
> 1, & \text{High water availability} \\
< 1, & \text{Low water availability (drought)}
\end{cases}
\]  

(6)

**Thermal units**

For thermal power plants equipped with OTC system, \(\forall i \in I^{\text{th,ote}}\), the efficiency \(z_{i,j}^{\text{ewe}}\) of the power plants which is the ratio of \(P_{i,j}^{\text{usable}}\) to \(P_i^{\text{max}}\) as a function of the extreme weather parameters
$T_{i,j}$ and $A_{i,j}$ and can be expressed by the following piece-wise linear equations for different ranges of $T_{i,j}$:

$$z_{i,j}^{ewe} = \begin{cases} 
\min(1, A_{i,j}), & T_{i,j}^{in,w} \leq T_{health} \\
\min(1, A_{i,j}) \cdot \left[ 1 - \beta \cdot (T_{i,j}^{in,w} - T_{health}) \right], & T_{health} \leq T_{i,j}^{in,w} \leq T_{risk} \\
\min(1, A_{i,j}) \cdot \delta \cdot \frac{\left( T_{out,max} - T_{i,j}^{in,w} \right)}{\Delta T_{max}}, & T_{risk} \leq T_{i,j}^{in,w} \leq T_{shutdown} \\
0, & T_{i,j}^{in,w} \geq T_{shutdown}
\end{cases}$$

(7)

where $\beta$ is the efficiency degrading rate for $T_{i,j}^{in,w}$ in the range of $[T_{health}, T_{risk}]$. $T_{health}$ is the temperature up to which thermal power plants are at their normal operating efficiency and $T_{risk}$ is the temperature when the actual discharge of waste heat is equal to the maximum power unit design value, and is given by:

$$T_{risk} = T_{out,max} - \Delta T_{max}, \frac{1}{A_{i,j}}$$

(8)

Coefficient $\delta$ can be calculated based on the continuation of the piece-wise linear functions (7) at $T_{i,j}^{in,w} = T_{risk}$ and is given by:

$$\delta = A_{i,j} + \beta \cdot \Delta T_{max} - \beta \cdot A_{i,j} \cdot (T_{out,max} - T_{health})$$

(9)

The above piece-wise linear equations (7) hold when $T_{risk} \geq T_{health}$, i.e., $A_{i,j} \geq \Delta T_{max} / (T_{out,max} - T_{health})$. For the case where $T_{risk} \leq T_{health}$, i.e., $A_{i,j} \leq \Delta T_{max} / (T_{out,max} - T_{health}) \triangleq A_{i,j}^{sh tg}$, the piece-wise linear functions (7) can be simplified as follows:

$$z_{i,j}^{ewe} = \begin{cases} 
\min(1, A_{i,j}), & T_{i,j}^{in,w} \leq T_{health} \\
\min(1, A_{i,j}) \cdot A_{i,j}^{sh tg} \cdot \frac{\left( T_{out,max} - T_{i,j}^{in,w} \right)}{\Delta T_{max}}, & T_{health} \leq T_{i,j}^{in,w} \leq T_{shutdown} \\
0, & T_{i,j}^{in,w} \geq T_{shutdown}
\end{cases}$$

(10)

For a thermal plant using the CLC system, $\forall i \in I_{th, clc}$, the following piece-wise linear functions are used to describe the impact of the air temperature ($T_{i,j} \approx T_{i,j}^{in,c}$) on the usable power capacity of power plant $i$ at time $j$:

$$z_{i,j}^{ewe} = \begin{cases} 
1, & T_{i,j} \leq T_{health, air} \\
1 - \rho \cdot (T_{i,j} - T_{health, air}), & T_{i,j} \geq T_{health, air}
\end{cases}$$

(11)

where $\rho$ is the efficiency degrading rate when $T_{i,j}$ is higher than $T_{health, air}$.
Renewable energy units

Renewable energy generation is largely affected by weather conditions. Most notably, to obtain the future solar-PV and wind power generation capacity factor (CF), several weather parameters are needed such as the hourly solar irradiance and wind speeds. These parameters are location specific and, therefore, the location of the renewable generation units placement largely dictates their generation capacity. Moreover, since both wind turbines and solar panels do not require cooling water to generate electricity, the capacity of renewable generation will not be highly affected by an extreme drought event. The impact of an extreme heat wave on wind generation is ignored as it is assumed that wind turbines operate normally within the range of −20 to 50°C. For solar panels, it is assumed that in addition to solar irradiance, the solar-pv generation is affected by the ambient temperature. To calculate the future solar-PV and wind power generation capacity factor (CF), solar irradiance, ambient temperature and wind speed data obtained from the recent Coupled Model Intercomparison Project phase 5 (CMIP5) climate projections are used (as fully described in section (3.2)). These data are provided on a grid level for different locations and, therefore, the output wind speeds, solar irradiances and other climate parameters are location specific. Renewable energy generation is, then, obtained as proposed in the following models.

The wind speed at the turbine height is not a standard output of the CMIP5 climate projection models; the near-surface eastwards (\(u_{as}\)) and northwards (\(v_{as}\)) wind speeds are, therefore, used from which the directional wind speed at 10 meters \(V_{10m}\) is calculated as: \(V_{10m} = \sqrt{u_{as}^2 + v_{as}^2}\). A power-law relationship is assumed for extrapolating the vertical wind profile \cite{29, 30}. Then, the velocity at hub height \(H\) is calculated as:

\[
V_H = V_{10m} \cdot \left(\frac{H}{10}\right)^{\frac{5}{7}}
\]  

Then, the wind speed \(V_H\) is converted into turbine-generated electric power capacity factor \(z_{it}\), \(\forall i \in I_{res-wind}^t, t \in T\) using a standard power curve, described as follows:

\[
\forall i \in I_{res-wind}^t, CF_{i,j} = \begin{cases} 
0, & \text{if } V_H < V_l \text{ or } V_H > V_0 \\
\frac{V_H^3 - V_l^3}{V_R^3 - V_l^3}, & \text{if } V_l \leq V_H < V_R \\
1, & \text{if } V_R \leq V_H < V_0 
\end{cases}
\]  

where \(V_l, V_R\) and \(V_0\) are the cut-in, rated and cut-out velocity of a wind turbine, respectively. Wind power capacity factor is calculated at the grid cell level (defined in the climate projection model)
assuming a unique turbine model for all grid cells \((H = 80 \text{ m}, V_l = 3.5 \text{ m/s}, V_R = 12 \text{ m/s}, V_0 = 25\text{m/s})\), as in [31, 32].

Solar-PV power generation potential depends on solar irradiance, named surface-downwelling shortwave (i.e., wavelength interval 0.2-4.0 \(\mu\text{m}\)) radiation \((rsds)\) in the climate models, and other atmospheric variables affecting panel efficiency, i.e., surface air temperature \((tas)\) and surface wind velocity \((V_{10m})\). The PV power generation can be expressed as [33, 34]:

\[
\forall i \in I^{res-pv}, \ CF_{i,j} = \left[1 + \gamma (T_{cell} - T^0)\right] \cdot \frac{rsds}{rsds^0}
\]  

where the upper script 0 refers to standard test conditions for which the nominal capacity of a PV device is determined as its measured power output \((rsds^0 = 1000 \text{ Wm}^{-2}, T^0 = 25^\circ\text{C})\). Parameter \(\gamma\) is set at -0.005\(^{\circ}\text{C}^{-1}\), considering the typical temperature efficiency of monocrystalline silicon solar panels [33]. Finally, the PV cell temperature \(T_{cell}\) is obtained as:

\[
T_{cell} = c_1 + c_2 \cdot tas + c_3 \cdot rsds + c_4 \cdot V_{10m}
\]  

where \(c_1 = 4.3^{\circ}\text{C}, c_2 = 0.943, c_3 = 0.028\text{Cm}^2\text{W}^{-1}\) and \(c_4 = -1.528\text{Csm}^{-1}\) [33, 35].

The above models can be used to obtain the renewable generation capacity factor \((CF_{i,j})\) for different locations using the grid-cell level data from the CMIP5 climate models (i.e. for each longitudinal and latitudinal coordinate). While indeed the location of wind turbines or solar panels will affect their generation capacity, many of the practical power system planning applications do not require the grid-cell level granularity. Regional averages can, therefore, be calculated from the CF output of all grid-cell levels within a given region.

**System load**

Power demand is usually sensitive to weather conditions. To capture this, the power demand during the extreme weather event is represented by:

\[
Load^{ewe}_{j} = Load_{j} + C^l \cdot (T_{j} - T^{ref}_{j})
\]

where \(C^l\) is the temperature sensitivity coefficient of power load, e.g., it is around +500 MW/+1\(^{\circ}\text{C}\) during the summer time in France [36]. Here \(T_{j}\) and \(T^{ref}_{j}\) represent the geographical average values of the projected air temperature and historical reference air temperature, respectively.
2.2. Power system planning model with short-term operational constraints

Operational flexibility in long term planning should be accounted for by considering the short-term technical constraints of the generating units, such as the unit commitment of generation units, their ramping capabilities and minimum up and down times, to name a few [11]. This class of planning models are, typically, referred to as the integrated generation expansion planning (IGEP) models, since they combine both long-term investment constraints and short-term unit commitment constraints within a single optimization. The multi-period IGEP planning model used here seeks to minimize the total discounted system cost over the whole time horizon. These costs include: annualized equivalent investment costs, fixed operation and maintenance costs, and variable operation costs of the power system (fuel cost, start-up costs and cost of load not served). The plans obtained are subject to long-term constraints including the budget limit, adequacy requirement, renewable penetration level, and short-term constraints including supply-demand balance, generation limits, unit commitment decisions, ramping limits and minimum up and down times. The model is formulated as a mixed integer linear program (MILP) considering annual long-term generation expansion planning constraints and hourly short-term unit commitment decisions.

2.2.1. Objective function

The objective is the minimization of the total discounted costs over the planning horizon. Equation (17a) represents the total investment costs in new units, equation (17b) represents the total production costs including start-up costs and cost of LNS, and equation (17c) represents the fixed operation and maintenance (O&M) costs. It should be noted that the investment cost considered in this model is the Equivalent Annual Cost (EAC) that is obtained by using the AnnuityFactor calculated as: $$\text{AnnuityFactor}_i = \frac{1 - (1 + DR)^{-T_{life_i}}}{DR}.$$ This ensures the proper relationship between the annual investment and operational costs and the correct evaluation of the different investment options having different life spans $T_{life_i}$

$$\min_{\Omega} \sum_{y \in Y} (1 + DR)^{-y} \cdot \text{AnnuityFactor}_i \cdot \sum_{i \in I^{\text{new}}} C_{i}^{\text{inv}} \cdot \text{Capt}^{\text{max}}_{i} \cdot inv_{i,y}$$ (17a)
\[ + \sum_{y \in Y} (1 + DR)^{-y} \cdot \sum_{j \in J} \text{Weight} \cdot \left[ \sum_{i \in I} (C_{i,y}^{\text{norm}} \cdot \text{pwr}_{i,y,j}) \right] \\
+ \sum_{i \in I^\text{th}} \left( C_{i,y}^{\text{stup}} \cdot \text{st}_{i,y,j} \right) + C_{i,y}^{\text{ins}} \cdot \text{ln}_{i,y,j} \]

\[ (17b) \]

\[ + \sum_{y \in Y} (1 + DR)^{-y} \cdot \sum_{i \in I} C_{i,y}^{\text{OM}} \cdot \text{Capt}_{i,y}^{\text{max}} \cdot \sum_{l=1}^{y} \text{inv}_{i,l} \]

\[ (17c) \]

where \( \Omega \supset \{ \text{inv}_{i,y}, \text{avail}_{\text{unt}_{i,y}}, \text{pwr}_{i,y,j}, \text{ln}_{i,y,j}, \text{unt}_{\text{cm}_{i,y,j}}, \text{str}_{i,y,j}, \text{sh}_{i,y,j} \} \)

2.2.2. Constraints

Since a multi-period planning horizon is considered, Eq. (18) keeps track of the investment decisions made in year \( y \) taking into account the construction time of the unit following:

\[ \text{avail}_{\text{unt}_{i,y}} = \sum_{l=1}^{y} \text{inv}_{i,l} - T_{i}^{\text{const}} + 1, \quad \forall i \in I^\text{new}, y \in Y \setminus \{1, ..., T_{i}^{\text{const}} \} \]

The maximum allowable discounted investment budget is limited in Eq (19) such as:

\[ (1 + DR)^{-y} \cdot \sum_{i \in I^\text{new}} C_{i}^{\text{inv}} \cdot \text{Capt}_{i,y}^{\text{max}} \cdot \text{inv}_{i,y} \leq \text{Maxbudget}_{y}, \quad \forall y \in Y \]

Eq (20) ensures that the adequacy level requirement is met by ensuring enough firm capacity to satisfy a reserve margin above the maximum predicted load:

\[ \sum_{i \in I^\text{th}} (\text{Capt}_{i,y}^{\text{max}} \cdot \text{avail}_{\text{unt}_{i,y}}) \geq (1 + \text{Resrv}_{\text{min}}) \cdot \max_{j} (\text{Load}_{y,j}), \quad \forall y \in Y \]

Since the cost competitiveness of renewable energy sources may vary according to the specific characteristics of the system under study, the share of renewable generation endogenously decided by the model may vary accordingly. Eq (21) is, therefore, set to ensure that the desired renewable penetration level is achieved. This can be regarded, without loss of generality, as a proxy for the different regulatory policies that may be imposed for this purpose.

\[ \sum_{i \in I^\text{res}} \text{avail}_{\text{unt}_{i,y}} \cdot \text{Capt}_{i,y}^{\text{max}} \geq \text{Penlevel} \cdot \sum_{i \in I} \text{avail}_{\text{unt}_{i,y}} \cdot \text{Capt}_{i,y}^{\text{max}}, \quad \forall y \in Y \]

Eq (22) ensures the coupling between investment and operational decisions:

\[ \text{unt}_{\text{cm}_{i,y,j}} \leq \text{avail}_{\text{unt}_{i,y}} \quad \forall i \in I^\text{thermal}, y \in Y, j \in J \]
The hourly supply and demand balance as well as the amount of LNS is constrained by Eq (23):

$$\sum_{i \in I} \text{pwr}_{g, i, j} + \text{lns}_{y,j} = \text{Load}_{y,j} \quad \forall y \in Y, j \in J$$  \hspace{1cm} (23)

Eq (24) constraints the hourly unit commitment decisions by the startup and shutdown decisions:

$$\text{unt}_{cmt}_{i, y, j} - \text{unt}_{cmt}_{i, y, j-1} = \text{stup}_{i, y, j} - \text{shtdn}_{i, y, j}, \quad \forall i \in I^{th}, y \in Y, j \in J \setminus \{1\}$$  \hspace{1cm} (24)

The hourly maximum and minimum production levels for thermal units are given in Eq (25) and Eq (26), respectively:

$$\text{pwr}_{g, i, y, j} \leq (1 - \text{EFOR}_i) \cdot \text{Capt}_{i}^{\text{max}} \cdot \text{unt}_{cmt}_{i, y, j}, \quad \forall i \in I^{th}, y \in Y, j \in J$$  \hspace{1cm} (25)

$$\text{pwr}_{g, i, y, j} \geq P_{\text{min}} \cdot \text{unt}_{cmt}_{i, y, j} \quad \forall i \in I^{th}, y \in Y, j \in J$$  \hspace{1cm} (26)

The renewable sources production is limited by the hourly capacity factor $CF$ as given in Eq (27):

$$\text{pwr}_{g, i, y, j} \leq \text{avail}_{\text{unt}}_{i, y} \cdot \text{Capt}_{i}^{\text{max}} \cdot CF_{i, y, j}, \quad \forall i \in I^{\text{res}}, y \in Y, j \in J$$  \hspace{1cm} (27)

Eq (28) and Eq (29) constraint the hourly upwards and downwards ramping capabilities for thermal units, respectively:

$$\text{pwr}_{g, i, y, j} - \text{pwr}_{g, i, y, j-1} \leq \text{unt}_{cmt}_{i, y, j-1} \cdot \text{Rmp}_{i}^{\text{up}} + \text{strtup}_{i, y, j} \cdot P_{\text{wr}}^{\text{start}},$$

$$\forall i \in I^{th}, y \in Y, j \in J \setminus \{1\}$$  \hspace{1cm} (28)

$$\text{pwr}_{g, i, y, j-1} - \text{pwr}_{g, i, y, j} \leq \text{unt}_{cmt}_{i, y, j-1} \cdot \text{Rmp}_{i}^{\text{Dn}}, \forall i \in I^{th}, y \in Y, j \in J \setminus \{1\}$$  \hspace{1cm} (29)

Finally, Eq (30) and Eq (31) ensures that the minimum allowable up and down times for thermal units are respected:

$$\text{unt}_{cmt}_{i, y, j} \geq \sum_{\tau = j - M_{i}^{\text{up}}}^{j} \text{strtup}_{i, y, \tau}, \forall i \in I^{th}, y \in Y, j \in J \setminus \{1, \ldots, M_{i}^{\text{up}}\}$$  \hspace{1cm} (30)

$$\text{avail}_{\text{unt}}_{i, y} - \text{unt}_{cmt}_{i, y, j} \geq \sum_{\tau = j - M_{i}^{\text{dn}}}^{j} \text{shtdn}_{i, y, \tau}, \forall i \in I^{th}, y \in Y, j \in J \setminus \{1, \ldots, M_{i}^{\text{dn}}\}$$  \hspace{1cm} (31)
2.2.3. Integrating resilience requirement into system design

The impact of an extreme weather event to the power generation system is measured by the decrease of the generation capacity of affected thermal and PV plants, and the increase of power demand, as given above. Then, the power generation system resilience is evaluated by a deterministic metric, which is referred to as the total load not served (LNS) during the period of the extreme weather event, and is defined as:

\[
LS_{y,j}^{ewe} = \left( Load_{y,j}^{ewe} - \sum_{i \in I} pwr_{i,y,j}^{ewe} \right), \quad \forall y \in Y, j \in J^{ewe} \tag{32}
\]

\[
pwr_{i,y,j}^{ewe} \leq z_{i,y,j}^{ewe} \cdot Capt_{i}^{max} \cdot unt_{i,y,j}, \quad \forall i \in I, y \in Y, j \in J^{ewe} \tag{33}
\]

\[
\sum_{j \in J^{ewe}} LS_{y,j}^{ewe} \leq LS_{max}, \quad \forall y \in Y \tag{34}
\]

where \( unt_{i,y,j} \) is the unit commitment state of generation units of technology \( i \) at time \( j \) in year \( y \), and \( z_{i,y,j}^{ewe} \) is the efficiency factor of the generation units of technology \( i \) during the extreme weather event for year \( y \), time \( j \), calculated using the above piece-wise linear equations (7)-(15), and \( J^{ewe} \) is the total duration of the event. Equation (32) calculates the total amount of load shedding \( LS_{y,j}^{ewe} \) in each hour \( j \) of year \( y \) during the extreme weather event as the difference between the hourly load and the total power generation from all power units. Equation (33) limits the power generation output \( pwr_{i,y,j}^{ewe} \) of generation units of technology \( i \) at year \( y \) during the extreme weather event \( j \in J^{ewe} \) to the efficiency factor \( z_{i,y,j}^{ewe} \). Finally, constraint (34) limits the amount of load shedding allowed during the extreme weather event \( LS_{y,j}^{ewe} \) to a maximum limit \( LS_{max}^{ewe} \).

It should be noted that the resilience metric used here is focused on the ability of the power system to mitigate the impact of the extreme heat wave and drought events and not on the recovery from those events. This is because in these specific extreme weather events the main action is to reduce the thermal units production levels or to shut them down completely to avoid overheating and further damages to the units, so that recovery of normal operation is immediate once weather conditions go back to normal.

2.2.4. Assessing the flexibility of the power system design

High shares of IRES production increase the inter-temporal variability of the remaining net system load. Enough available thermal units, then, need to be operational and sufficiently flexible to
cope with these variations and ensure production reliability. Proper metrics are needed to evaluate the operational flexibility of the plans obtained under different weather and IRES scenarios.

In this work, the Expected Flexibility Shortfall (EFS) metric presented in [11] is adopted. This probabilistic metric takes into account detailed technical and temporal attributes of the thermal units to quantify the system ability to meet inter-temporal variations. The EFS is the conditional expectation of load loss due to insufficient flexibility, given that it is beyond the Value-at-Risk (VaR) level of the flexibility losses distribution and at a specific confidence level ($\alpha$) or:

$$EFS_{\alpha}(\xi) = E[\xi \mid \xi \geq VaR_{\alpha}(\xi)]$$  \hspace{1cm} (35)

where $(\xi)$ is the variable denoting the loss of load due to insufficient flexibility and the confidence level ($\alpha$) can take values between $(0, 1)$. At the desired confidence level (e.g. $\alpha = 0.95$ or $0.99$), the corresponding VaR is defined as:

$$VaR_{\alpha}(\xi) = \sup \{x \mid P[\xi \geq x] > \alpha\}$$  \hspace{1cm} (36)

where $\sup \{x \mid P[\xi \geq x] > \alpha\}$ indicates the highest $100\alpha$ percentile of the loss distribution.

In summary, the EFS is obtained as follows:

- The available hourly flexibility of thermal units is calculated based on their current operational state, as optimally given by the planning model. This means that for each hour, information about the unit commitment status, production levels, capacity limits and ramping capability of each unit is used to calculate how much it can increase or reduce production in the following hour. This data is aggregated for all thermal units for the whole planning horizon.

- The hourly net-load ramping time series (i.e. the flexibility needed) is calculated as the difference between the system hourly load and the IRES production. This indicates how much ramping is needed to satisfy the load in each following hour.

- The absolute difference between the net load ramping time series and the available flexible resources results in the hourly flexibility losses distribution for the whole planning horizon.

- From this, the VaR for the flexibility losses can be calculated at the desired confidence level as given in Eq (36).
The EFS is, then, obtained as the average load loss due to insufficient flexibility for observations exceeding the VaR level.

Figure (1) shows a schematic illustration of the EFS calculation method.

3. Power system characteristics and climate scenarios

3.1. Power system modeling

A multi-annual planning horizon representing the period between the year 2041 to 2046 is considered. The period is selected so that it would fall within the lifespan of current or near future power generation investments. This lifespan is, generally, around 30 to 40 years depending on the generation unit technology. Moreover, a reasonably distant period is chosen so that a significant difference of the effect of different greenhouse gas trajectories on the climate would be observed. For the selected period, this difference can be observed for the different Representative Concentration Pathways (RCPs), as described in the Intergovernmental Panel on Climate Change (IPCC) - fifth assessment report [37]. Linear regression is used to obtain the system hourly load from the historical electricity load time series of France from the year 2008 to 2012 (publicly available at [38]), assuming a growth of 1% to 1.5% from the beginning to the end of the planning horizon. The cost data for the generation technologies considered for the expansion planning are
based on the IEA/NEA Projected Costs of Generating Electricity report (2015) [39]; the remaining technical characteristics are assumed based on values found in the literature and are summarized in Table (2).

### Table 2: Technical parameters for power generation technologies

<table>
<thead>
<tr>
<th>Technology</th>
<th>Nuclear</th>
<th>Coal</th>
<th>CCGT</th>
<th>Solar-PV</th>
<th>On-shore Wind</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum Capacity per installed unit [MW]</td>
<td>1400</td>
<td>1100</td>
<td>550</td>
<td>60</td>
<td>80</td>
</tr>
<tr>
<td>Minimum stable load [MW]</td>
<td>700</td>
<td>550</td>
<td>165</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Maximum upward ramping [MW/min]</td>
<td>0.5% ( P_n )/min</td>
<td>1.5% ( P_n )/min</td>
<td>5% ( P_n )/min</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>Maximum downward ramping [MW/min]</td>
<td>0.5% ( P_n )/min</td>
<td>1.5% ( P_n )/min</td>
<td>5% ( P_n )/min</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>Minimum up time [hours]</td>
<td>12</td>
<td>6</td>
<td>3</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>Minimum down time [hours]</td>
<td>24</td>
<td>10</td>
<td>5</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>Start-up cost [€]</td>
<td>15.0</td>
<td>11.26</td>
<td>7.53</td>
<td>/</td>
<td>/</td>
</tr>
</tbody>
</table>

Thermal generation units can be equipped with one of two different cooling technologies, that have different cost and technical characteristics. Under normal conditions, cooling towers with recirculating water (CLC) reduce the overall efficiency of power plants by 2 – 5% compared to once-through use of water from seas, lakes or large streams (OTC). Thus, these towers are associated with larger operational/marginal costs compared to OTC systems. Moreover, the investment costs of CLC systems are around 20% higher than those for OTC systems. Table (3) summarizes the specific technical and cost parameters of the generation units equipped with each cooling technology [24, 40, 41].

### Table 3: Technical and economic characteristics for the different generation technologies

<table>
<thead>
<tr>
<th>Technology</th>
<th>( \beta / \rho / C_T )</th>
<th>( T_{health} )</th>
<th>( T_{health,air} )</th>
<th>( T_{ref,clw} )</th>
<th>( T_{shutdown} )</th>
<th>( T_{out,max} )</th>
<th>( \Delta T_{max} )</th>
<th>( C_{inv} )</th>
<th>( C_{mrgl} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear-OTC</td>
<td>0.44</td>
<td>15</td>
<td>32</td>
<td>32</td>
<td>10</td>
<td>3.95</td>
<td>13.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nuclear-CLC</td>
<td>0.44</td>
<td>10</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>4.74</td>
<td>14.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coal-OTC</td>
<td>0.97</td>
<td>15</td>
<td>32</td>
<td>32</td>
<td>10</td>
<td>2.08</td>
<td>38.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Coal-CLC</td>
<td>0.94</td>
<td>10</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>2.60</td>
<td>39.75</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCGT-OTC</td>
<td>0.31</td>
<td>15</td>
<td>32</td>
<td>32</td>
<td>10</td>
<td>1.02</td>
<td>70.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCGT-CLC</td>
<td>0.30</td>
<td>10</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>1.22</td>
<td>71.50</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar-PV</td>
<td>0.50</td>
<td>25</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>1.5</td>
<td>1.71</td>
<td></td>
<td></td>
</tr>
<tr>
<td>On-Shore Wind</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>1.9</td>
<td>2.16</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Within the optimization planning framework, the investment decisions are grouped by technology option using the unit clustering method proposed in [42]. The yearly load is optimally approximated by four representative weeks as proposed in [43] and the chronological order within
each week is maintained. This is especially important for correctly capturing the operational flexibility attributes of the system while ensuring the computational tractability of the optimization problem. An additional week corresponding to the one containing the peak summer load is, then, added to simulate the impact of the heat wave and drought events during summer time.

3.2. Climate projections data of heat wave and drought events

Historical baseline temperature as well as future temperature projections for the years 2041 to 2046 are based on data obtained from the Coupled Model Intercomparison Project (CMIP5) experiments [44]. Similarly, wind speeds and solar irradiance data used to calculate the wind and solar CF are obtained from the CMIP5 experiments, following the models presented in section (2.1.2). Three Representative Concentration Pathways (RCPs) are considered that cover the impact of different trajectories of greenhouse gas concentration on future climate, compared to pre-industrial levels. In particular, we consider the RCP 8.5, RCP 4.5 and RCP 2.6, which represent an increased in radiative forcing of $+8.5 \text{ Wm}^{-2}$, $+4.5 \text{ Wm}^{-2}$ and $+2.6 \text{ Wm}^{-2}$ respectively, compared to pre-industrial values. Table (4) summarizes the details of the CMIP5 experiments used for the different climate projections.

Table 4: Details of the experiments used for the historical and projected temperature scenarios

<table>
<thead>
<tr>
<th>Experiment type</th>
<th>Modeling Center (or group)</th>
<th>Institute ID</th>
<th>Model Name</th>
<th>Experiment</th>
<th>Period</th>
<th>Variable</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Historical (baseline)</td>
<td>Meteorological Research Institute</td>
<td>MRI</td>
<td>MRI-CGCM3</td>
<td>historicalEXT</td>
<td>2008-2012</td>
<td>tas</td>
<td>3hr</td>
</tr>
<tr>
<td>Projection</td>
<td>Centre National de Recherches Météorologiques</td>
<td>CNRM</td>
<td>CNRM-CM5</td>
<td>rcp85, rcp45, rcp26</td>
<td>2041-2046</td>
<td>tas</td>
<td>3hr</td>
</tr>
<tr>
<td>Projection</td>
<td>Meteorological Research Institute</td>
<td>MRI</td>
<td>MRI-CGCM3</td>
<td>rcp85, rcp45, rcp26</td>
<td>2041-2046</td>
<td>uas, vas, rsds</td>
<td>3hr</td>
</tr>
</tbody>
</table>

where (tas) denotes temperature-at-surface, (uas) and (vas) denote eastward and northward wind speeds at surface, respectively, and (rsds) denotes surface down-welling shortwave flux in air, as described in Section (2.1.2).

Since we are primarily interested in extreme weather scenarios related to the region of southern France, the climate data considered have been limited to the geographical scope of interest: that
is, data spanning the longitudinal and latitudinal scope of approximately \( (W 2^\circ 35'00'' - E 8^\circ 10'00'') \) and \( (N 46^\circ 06'00'' - N 41^\circ 19'00'') \), respectively. To quantify the impact of an extreme heat wave, the average temperature time series as well as the average wind-CF and solar-CF are, then, computed for the geographical area considered, for each projected climate scenarios. Regarding water availability levels, different water level scenarios during the heat wave events are assumed to cover: high availability levels \( (A > 1) \), normal levels \( (A = 1) \) and low availability levels (drought) \( (A < 1) \).

4. Results and discussion

4.1. Impact of extreme heat wave and drought events on system load and efficiency of power generation

We start our investigation with a focus on future climate parameters obtained from the RCP 8.5 experiments, which is the representative concentration pathway assuming no decrease in current carbon emission trends throughout the 21st century. Significant temperature increase during the summer period is observed under the Representative Concentration Pathway (RCP 8.5), compared to the historical baseline scenario. The impact of this temperature increase on the load and power generation units are computed for a typical summer week for each year of the planning horizon. As an example, Figure (2) illustrates the projected temperature increase and its impact on system load during the period between the 30th of July and the 6th of August for the year 2041 in southern France, compared to the historical average levels in the same period and location. The temperature difference is seen to reach levels of \(+9.2^\circ C\), while its impact on the system load (calculated as per the proposed impact model) can increase up to \(+1840\) MWh. Similar order of differences are observed for the other planning years considered.
The effect of heat wave and water shortages on the efficiency of thermal units depends on the cooling technology deployed. We consider three different levels of water availability and calculate their impact on the efficiency of thermal units during the heat wave event. Figure (3) illustrates the resulting efficiency for nuclear power plants during a heat wave and under different water availability levels, using data for the year 2041. It can be seen that OTC-based generators are highly affected by water shortages, compared with CLC units, which are impacted by the heat wave but maintain the same efficiency levels regardless of the water availability level.

Figure 3: Example of nuclear generation units efficiency derating during a heat wave event for different cooling technologies (OTC and CLC) and under different water availability scenarios (high availability: $A > 1$, normal availability: $A = 1$, low availability (drought) $A < 1$)

### 4.2. Resilient power system planning vs conventional planning

Resilient power systems planning should account for the impact of extreme weather events as an integral part of the planning problem, as discussed in the previous sections. We compare the
resilient plans (denoted RP) to conventional plans (CP), obtained assuming no climate impact on the efficiency of the generation units. CP future investment plans are, then, used to simulate operation under different realizations of climate scenarios, to assess operational performance. We focus first on the results obtained under no IRES penetration level requirements.

The total amount of load not served (LNS) during the heat wave period is taken as the primary performance measure for the plans obtained. Figure (4) illustrates the resulting LNS for both RP and CP under the extreme weather events. The results show a significant load loss for the conventionally planned systems, that sharply increases with the worsening of the climate conditions. The loss reaches up to 851 GWh under the worst scenario of climate impact. This is not the case for the RP, which are shown to suffer an LNS significantly lower than CP, with a maximum of 17 GWh under the worst scenario of climate impact.

![LNS during different extreme weather events. Comparison between Resilient Planning (RP) and Conventional Planning (CP) under no IRES penetration.](image)

In terms of system costs, RP have overall higher annualized investment and operational costs compared to CP, as can be seen in Figure (5). This is directly related to the fact that for RP the extreme weather impact on the power system is taken into account and so the plan compensates the lower thermal units efficiency by investing in more and better performing units. The slightly higher investment and operational costs, however, are fully offset by the reductions in LNS costs, as can be seen in Figure (5). The maximum difference between the total annualized investment and operation costs of the RP compared to the CP is equal to 1.23 B€ (low water availability scenario in Figure (5)), while the LNS cost saving for the same scenario is around 9.52 B€.
Next, the analysis is extended to evaluate the impact of increasing IRES penetration levels on the system performance. Most notably 0%, 25% and 50% IRES energy penetration levels are considered (percentages of total system load) and the optimization problems are solved under all extreme weather events, for both the RP and CP.

Figure (6) shows the impact of the increasing share of IRES levels on the LNS of the system during the extreme weather events, for RP and CP. Higher IRES penetration has a clear effect on reducing the amount of LNS during the extreme events. RP maintain low LNS levels in all cases considered, and slightly improves with increasing IRES levels, while CP show a significant decrease in LNS as IRES power compensates for the lack of system resilience.
Moreover, it is shown that the increased IRES capacity reduces the gap between RP and CP, in terms of annualized investment and operational costs. For example, the difference in the total annualized investment and operation costs between the RP and CP plans decreases from +5.70% to +1.60% under the 0% and 50% IRES levels respectively, under the “Extreme heat wave - Low water availability” scenario in Table (5). The same trends are also found under the other extreme weather scenarios considered.

![Diagram of LNS during different extreme weather events. Comparison between Resilient Planning (RP) and Conventional Planning (CP).](image)

Figure 6: Impact of high IRES penetration on LNS during different extreme weather events. Comparison between Resilient Planning (RP) and Conventional Planning (CP)

<table>
<thead>
<tr>
<th>Extreme heat wave scenario</th>
<th>High water availability</th>
<th>Normal water availability</th>
<th>Low water availability (drought)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>RP</strong></td>
<td><strong>CP</strong></td>
<td>Difference</td>
<td><strong>RP</strong></td>
</tr>
<tr>
<td>0% IRES</td>
<td>7.19</td>
<td>6.95</td>
<td>3.52%</td>
</tr>
<tr>
<td>25% IRES</td>
<td>9.37</td>
<td>9.37</td>
<td>0.05%</td>
</tr>
<tr>
<td>50% IRES</td>
<td>12.92</td>
<td>12.92</td>
<td>0.04%</td>
</tr>
<tr>
<td>0% IRES</td>
<td>7.51</td>
<td>6.95</td>
<td>8.02%</td>
</tr>
<tr>
<td>25% IRES</td>
<td>9.55</td>
<td>9.37</td>
<td>2.00%</td>
</tr>
<tr>
<td>50% IRES</td>
<td>13.05</td>
<td>12.92</td>
<td>0.99%</td>
</tr>
<tr>
<td>0% IRES</td>
<td>7.55</td>
<td>6.95</td>
<td>6.83%</td>
</tr>
<tr>
<td>25% IRES</td>
<td>9.66</td>
<td>9.37</td>
<td>3.09%</td>
</tr>
<tr>
<td>50% IRES</td>
<td>13.17</td>
<td>12.92</td>
<td>1.92%</td>
</tr>
</tbody>
</table>

Table 5: Comparison between Resilient Planning (RP) and Conventional Planning (CP) costs under different IRES penetration levels (0%, 25% and 50%) and extreme weather impacts.

4.3. Impact of extreme weather events on technology choice and system flexibility

The previous section has illustrated how power system RP cope with the detrimental impact of extreme weather events, with no significant increase in the system cost. In this section, the choices
in the RP under the different scenarios are analyzed in details. Most notably, the generation technology choice and capacity installed are major contributors to the system performance. Figure (7) summarizes the investment capacities and technologies choices under the different extreme weather events and IRES penetration levels. For clarity, the results illustrate the total capacity installed per each cooling technology type (OTC-based capacity vs CLC-based capacity) summed over all thermal power plants installed, under each scenario.

Figure 7: Resilient Planning (RP) technology choice and capacity installed under different IRES penetration levels and extreme weather events. (Total capacity installed per each extreme weather scenario indicated by horizontal bracket)

The results show a clear shift from (the cheaper) OTC-based capacities to the (more expensive) CLC-based technology when the heat wave event is accounted for, primarily as a result of internalizing in the system design the impact of the extreme event. This shift to CLC-based units further increases considering lower water availability levels during the heat wave event. The results also
show that the total capacity of all technologies installed does not in fact vary in response to different extreme weather events but is rather significantly impacted by the amount of IRES penetration in the system, for an average of 39.3GW, 64.8GW and 101GW for the 0%, 25% and 50% IRES penetration scenarios, respectively, with low standard deviations of 2.9, 0.5 and 0.08 within each IRES scenario. On the other hand, the significant increase of capacity installed across different IRES penetration scenarios is directly attributed to the increased capacity required to satisfy the operational flexibility needs of the system under these scenarios, as has been discussed in previous work [11].

Finally, the effect of the different extreme climate events on the operational flexibility levels of the RP and CP plans is explored. Table (6) summarizes the EFS results at the 99% confidence level, for all IRES and climate scenarios. It can be seen that when the extreme weather events are not taken into account in the planning phase (as per the CP), the operational flexibility shortage is multiple times that of its RP counterpart under the same extreme weather events. This flexibility shortage difference further increases considering higher levels of IRES penetration. For instance, the EFS reaches approximately 7355 MW for CP compared to 2655 MW for RP, during the extreme weather event for a system with 50% share of IRES capacity. The flexibility shortages, however, are significantly lower than the load losses for the CP due to the lack of resilience, which were shown to be in the order of several hundred GWh in the previous sections. This is important to note since both RP and CP accommodate the operational flexibility attribute.

<table>
<thead>
<tr>
<th>Extreme heat wave scenario</th>
<th>0% IRES</th>
<th>25% IRES</th>
<th>50% IRES</th>
</tr>
</thead>
<tbody>
<tr>
<td>High water availability</td>
<td>28.84</td>
<td>618.18</td>
<td>2655.01</td>
</tr>
<tr>
<td>Normal water availability</td>
<td>785.57</td>
<td>1472.30</td>
<td>1038.70</td>
</tr>
<tr>
<td>Low water availability (drought)</td>
<td>1933.98</td>
<td>1621.71</td>
<td>1621.71</td>
</tr>
</tbody>
</table>

Table 6: Expected Flexibility Shortfall (EFS) under different IRES penetration levels and climate scenarios. Comparison between Resilient Planning (RP) and Conventional Planning (CP)
4.4. Sensitivity of the results for different climate projections (RCP8.5, RCP4.5 and RCP2.6)

In the previous sections, the improvements achieved by RP which account for extreme heat waves and drought events have been shown. Both RP and CP were optimized and/or evaluated under the climate parameters of the RCP 8.5, that is the most pessimistic radiative concentration pathway for the 21st century. In this section, a sensitivity analysis is performed considering other RCP projections from the CMIP5 climate experiments to confirm the relevance of the planning framework proposed under less pessimistic concentration pathways.

RCP 2.6 and 4.5 climate data are used to calculate future power system operating conditions. Most notably, solar irradiance and wind speed data are used to obtain wind and solar-PV CF, and temperature data during the summer period are used to simulate the future heat wave scenarios and their impact on thermal generators. We, then, use the RP and CP under the RCP 8.5 scenario to check their operational performance under the other RCP scenarios.

Figure (8) shows the performance of the RP and CP obtained under the RCP 8.5, in terms of LNS during the extreme heat event under all RCP pathways considered. The values shown are the average LNS amounts for all water availability scenarios per each RCP. The results confirm the consistently lower LNS for the RP under all RCP scenarios and for all IRES penetration levels. In addition, as expected, the LNS decreases as less pessimistic RCP scenarios are considered. For example, the average LNS for the RP under 0% IRES penetration decreases from 10 GWh for the RCP 8.5 to 0.05 GWh for the RCP 2.6 scenarios.

Figure 8: Average amount of LNS under each RCP scenario (8.5, 4.5 and 2.6) and IRES penetration levels (0%, 25% and 50%). Comparison between the results of Resilient Planning (RP) and Conventional Planning (CP).
With regards to the operational flexibility, the results reported in Figure (9) show the average EFS of the plans obtained under all extreme weather events for different IRES penetration levels. Less obvious trends can be found for the operational flexibility levels of the obtained plans across the different RCPs, as measured by the EFS metric. It can be confirmed, however, that RP consistently outperform CP also in terms of flexibility, as can be seen in the overall lower shortage levels illustrated in Figure (9). The improved flexibility performance of the RP highlights an important interaction between the resilience of the system and its flexibility, and the compound impact of failing to consider either aspect in the power system design phase.

![Figure 9: Average amount of EFS under each RCP scenario (8.5, 4.5 and 2.6) and IRES penetration levels (0%, 25% and 50%). Comparison between the results of Resilient Planning (RP) and Conventional Planning (CP).](image)

5. Conclusions

This work proposes a framework for power systems planning considering operational flexibility and resilience against extreme weather events. Specifically, a set of piece-wise linear models to quantify the impact of extreme heat waves and drought events are proposed, as well as methods to integrate their impacts within the power system planning models.

A practically sized case study is investigated based on realistic climate projections and system attributes representatives of the southern French geographical area. Several extreme climate scenarios related to heat waves and water shortages are investigated and the results are compared between the resilience-driven planning framework proposed and the conventional planning results.
The results show that significant improvements in terms of load supply during an extreme heat wave and drought events can be achieved under the resilient planning framework compared to conventional planning. It is also shown that although these improvements come at higher investment and operational costs, they are fully offset by the economic savings achieved by reducing the amount of load loss during those events. In terms of system flexibility, the results further show that although the plans obtained have higher flexibility shortage levels, they keep at least an order of magnitude lower than the load losses due to the lack of system resilience. This further highlights the advantage of adopting such comprehensive planning framework.

The modeling and optimization framework presented here can be directly extended to multi-regional planning, to account for the differences in weather conditions across the different regions. Moreover, since extreme weather events are uncertain and stochastic in nature, the presented deterministic framework for resilient power system design can be improved by accounting for the uncertainties within a probabilistic framework. This is especially true if credible probability distributions can be obtained for the different climate parameters. Using methods such as Monte-Carlo simulation, the decision maker can, then, generate a high number of scenarios for the climate impact models and evaluate the expectation of load loss due to the lack of system resilience against the extreme weather events, instead of the worst-case deterministic impact considered in this study.

References


