Concepts and methods for multi-energy system expansion and operations planning for (nearly) zero-energy districts with a focus on electricity - a review.

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Abstract

A (nearly) zero-energy district, (N)ZED, is a highly energy-efficient community that meets the majority of their energy demands through locally produced renewable energy. The evolution of districts towards (N)ZEDs is vital for us to reach our climate protection goals.

In this review, expertise is drawn from multiple research branches to analyze and understand the requirements for a better planning approach to electricity distribution systems for (N)ZED. The review aims to set the direction towards conceptualizing an improved planning method for active distribution networks that takes into account the interactions of electricity flow with other energy carriers. We study 48 recent publications about the expansion planning and operation of energy systems that describe the planning problem for both single and multiple energy carriers. We highlight the potential benefits of multi-energy system (MES) planning and discuss different planning objectives, planning methods, stochastic representations of input parameters, reliability considerations, and network models. We also present some of the opportunities to handle uncertainties in the power systems, accurately solve large and complex planning problems, and integrate the district-scale properties.

Finally, there is a strong need for a better understanding of the different value streams of MES to maximize the economic value-addition of MES.

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Acronyms

(N)ZED  (Nearly) zero-energy district.
ADNP  Active distribution network planning.
ADPS  Active and distributed power systems.
AENS  Average energy not supplied.
ASAI  Average service availability index.
BESS  Battery energy storage system.
BS  Black-start.
CAES  Compressed-air energy storage.
CAIFI  Customer average interruption frequency index.
CHP  Combined heat and power.
DER  Distributed energy resources.
DG  Distributed generator.
DP  Dynamic programming.
DR  Demand response.
EENS  Expected energy not served.
EIU  Energy index of unreliability.
EV  Electric-vehicle.
GA  Genetic algorithms.
GHG  Green-house gas.
IG  Induction generator.
LOLE  Loss of load expectation.
LOLP  Loss of load probability.
LP  Linear programming.

MES  Multi-energy system.

MILP  Mixed-integer linear programming.

MINLP  Mixed-integer non-linear programming.

NLP  Non-linear programming.

NSGA  Non-dominated sorting genetic algorithm.

OPF  Optimal power-flow.

PSO  Particle swarm optimization.

PV  Photovoltaic.

QP  Quadratic programming.

RE  Renewable energy.

RES  Renewable energy sources.

RoR  Run-off-the-river.

SA  Simulated annealing.

SAIFI  System average interruption frequency index.

SoC  State of charge.

SQP  Sequential quadratic programming.

TS  Tabu-search.

UC  Unit commitment.

UESM  Urban energy simulation model.

VOLL  Value of lost load.

WT  Wind turbine.
1. Introduction

The modern viewpoint toward energy system planning transcends the conventional "least cost" paradigm into simultaneously pursuing multiple overlapping (sometimes conflicting) concerns related to climate protection, reliability of power supply, politics, and economics.

At the climate protection front, we have less than a decade to go until we run out of the remaining carbon budget for a 66% chance to limit the global temperature increase to 1.5 degrees [1]. Over the past decades, we tried to integrate more and more RES into our energy mix. At present, most of the RE capacities are connected at the building and community level to meet a fraction of their energy demand. As the share of RE increases, maintaining the reliability of supply becomes a challenging task. District-scale energy systems studies attempt to answer such questions related to the integration of DER, reliable operation, cost-effectiveness, climate-friendliness etc.

In this article, we present a comprehensive review of 48 articles related to the planning and operation of energy systems. We discuss, holistically, the necessity to look at multiple energy systems present in a district, and their mutual interactions. This approach differs from the traditional energy systems planning where different energy networks such as electricity, heat, and gas are planned separately by respective distribution network operators.

Then we try to build on this idea to conceptualize the requirements for a better planning approach for active distribution networks. Our comprehensive review consists of 48 articles related to the planning and operation of energy systems, out of which 44 were published in or after 2015.

We look at the ADNP problem in an integrated and way with an application focus to (N)ZED. Therefore, we selected a diverse pool of research articles comprised of,

- studies of energy systems with one energy carrier and several energy carriers,
- energy system planning and operation models based on one objective function and several objectives functions,
- energy system planning and operation models with one optimization stage and several optimization stages,
- studies that represent the stochastic nature of input parameters and those that do not,
- studies with different levels of granularity regarding the representation of the power network.

Table 1 summarizes the distribution of the reviewed articles based on their key features.

[Table 1 about here.]
We organize the paper as follows. In section 2, we try to understand the concept of ZED and NZED by referring to formal definitions as well as by looking at some real-life examples. Section 3 describes the role of DER in a ZED. Section 4 introduces the two main types of planning problems that an energy system planner comes across. The section 4 also explores the specific kind of planning models called "co-planning models" in detail. In section 5, we present state-of-the-art concepts for multi-energy system planning. In section 6, we zoom into the state-of-the-art ADNP planning concepts. In section 7, we briefly summarize the core ideas presented in this article and look at the future research potential related to the key topics we addressed.

2. Zero Energy Districts (ZED) and Nearly Zero Energy Districts (NZED)

There is no universal definition for ZED. [2] and [3] propose a strategy for communities to become ZED. According to their strategy, at first, communities must reduce their energy demand through efficiency measures and behavior modification. Next, communities must try to fulfill their reduced energy demand with on-site RE generation. Any remaining energy requirement is satisfied by the purchase of RE via certificates. An essential feature of ZED and NZED is the highly energy-efficient and passive neighborhood design, which reduces the energy demand is significantly [3, 4]. The understanding of a "district" herein is not restricted to the administrative boundaries, but it is a loose term that indicates the geographical limit (also referred to as the system boundary) of the study [2]. The energy consumption of (N)ZED must include the energy consumption in the transportation sector. However, complexities arise when defining which type of transportation, e.g., transportation within the community, between communities, long-distance transport, etc. that must be accounted for when calculating the energy consumption of an (N)ZED [4].

We reviewed some case studies of communities that intend to become ZED/ NZED. The Danish city of Frederikshavn is planning to achieve 100% RE supply by exploiting the off-shore wind potential for electricity. Waste-to-heat co-generation plants and low-temperature geothermal plants provide energy for heating purposes. Frederikshavn is a coastal city and has direct access to electricity from off-shore wind power plants. The study assumes that all electricity imports from outside the system boundary come from a coal power plant with 40% efficiency. The city intends to use biogas for its transportation sector [5]. The city of Aalborg in Denmark has investigated the possibilities to become fossil fuel-free by the year 2050, including the transportation sector. Aalborg has significant locally available wind energy, biomass, and low-temperature geothermal potential. Optimal use of those local energy resources and significant energy efficiency measures allows the city to supply 100% of its energy from RES [6]. Altavilla Silentina municipality in Italy plans to reduce their GHG emissions to zero by integrating multiple locally available RE technologies for energy production [7]. The Spanish city of Seville has shown the potential to meet 100% of its energy demand, including the transportation sector, self-supplied using RES. In the study, 72% of
the RE generation comes from PV roof-mounted units and 25% from PV ground-mounted units [8]. The Danish city Sonderborg intends to become CO2-neutral by 2029, including its transport sector by replacing conventional power generation with wind turbines, heat pumps, biomass boilers, and solar heating. They plan to replace the natural gas supply with locally produced biogas. Similar to the other Danish case studies, the coastal location of Sonderborg enables the city to integrate near-coastal off-shore wind generation into their electricity mix [9].

From the examples, we observe that the understanding of ZED (or NZED) is primarily based on the matrices of emission reduction and transitioning into a fully renewable-based energy system predominantly by producing renewable energy within the system boundary.

3. Role of distributed resources and technologies in ZED

3.1. Energy supply

The most important role of the DER is the fulfillment of the energy demand of energy consumers. A typical district comprises of various types of energy consumers such as residential, commercial, or industrial consumers. Electrical appliances (e.g., lighting, washing machine, TV, etc.), heating/cooling, and transportation applications typically cover the largest share of energy consumption in a district. Energy carriers are converted into a type of end-use such as heat or light by the conversion technologies. Figure 1 shows the energy sources, carriers, conversion technologies, and end-use that interact in a typical district.

3.2. Security and quality of energy system operation

[10] defines "security" as the level of risk in the power system’s ability to survive disturbances (contingencies) without interruption to customer service. It relates to the robustness of the power system against disturbances; therefore, it depends on the system’s operating condition as well as the contingent probability of disturbances. "Power quality" relates to the susceptibility of the end-use equipment to the variations in supply voltage, current, or frequency. Therefore, it is the end-use equipment that defines the necessary level of power quality [11].

As the share of distributed generation increases, the DER must take over the role of providing the grid services that are provided by the conventional synchronous generators in the past. Some of these services include frequency regulation (control reserve), voltage regulation, and black-start capability.

Control reserves are used to regulate the short-term, dynamic fluctuations that occur in the power system. Many DER such as DGs, BESS, and DR offer operating reserves to the power system. PV inverters are capable of rapidly controlling the active power output [12, 13] and WTs can operate under de-rated
conditions to provide frequency regulation [14, 15]. Storage systems, e.g., BESS, fly-wheels, CAES, hydrogen storage, EVs, etc. also provide operating reserves at almost instantaneous time-scales due to their rapid response times [16–21]. Rapid cycling causes the BESS to degrade faster, and this is an important economic consideration when choosing technology options for providing control reserves [16].

Voltage regulation enables the power system to maintain a steady voltage profile. PV units, inverter-coupled micro-CHP units, and WTs, except IG type, offer voltage regulation. The inverter’s ability to provide voltage regulation is constrained by its maximum capacity [22, 23]. In Germany, since 2012, PV inverters can supply reactive power based on standard factory settings [24]. Doubly-fed IG type WTs also provide reactive power, but the maximum reactive power feed-in depends on the rotor current and the stator current [25]. Some synchronously connected RoR plants and CHP plants control their reactive power through the excitation system [23, 26]. BESS can absorb and discharge active power, reactive power, or both up to the capacity limit of the inverter [17, 27, 28]. Activating DR on flexible loads provides voltage and frequency regulation to the power system. Residential loads, particularly thermostatically-controlled loads, have higher flexibility to respond to a DR control signal more rapidly than commercial and industrial loads [29–31]. Even though the adjustable load in a single house is small, the aggregate flexible load from many households or a neighborhood is large and sufficient to provide primary or secondary control reserves to the power system [32, 33]. Therefore, aggregating the load flexibility increases the available potential of DR services [34, 35].

Black-start (BS) refers to the service that restores a power system to its normal operation after a blackout. BS-units are generators that can start without support from grid power supply, which can be used to restore the power system in the aftermath of a blackout, e.g., hydro units, diesel generators, biogas generators, etc. Especially in rural grid islands, use of biogas generators as BS-units can be a viable option [36]. Case studies from [37] and [38] show the application of onsite BESS to provide the start-up power required by the BS-units. During the power system restoration process, BESS is used to overcome the imbalances between generation and load to maintain steady voltage and frequency conditions [39–41]. Renewable power plants that are equipped with BESS can operate as BS-units, energize the network, and supply cranking power to non-BS units depending on the availability of RES and the initial SoC of the BESS [41–43].

District heating is a mature technology that is used by many cities and communities to supply their heating energy needs [44, 45]. It is highly robust, reliable, and cost-effective [45, 46]. Most district networks employ several energy sources [47]. Communities and dwellings that do not have a connection to a district heating rely on decentralized heating technologies such as oil or gas boilers/furnaces and residential heat pumps [48].

Similar to electricity, the security of heat supply depends on the availability of the respective energy source(s), while thermal storage and DR provide flexibility [49]. Moreover, the thermal inertia of the
buildings provides an additional safety margin in situations when there is a short-term mismatch of heat demand and supply [49, 50].

3.3. **Positive economic incentives and opportunities for business innovation**

Several authors have demonstrated the potential of DER for providing economic incentives. Energy arbitrage, the action of shifting the energy demand from the grid from high price times too low price times, is a typical application of energy storage technologies [51–54]. Demand response arbitrage shifts the operation of flexible loads from the times of high prices to low prices [55, 56].

Distributed asset owners can participate in energy market activities. In Germany, to participate in the primary reserve market, a bidder must submit a minimum capacity of 1MW. The minimum bid size for the secondary reserve market and the minute reserve market is 5MW [57]. There is the opportunity for aggregation service providers to pool available reserve capacities from small distributed asset owners and participate in the energy market [58].

Network operators have economic incentives to strategically schedule the operation of distribution network assets to minimize network congestion. As a result, the future investment for network expansion may get avoided or delayed [28, 59–64].

The growth in RE has created the opportunity for innovative business ideas, business models, and increase of citizen participation in the energy transition. [65] presents a review of business models for the application of energy management concepts, storage systems, and solar PV generators.

Energy cooperatives, a popular community-based business model in Germany, encourage citizens to invest in sustainable technologies and actively participate in the energy transition. Similar community-based initiatives exist in Denmark, Sweden, and the Netherlands [66, 67]. Smart-contracts based on blockchain technology enable peer-to-peer energy trading and distributed asset ownership sharing [68, 69].

3.4. **Emission reduction**

Many communities, cities, and regions have publicly declared commitment to reduce their GHG emissions in response to climate change [70]. In Europe, there is an active social movement for climate action and political ambition to reach ambitious emission reduction targets, which have led to initiatives like "100%-RES-Regions" [71]. Such communities can invest in DER to supply their energy demand using locally available RES, for example, some communities that are part of the "100%-RES-Regions" initiative use agriculture waste to generate a significant share of their electricity and heat demand locally with small CHP plants [72].

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4. Energy system expansion, operation and co-planning

4.1. Energy system expansion and operation planning

There are two main planning concepts related to energy systems: 1) Energy system expansion planning and 2) Operation planning. Expansion planning is the process of making long-term investment decisions by evaluating the cost-optimal type, capacity, and location of DER in the energy system [73–77]. Most of the operation planning studies solve the power plant unit commitment and economic dispatch problem [78–83]. The other operation planning models that we evaluated are designed to find the optimal network reconfiguration [84], optimal strategies for reserve capacity provision [85, 86], optimal operation set-points [87], and optimal reactive power control [88].

4.2. Energy system co-planning

The increase of intermittent RES and smart-grid technologies has necessitated the consideration of energy system operational details in the expansion planning process. The weather-dependent generation, behavior dependent demand, and incentive-driven control strategies directly influence the future technology mix we must have to achieve the economic optimality while meeting other environmental and reliability requirements. Recent research that focuses on the co-planning of energy system expansion and operation addresses this need.

The co-planning models in the reviewed articles employ two main strategies to maintain the coupling between expansion and operation planning stages, 1) Expansion and operation planning stages are linked in an iterative process, 2) The operation related constraints of the power system are modeled within the expansion planning problem (co-optimization models).

[89–95] present iteratively-coupled energy system co-planning models. The expansion stage iteratively proposes an expansion solution that is subsequently evaluated by the operation stage. The operation stage has different objectives, i.e., minimize EENS [89], minimize power loss [90, 92], minimize load shedding [93], and minimize operation and penalty costs [91]. The two-stage stochastic, iterative algorithm in [95] evaluates, for each Monte Carlo scenario, the least-cost grid reinforcement strategy. The operation stage of the model evaluates least-cost DR strategies (linear programming) and network reconfiguration options (exhaustive search) that reduce the grid reinforcement requirements.

We identified 13 co-planning models among the studied literature that we classify as co-optimization models. These models generally have higher complexity. The level of complexity of the model depends on the extent of the operational details included in the model. Models with a high level of operational details may result in computational difficulties. As a result, it is possible to relax some operational constraints but at the expense of solution accuracy. The study from [96] shows that the accurate representation of some operational constraints in a electrical power system model can impact the solution accuracy more than the...
others. The study has found that operating reserves and maintenance constraints have the most influence on the cost. LP relaxation resulted in the best computational performance increase with the lowest reduction of solution accuracy.

Despite the findings by [96], we made the following observations regarding the 13 co-optimization models that we reviewed, i.e., [74–76, 97–106]:

1. None of the co-optimization models contained constraints regarding asset maintenance.
2. None of the co-optimization models contained constraints regarding operating reserves.
3. None of the co-optimization models contained constraints regarding reserve margins.
4. None of the co-optimization models contained constraints regarding availability of power plants or other DER. This consideration is important in situations when the maximum RE potential is not utilized for power generation. There maybe similar constraints related to other distributed assets, e.g., available capacity of distributed ESS for providing flexibility to the power system.
5. None of the co-optimization models contained constraints regarding long-term performance degradation of equipment.
6. Many studies implemented mixed-integer solution algorithms with linearized constraints. None of the studies have implemented LP relaxation for performance enhancement. Non-linear constraints combined with heuristic techniques is also a preferred choice amongst the studied models.

5. Multi-energy system planning concepts for ZED

5.1. Motivation and main concepts

The motivation for MES planning derives from the resulting increase of flexibility of the energy supply [107, 108]. The interconnectedness of different energy systems allows for the exchange of energy between the networks, energy conversion, and storage that counter-balances RE fluctuations and increases supply reliability and economic and environmental benefits [99, 109, 110]. MES planning requires modeling the expansion and operational constraints related to multiple energy carriers [107, 108].

In this section, we introduce three concepts that are important for the development of MES planning models, i.e., microgrids, energy-hubs, and urban energy simulation models.

5.2. Microgrids

A microgrid is a group of distributed loads and generators within a clear electrical boundary that are interconnected and controlled as a single unit with respect to the electricity grid [107, 111, 112]. A community microgrid can serve up to several thousands of prosumers, e.g., the NiceGrid project [113]. Microgrids should have sufficient generation, flexibility such as storage, and control capability to be able to operate as an
independent grid island [107, 111, 112]. The research of microgrid mainly focuses on rural energy systems and 100% RE communities [107, 111, 112].

Microgrids support the integration of locally produced RE and reduces the negative environmental impacts of energy use [114]. Besides those benefits, microgrids enhance the potential of local DR programs, including those that provide services to the utility grid, create platforms for local energy markets, increase the resilience of energy supply during extreme power outages or natural disasters, and provide a source of electricity to the utility grid [115]. Microgrids also reduce the costs of recurring system upgrades by reducing the peak burden on the utility grid and thus reducing the chances of network congestion [114].

Quality and reliability are essential considerations for microgrid operation and control [112, 116]. Microgrids rely on their operating reserve capacities and control systems to respond to the variabilities of the power system [112, 116]. In grid-connected mode, the utility grid provides inertia and an external voltage and frequency reference to the microgrid. Therefore, an active-reactive power control (PQ control) strategy is mainly used to regulate the output power of DER units [116, 117]. In the islanded mode, when the inertial support of the utility grid is absent, the DER units must ensure the voltage and frequency of the microgrid remain within the safety limits irrespective of the DER power output [116, 117].

We can envision the future power distribution systems as a large number of microgrids that interconnect with each other through the utility grid. A district can host several small-sized microgrids; therefore, a district can function as an aggregator of microgrids [107]. Likewise, if adequate generation and storage capacities are present, the whole local distribution grid can operate as a microgrid. In such a multi-microgrid configuration, the power system must possess adequate flexibility to maintain the quality and reliability of power supply. Therefore, flexibility adequacy becomes a critical planning objective for micro-grids. Examples of micro-grid planning models with reliability considerations are given in [89, 93, 94, 118].

Regulatory restrictions and high capital costs are the main barriers to widespread microgrid adoption [111]. A study by [119] shows that innovative community ownership strategies can lower the capital cost burden of microgrid projects. The study also identifies that there is a very high perceived risk regarding microgrid projects among investors.

The possibilities to improve the business outlook of microgrid investments include innovative market mechanisms, business models, and incentive schemes that recognize the benefits of microgrids and their economic returns [111]. Existing microgrid studies attempt to include the different value streams of microgrids as planning objectives, e.g., emission cost reduction [81, 94, 120], energy cost reduction [94, 118], energy export [94]. Nevertheless, there is a shortage of published research work regarding the benefits of (multi) microgrids and strategies to exploit those benefits at the planning stage.
5.3. Multi-energy system models and energy-hubs

“Energy-hub” is a system with a fixed system boundary. Production, conversion, and storage of multiple energy carriers take place inside an energy-hub. An energy-hub can connect to external energy supplies such as the local electricity grid or the district heating network. The advantage of an energy-hub is that it provides an interface between multiple energy carriers and energy end-uses that enables a simple representation of the interactions between those energy carriers and end-uses. [121, 122]

[Figure 2 about here.]

Figure 2 shows the concept of an energy-hub where there are multiple energy carriers coupled together. The coupling between energy carriers is expressed by a conversion matrix (equation 1), where the conversion matrix element $C_{\alpha\beta}$ defines the coupling between the energy carriers $\beta$ and $\alpha$. The elements $[L_\alpha, L_\beta, ..., L_\omega]^T$ represent the output energy vector of the energy-hub and the elements $[P_\alpha, P_\beta, ..., P_\omega]^T$ represent the energy source vector of the energy-hub [121]. $C_{\alpha\beta} = 1$ if the coupling between energy carriers $\beta$ and $\alpha$ is loss-less, $0 < C_{\alpha\beta} < 1$ if the coupling is with losses, and $C_{\alpha\beta} = 0$ if there is no coupling [121].

$$
\begin{pmatrix}
L_\alpha \\
L_\beta \\
\vdots \\
L_\omega
\end{pmatrix} = 
\begin{pmatrix}
C_{\alpha\alpha} & C_{\beta\alpha} & \cdots & C_{\omega\alpha} \\
C_{\alpha\beta} & C_{\beta\beta} & \cdots & C_{\omega\beta} \\
\vdots & \vdots & \ddots & \vdots \\
C_{\alpha\omega} & C_{\beta\omega} & \cdots & C_{\omega\omega}
\end{pmatrix}
\begin{pmatrix}
P_\alpha \\
P_\beta \\
\vdots \\
P_\omega
\end{pmatrix}
$$

(1)

In some of the reviewed articles, energy-hubs represent the individual buildings that connect to the local energy network (multi-energy-hub models) [77, 87, 103, 105, 109, 123, 124]. In other articles, energy-hubs represent the entire community or the district [99, 110, 120]. In the latter method, the energy transactions within the energy-hub are written as energy balance equations. Multi-energy-hub models, by contrast, have more detailed distribution grid representations, i.e., DC power-flow equations [77] and AC power-flow equations [87, 103, 105, 123, 124]. [123] uses approximated "Distflow" equations, ignoring the loss terms.

5.4. Urban energy simulation models

Following the definition by [125], an UESM is a formal system that represents the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area. The main application clusters of UESM consist of technology design, building design, urban climate design, system design, policy assessment, and transportation [125]. A conceptual UESM comprises of several sub-modules that are capable of modeling and reproducing the behavior of a specific subsystem, e.g., urban meteorology, building energy demand, energy supply, transportation energy, etc., in the urban context [126].

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UESMs are powerful tools for public authorities and the industry to make better decisions regarding the energy transition [127]. They enable the visualization of interdependencies such as building design, city geometry, urban climate, transportation, land-use, etc. all of which influence the design of the urban energy system.

An urban energy simulation case study with the focus of evaluating emission reduction strategies is presented by [127]. The model uses the CityGML data model as its basis and integrates the aspects of urban meteorology, building stock, and local solar PV generation [127].

6. Power system expansion and operation planning concepts

6.1. Optimal planning methods

The objective of this section is to zoom into the expansion and operation planning concepts for electrical power systems that are important and transferable in the context of MES. Several authors have reviewed the distribution system planning techniques in the past. The table 2 shows a small subset of existing state-of-the-art reviews on power system expansion and operations planning.

According to the authors presented in table 2, the power system planning methods belong to three broad categories, i.e., 1) Numerical techniques, 2) Heuristic techniques and, 3) Hybrid techniques.

Numerical techniques are classical optimization techniques such as linear and non-linear programming methods, e.g., LP, NLP, MILP, MINLP, DP, QP, SQP. A significant disadvantage of numerical techniques is that they generally require high computational times to solve complex power system planning problems with a large number of binary decision variables [128, 129]. The computational burden further increases in the presence of non-linear constraints such as the ones caused by a detailed network representation using AC power-flow equations and the operational constraints of DER [130, 131]. Numerical techniques also show performance degradation when faced with non-linear objective functions or multiple objective functions [132].

Heuristic methods search for the optimal solution from a large pool of feasible solutions. They require less computational effort compared to numerical optimization techniques and can balance the computational efficiency and accuracy effectively [131]. SA performs better amongst other trajectory-based heuristic methods. Although it is computationally slower, it can find the global optimum solution independent of the initial condition [133]. Although computationally robust, the performance of SA depends on the proper adjustment of its tuning parameters, which can be quite difficult for large problems [132]. GA and PSO are
two widely used population-based heuristic algorithms for solving power system planning problems. GA is a method that is simple and easy to implement and is capable of solving problems with a wide range of complexity, as shown by [133]. It requires comparatively higher computational time and may converge to local optima [132]. PSO is a computationally efficient algorithm and demonstrates good convergence properties, particularly when solving less complex problems. But the algorithm becomes less robust when the problem gets larger and more complex [132, 133]. NSGA-II is a genetic algorithm that is developed to solve multi-objective optimization problems. The method has fast non-dominated sorting, but its performance decreases with the increase in search space [132].

Hybrid algorithms overcome much of the performance issues in heuristic algorithms [132]. TS/GA hybrid algorithm has demonstrated superior performance to GA, where the resulting objective value at each iteration lies in closer proximity around the optimal solution [133]. However, hybrid methods are much harder to implement, may require a larger number of iterations to converge, e.g., Hybrid-GA, and may require adjustment of several control parameters, e.g., Hybrid-PSO [132].

GA and PSO and their modified or improved variations are the most widely used heuristic techniques that we found in the papers cited in this review. Please refer to table 3 for the complete list of optimization methods used by the authors of the articles reviewed by us.

Since computational performance is the most critical constraint to complex and large-scale power system planning problems, we look at some of the strategies the scientists have used in the past to improve the performance of their power system planning models. Two strategies that are often used by the scientists to improve the computational performance of power system planning problems are, 1) linearization techniques, 2) problem decomposition.

Linearization techniques allow replacing the non-linear constraints of an optimization problem with equivalent linear approximations. Although linearization results in lower solution accuracy, it is often regarded as a reasonable trade-off to gain computational speed. Decomposition techniques are methods that can be used to divide (decompose) a large optimization problem into two or more sub-problems, each of which requires lesser computational effort than the original problem. Table 4 presents several studies that use linearization and decomposition strategies.

6.2. Planning horizon and temporal resolution

The planning horizon of an expansion planning model can be extended up to about 20 years or more. The planning horizon of operation planning models is much shorter, typically one day. Majority of operations
planning models that we looked at have an hourly time resolution but some models are programmed with much higher time resolution, e.g., 5, 15 or 30 minutes [78, 81, 86]. The chronology of the time-series is important for power system operation planning. Therefore, the full hourly or sub-hourly demand and generation time-series are always used.

We categorize the methods for representing temporal variability of the loads and RES into, 1) Static time-step representation, 2) Load duration curve or discrete load levels, 3) Representative time-steps representation, 4) Probabilistic representation, 5) Full hourly time-series representation.

The static time-step representation represents one particular instance of the planning horizon, e.g., 1) Maximum demand/ minimum generation (heavy load-flow) and maximum generation/ minimum demand (reverse power-flow) [134], 2) High/ nominal/ low load and generation scenarios [91]. Probability-based scenario determination using co-incidence factor (for loads) and diversity factor (for generators) are used to make the extreme scenarios realistic and representative of any given state of the power system [134].

Several studies represent the temporal variability of the demand by a set of discrete load levels [74, 77, 89, 90, 92, 97, 98, 135]. Each load level has a probability of occurrence, which is defined as the fraction of hours in a year the demand is equal to the load level. The equivalent load that represents the temporal variations of the year is then determined as a combination of all the load levels.

Representative time-steps are a method used to represent the temporal variability of load and generation of the planning horizon by using a limited number of proxy time-steps. Common ways to select representative time-steps include, 1) Weekdays, Saturdays, and Sundays [95], 2) One representative day per each month [105], 3) One representative day per each season, often considering weekday and weekend variations [93, 94, 103, 110, 120, 123], 4) One representative month per season [136], 5) Clustering techniques [100, 101].

The electricity demand of EVs depends on several uncertain factors such as mileage, trip starting time, trip duration, etc. [78, 86, 137] presents examples of probabilistically modeling the EV charging profiles.

The full hourly or sub-hourly time-series provide a more accurate temporal representation of load and generation to the previously mentioned strategies but also takes more computational effort. Therefore, the application of this method is limited to short-term and operational planning models [80–85, 87, 88, 118, 124, 138].

6.3. Network constraints

The network constraints imposed by the electrical power system are mathematically expressed using AC power-flow equations. AC power-flow equations are non-linear [139]. The number of AC power-flow equations in the planning model per each time-step is equal to the number of nodes in the power system [139]. Hence, the detailed network representation can be computationally demanding for large power systems with long planning horizons [140]. Thus, such models may disregard the network constraints by either stipulating a copper plate assumption [73, 137] or linear power balance constraints [74, 94, 135, 141]. Some studies that
represent the network constraints with AC power-flow equations reduce the computational effort by lowering
the temporal representation of the model, e.g., representative time-steps [75, 91, 95, 106].

Studies with shorter planning horizons, e.g., one year [97, 98, 101, 102] or one day [78–80, 82, 84, 85, 88,
138], incorporate network-related constraints such as active and reactive power-flow, node voltage magnitude,
and feeder capacity constraints.

MES models represent the energy flows from multiple energy carriers, e.g., electricity, heat, and gas
[108]. Network constraints in the MES planning models are formed differently to electricity-only planning
models because energy carriers such as heat and gas do not have physical equivalents to electrical voltage
angle, reactive power, etc. [142]. [93, 99, 109, 110, 120] represent the network constraints with the maximum
power transfer capacities between two nodes and the node power balance equations. The authors ignore
the physical power-flow. [77, 118, 143] use linearized DC power-flow constraint for network constraint
representation and [83, 87, 90, 92, 103, 105, 123, 124] represent network constraints using both the active
and reactive power-flows in the electricity.

6.4. Power system reliability aspects

Power system reliability falls under two main categories, i.e., 1) Capacity adequacy, 2) Power system
security [144]. Capacity adequacy is a property of the power system that refers to having a sufficient amount
of generation, storage, and power transport capacity to meet the end-user demand [144]. The adequacy
studies involve the analysis of the power system under static and quasi-static conditions but not the system
operation under dynamic and transient conditions. Power system security refers to the safe operation of the
power system under dynamic and transient conditions [144]. Power system security addresses the behavior
of the power system when equipment failure and network disturbances.

The scientists use various indicators to quantify power system reliability. An overview of different power
system reliability indices is presented by [145]. The system reliability indices such as LOLE and LOLP
are calculated based on the interrupted capacity or power. Reliability indices such as EIU and EENS
incorporate information about both the inadequate capacity and the duration of supply inadequacy. SAIFI,
CAIFI, AENS, and ASAI are customer-oriented indices that incorporate information about the number and
size of customer loads that are affected by the supply inadequacy.

Several studies have evaluated the optimal sizing and siting of DER, e.g., storage and vehicle charging
stations, such that they can provide reserve capacity to the power system in a contingency scenario [76, 98,
135]. [104] evaluates feeder outage scenarios in which the interrupted feeders can locate both inside and
outside the grid-island. If the interrupted feeder is outside the grid-island, the grid-island can operate in
islanded mode.

The reliability of supply is one of the performance objectives of the power system design. Several studies
represent this reliability objective in terms of minimizing the cost of supply inadequacy [74, 76, 84, 94, 98,
The conversion of the reliability index to a reliability cost is performed using a unit price for energy not supplied. [77] presents a model for evaluating the reliability aspects of a multi-energy system. This study adopts EENS as the reliability indicator. The model defines the EENS limit, which is the maximum allowable unserved energy capacity for each year. The VOLL converts EENS to an economic equivalent that is a component of the total operational cost.

6.5. Handling uncertainties

Adequately representing the uncertainties related to input parameters is extremely important for ADPS planning models. An article by [131] discusses several probabilistic techniques found in ADPS planning models, e.g., Monte Carlo simulation, probabilistic power-flow, chance-constrained programming, and multi-scenario based approaches, to represent the variabilities in RE generation, flexible loads, etc. In this subsection, we briefly look at how some of the authors reviewed by us handle uncertainties of their models.

Table 5 lists different stochastic methods used by the authors to represent the uncertainties related to the planning model inputs. In the expected value method, each uncertain parameter is represented by its expected value [78, 120]. The point estimation method evaluates the distribution of each uncertain variable to a single value point and uses that value to form the optimization problem as a deterministic set of constraints [73, 146]. Monte Carlo simulation may require longer computational times due to the large number of iterations required. Scenario reduction techniques can help to improve the computational time; however, it may result in lower solution accuracy [83, 89].

In stochastic programming, we represent each uncertain parameter by its discrete probability distribution that results in a set of stochastic scenarios. The number of uncertain parameters and the discrete probability intervals of each parameter determines the size of the scenarios. Scenario reduction techniques are applied to reduce the total number of scenarios to a feasible limit if the number of scenarios is very large. The optimization problem evaluates each of the scenarios and minimizes the expected value of the objective function. [104, 118, 135]

In robust programming, we define the plausible values of the uncertain parameters in terms of a continuous range called "uncertainty sets". The optimization problem is written as a min-max problem, where the optimal (best-case) value of the objective function is evaluated for the worst-case of the uncertain parameters. [82, 91, 99]

In chance-constrained optimization problems, the probability of meeting a constraint with an uncertain parameter is set above a certain level. [79, 88]
Multi-scenario techniques use a pool of uncertain data to generate a limited number of representative scenarios. To limit the number of scenarios, different methods such as clustering [101] and Taguchi’s orthogonal arrays [141] are used.

7. Conclusion

In this article, we looked at the state-of-the-art knowledge linked to energy system expansion and operation planning focusing on (N)ZED. The traditional approach to energy systems expansion and operations planning does not recognize the potential benefits of the MES. The main advantages of integrated energy systems are:

1. They increase the flexibility of the energy system and as a result the hosting-capacity. This refers to an evolution of the state of the energy system.
2. They offer more possibilities to provide flexibility services that includes the grid ancillary services. This refers to a set of tradable products with "situation-dependent" economic value.
3. They create more opportunities for the prosumers and other market actors to interact through innovative market designs. This refers to the platform where the flexibility-based products are exchanged by the market actors. The availability of the flexibility-based products and a market platform enables the future evolution of the energy system.

While the scientists agree on the benefits of coupled energy systems, the existing research does not provide sufficient insight into quantitatively evaluating various value streams linked with MES. We need a deeper understanding of how MES can improve the flexibility of the power system, operating reserves, and increase the availability of grid services. An important consideration for future MES design concerns the adequacy of operational flexibility and planning for the optimal mix of flexibility sources. Translating the value streams of MES into products, and designing business models and markets for those products are also extremely valuable research avenues.

The application of energy-hubs to represent the interactions between multiple energy carriers has shown its promise in several studies that we examined. Multi-energy-hub models are capable of representing the energy carrier interactions at the district level with detailed grid representation and operational constraints. However, due to computational complexities, the existing studies are limited to relatively small problems with few operational details. Urban energy simulation models is a promising research area where scientists from various fields, e.g., power systems, building physics, geo-information, urban planning, etc. can synergize their research expertise.

Finally, restrictive regulatory regimes, market structures, and lack of social acceptance may prohibit the realization of certain benefits of MES, such as the case for micro-grids. The existing policy and regulatory
framework were set based on the knowledge of the past. Therefore, our future research on urban energy systems must accommodate our philosophical ambitions and plausible techno-economic innovations based on the state-of-the-art knowledge we possess. We also see a need for closer research collaborations with social scientists and economists to understand the "perceived" value/ risk of climate-friendly technologies, and designs among people and groups. This is an essential step for us to understand better ways to communicate technological and market innovations to different stakeholder groups.

8. Acknowledgement

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<td>MILP</td>
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<tr>
<td>[77]</td>
<td>Invest. cost, operation cost</td>
<td>IT — —</td>
<td>CHP, Gas furnace</td>
<td>E,H,G 6</td>
<td>DCPF EENS cost</td>
<td>10y</td>
<td>LC</td>
<td>MILP</td>
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<tr>
<td>[118]</td>
<td>Capital recovery cost, operation cost</td>
<td>EO L,G,E —</td>
<td>PV, BESS, FC, DR, MT</td>
<td>E,G 14</td>
<td>DCPF LOLE</td>
<td>1d</td>
<td>FT</td>
<td>MIQP</td>
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<tr>
<td>[124]</td>
<td>Total hub energy usage cost, electricity and heat generation cost</td>
<td>EO — —</td>
<td>MT, Gas boiler</td>
<td>E,G 30</td>
<td>ACPF — —</td>
<td>1d</td>
<td>FT</td>
<td>GSO</td>
<td></td>
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<tr>
<td>[123]</td>
<td>Invest. cost, operation cost</td>
<td>EO L,G —</td>
<td>CHP, HP, TESS, EESS</td>
<td>E,H,G 33</td>
<td>ACPF — —</td>
<td>10y</td>
<td>TS</td>
<td>LP</td>
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<tr>
<td>[105]</td>
<td>Invest. cost, operation cost, emission cost</td>
<td>EO — —</td>
<td>PV, CHP, Gas boiler, TESS</td>
<td>E,H,G 7</td>
<td>ACPF — —</td>
<td>1y</td>
<td>TS</td>
<td>NSGA-II, MILP</td>
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<tr>
<td>[92]</td>
<td>Invest. cost, operation cost</td>
<td>IT — —</td>
<td>MT</td>
<td>E,G 54</td>
<td>ACPF — —</td>
<td>10y</td>
<td>LC</td>
<td>MILP, MILP</td>
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<tr>
<td>[135]</td>
<td>Total expected cost</td>
<td>EO G G —</td>
<td>WT, PV, Conventional DG</td>
<td>E 54,86,138</td>
<td>PB EENS cost, SAI cost, CI cost</td>
<td>10y</td>
<td>LC</td>
<td>SP</td>
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<tr>
<td>[104]</td>
<td>Expansion cost, invest. cost, operation cost, reliability cost</td>
<td>EO L,G —</td>
<td>WT, EESS</td>
<td>E 33</td>
<td>ACPF ENS cost</td>
<td>4y</td>
<td>TS</td>
<td>IGA, MILP</td>
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*Continued on next page*
<table>
<thead>
<tr>
<th>Ref.</th>
<th>Objective</th>
<th>Planning type</th>
<th>Uncert.</th>
<th>DER types</th>
<th>Carrier types</th>
<th>Network nodes</th>
<th>Network constraint</th>
<th>Reliability obj.</th>
<th>Planning horizon</th>
<th>Temporal representation</th>
<th>Method</th>
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<tbody>
<tr>
<td>[146]</td>
<td>Invest. cost, O&amp;M cost, technical constraint violations</td>
<td>IT</td>
<td>L,G</td>
<td>WT, EV, OLTC, Capacitors</td>
<td>E</td>
<td>21</td>
<td>ACPF</td>
<td>—</td>
<td>15y</td>
<td>PD</td>
<td>PSO, MPSO</td>
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<td>[89]</td>
<td>Total cost</td>
<td>IT</td>
<td>L,C</td>
<td>Generic DG, EESS</td>
<td>E</td>
<td>118</td>
<td>DCPF</td>
<td>EENS cost</td>
<td>20y</td>
<td>LC</td>
<td>MIP</td>
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<td>[83]</td>
<td>Energy cost, thermal comfort violation</td>
<td>O</td>
<td>L,G</td>
<td>PV, ESS, DR</td>
<td>E,H</td>
<td>37</td>
<td>ACPF</td>
<td>—</td>
<td>1d</td>
<td>FT</td>
<td>SOCP</td>
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<td>[91]</td>
<td>Total invest. and operation cost</td>
<td>IT</td>
<td>L,G</td>
<td>WT</td>
<td>E</td>
<td>33,123</td>
<td>ACPF</td>
<td>—</td>
<td>10y</td>
<td>TS</td>
<td>MILP</td>
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<tr>
<td>[141]</td>
<td>Total cost</td>
<td>EO</td>
<td>L,G</td>
<td>WT, DR</td>
<td>E</td>
<td>34</td>
<td>PB</td>
<td>—</td>
<td>10y</td>
<td>TS</td>
<td>Cuckoo-search</td>
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<tr>
<td>[75]</td>
<td>DGO benefits, DSO costs</td>
<td>EO</td>
<td>—</td>
<td>Generic DG</td>
<td>E</td>
<td>33</td>
<td>ACPF</td>
<td>Interruption cost</td>
<td>20y</td>
<td>TS</td>
<td>MPSO</td>
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<td>[103]</td>
<td>Project NPV</td>
<td>EO</td>
<td>L,E</td>
<td>PV, BESS, TESS, HP, Gas boiler, absorption &amp; compression chillers, CHP</td>
<td>E,H,G</td>
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<td>ACPF</td>
<td>EENS cost</td>
<td>15y</td>
<td>TS</td>
<td>MINLP</td>
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<tr>
<td>[143]</td>
<td>Energy cost</td>
<td>O</td>
<td>—</td>
<td>CHP</td>
<td>E,H</td>
<td>33</td>
<td>DCPF</td>
<td>—</td>
<td>Not given</td>
<td>—</td>
<td>MILP</td>
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<td>[93]</td>
<td>Invest. cost, load shedding</td>
<td>IT</td>
<td>C</td>
<td>PV, FC, HP, Gas boiler, CHP, H2 storage, Electrolyzer</td>
<td>E,H,G</td>
<td>30</td>
<td>PB</td>
<td>Load shedding</td>
<td>1d</td>
<td>TS</td>
<td>GA, MILP</td>
</tr>
<tr>
<td>[110]</td>
<td>Invest. cost, operation cost, reliability cost, emission cost</td>
<td>EO</td>
<td>L,G,E</td>
<td>WT, Trafo, CHP, Gas boiler, TESS, EESS, DR</td>
<td>E,H,G</td>
<td>—</td>
<td>PB</td>
<td>ENS cost</td>
<td>20y</td>
<td>TS</td>
<td>MILP</td>
</tr>
</tbody>
</table>

Planning type - Expansion only (E), Operation only (O), E&O iterative co-planning (IT), E&O co-optimization (EO)
Uncertainties - Load (L), Generation (G), Reliability (R), Economic (E)
Carrier types - Electricity (E), Heat (H), Gas (G)
Network constraint - Power balance (PB), DC power-flow (DCPF), AC power-flow (ACPF)
Temporal representation - Static (S), Load levels or duration curve (LC), Representative time-steps (TS), Probabilistic (PD), Full time-series (FT)
Table 4: Strategies to improve computational performance.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Strategy</th>
<th>Description</th>
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<tr>
<td>[74]</td>
<td>Linearization</td>
<td>Piece-wise linear approximation and equivalent transformations used linearize non-linearities related to energy losses and bi-linear terms.</td>
</tr>
<tr>
<td>[82]</td>
<td>Linearization</td>
<td>Piece-wise linearization to solve AC-OPF problem using MILP method.</td>
</tr>
<tr>
<td>[85]</td>
<td>Decomposition</td>
<td>Non-linear power-flow constraints and the scheduling problem with binary decision variables are separated.</td>
</tr>
<tr>
<td>[87]</td>
<td>Decomposition, linearization</td>
<td>UC problem and network constraints are separated. Network model uses the solution from UC to calculate AC power-flows and to piece-wise linear approximate the losses and network constraints that are fed back to the optimization model.</td>
</tr>
<tr>
<td>[104]</td>
<td>Decomposition, linearization</td>
<td>Investment stage and operation stage are separated. Non-linear constraints are linearized.</td>
</tr>
<tr>
<td>[94]</td>
<td>Decomposition</td>
<td>PSO is used to solve optimal expansion planning problem. The optimal dispatch for the planned technology mix is calculated using QP.</td>
</tr>
</tbody>
</table>
Table 5: Methods used to handle uncertainties of input parameters.

<table>
<thead>
<tr>
<th>Stochastic method</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected value rule</td>
<td>[78, 120]</td>
</tr>
<tr>
<td>Point estimation method</td>
<td>[73, 146]</td>
</tr>
<tr>
<td>Monte-Carlo simulation based</td>
<td>[83, 89, 95, 103, 106, 110]</td>
</tr>
<tr>
<td>Multi-scenario technique</td>
<td>[87, 93, 100, 101, 141]</td>
</tr>
<tr>
<td>Stochastic programming</td>
<td>[98, 104, 118, 135]</td>
</tr>
<tr>
<td>Chance constrained programming</td>
<td>[79, 88]</td>
</tr>
<tr>
<td>Robust optimization</td>
<td>[82, 91, 99, 123]</td>
</tr>
</tbody>
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