

Article

A Resilience-Oriented Screening Framework for Critical Infrastructure Power Supply Against High-Impact Low-Probability Disruptions: A Case Study from Poland

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Abstract

Increasing high-impact, low-probability (HILP) disruptions requires a paradigm shift in emergency power for critical infrastructure (CI), moving away from traditional cost-driven assessments toward physical resilience. Existing multi-criteria decision frameworks for microgrid technology selection typically treat survivability as one criterion among several, with economic performance retained as an equal or dominant factor. This study addresses this gap by inverting that hierarchy: it develops a resilience-oriented, two-stage screening framework that prequalifies energy technologies (including CHP and CCHP) for CI facing prolonged outages based exclusively on survivability criteria, deferring economic optimization to later design stages. The methodology prioritizes islanding readiness, black-start capability, fuel autonomy, multi-vector energy coverage, implementation feasibility, and operational safety. A hospital serves as the reference CI due to its rigorous demand for simultaneous electricity, heat, cooling, and process loads. The framework applies a Stage I Go/No-Go boundary filter followed by a Stage II weighted scoring matrix, evaluating a broad technology basket encompassing gas, biogas, and biomass CHP, CCHP with absorption cooling, hybrid CHP/BESSs, RESs + BESSs, and diesel generators. Rather than providing a definitive techno-economic ranking, this study contributes a transparent, replicable, front-end engineering tool that can be generalized to other critical infrastructure classes. The results define boundary conditions for prequalifying multi-vector energy architectures, establishing a foundation for future FEED-stage modeling and dynamic simulation of CI microgrids.

Keywords: critical infrastructure resilience; hybrid microgrids; energy autonomy; emergency power supply; multi-vector energy systems



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1. Introduction

Over the past decade, the European energy sector has become exposed to both physical and cyber disruptions. The turning point and definitive end of the era of theorizing about such threats came in December 2015, when a precise cyberattack on the Western Ukrainian distribution network cut off power in the middle of winter to hundreds of thousands of residents [1–3]. One year later, in a similar pattern, transmission nodes in Kyiv were

targeted using even more advanced cyber tools, once again demonstrating the weaknesses of centralized networks to paralysis [4,5].

The vulnerability of large-scale systems in Europe was exposed at the beginning of Russia's invasion of Ukraine in 2022, when attacks on Viasat satellite modems not only disrupted military communications but also limited control over thousands of wind turbines nearby [6,7]. Also, at the beginning of 2022, a massive ransomware attack paralyzed the operational systems of German logistics giants Oiltanking and Mabanaft, cutting off fuel supplies across much of the country and showing that attacks on supporting digital networks can quickly trigger broader crises [8–10]. In May 2023, Denmark experienced a coordinated cyberattack on 22 energy network operators, forcing several companies to disconnect from the grid to prevent a wider blackout [11–13]. However, centralized infrastructure is equally vulnerable to its own internal instability. A prime example is the blackout on the Iberian Peninsula, where, on 28 April 2025, the system lost as much as 15 GW of power. According to the ENTSO-E report published in March 2026, the cascading loss of voltage stability was the main reason why millions of people were deprived of electricity [14–16]. There have been many such examples in recent years: the EU agency ENISA reports that hundreds of critical incidents occur annually, which only confirms the risks associated with relying on centralized energy architecture [17,18].

Understanding the scale of such threats, however, primarily requires defining the specific nature of infrastructure entities, for which power outages are extremely dangerous. According to the Polish definition, *critical infrastructure consists of systems and functionally connected components, including buildings, equipment, installations, and services that are essential for the security of the state and its citizens, and that ensure the efficient functioning of public administration bodies, as well as institutions and businesses* [19].

Critical infrastructure facilities constitute a distinct category of energy consumers and cannot be assessed in the same way as residential or commercial buildings. Their operation requires maintaining a predefined functional minimum, often involving not only electricity but also heat, cooling, and, depending on the facility, process steam. In response to these requirements, several European countries have increasingly emphasized local resilience and energy autonomy for key infrastructure facilities. Finland is a prominent example, as its 2025 CER Act introduced a 72 h energy autonomy requirement for selected critical infrastructure facilities, particularly hospitals and water supply systems (concept shown in Figure 1) [20–23]. Equally advanced measures are being taken by Sweden, which is developing its “Total Defense” (Totalförsvär) concept, requiring decentralization and islanded energy independence for the most important nodes supporting the state's civilian and military functions [24,25].

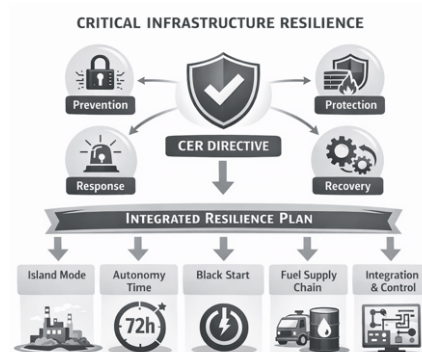


Figure 1. Diagram of the integrated resilience plan according to the CER Directive [own elaboration].

Building resilience in critical infrastructure is particularly important for frontline countries such as Poland. This need became more urgent in 2025 when Polish infrastructure

faced a major wave of cyberattacks, culminating in the December Sandworm attack that damaged remote-control terminals in dozens of energy network facilities [26,27]. Such incidents point to the need for changes to the current emergency power supply model, which relies on diesel generators operating for several hours [28]. Increasing the safety margin and strengthening local energy and resource independence are crucial to improve resilience against system failures, human error, and the ever-growing risk of cyberattacks. Achieving multi-day autonomy in critical infrastructure therefore requires diversification based on locally available resources and reliable modern technologies.

However, it should be emphasized that in safety engineering, there is no single universal solution that would work for every critical infrastructure facility. Individual systems often exhibit fundamentally different parameters in terms of availability of fuel, logistics in islanded operation mode, operating costs, and stability. There is undoubtedly a need to model, simulate, and compare diverse technological variants, from modern hybrid microgrids to the modernization of traditional backup solutions with a dual-use option. Each facility has a specific load profile (thermal and electrical) as well as its own spatial and logistical constraints. Only multi-variant analysis enables selection of an optimal configuration, with respect to reliability, stability, fuel availability, and economic constraints [29–31].

Recent years have definitively set a new direction for development and improvement in the security systems sector. In response to such challenges, this article aims to develop and test an analytical framework for assessing the real capability of energy systems to sustain critical functions. Its main objective is a multi-criteria analysis and comparative evaluation of different emergency power supply variants.

2. Literature Review

For years, power systems have been designed primarily for reliability, understood as the ability to continuously supply energy in the required quantity and quality under conditions of low-impact, high-probability (LIHP) failures. This concept focuses on preventing and minimizing interruptions during normal operation [32–34].

In response to the growing number of high-impact, low-probability (HILP) events, such as extreme weather phenomena, cyber-physical attacks, or political and economic fluctuations, there has been a shift towards models based on resilience [33,35]. Resilience is understood as the ability of a system to absorb disturbances, adapt to them, and efficiently return to its normal state while minimizing the impact on end users. This approach accepts the possibility of complete failure, but assumes that degradation will proceed in a controlled way and that adaptation and recovery will occur rapidly. Rather than relying solely on thick cables or redundant lines (i.e., robustness as passive reinforcement), resilience depends on active mechanisms such as automatic islanding (the capability of a power system to disconnect from the main grid and continue supplying local loads autonomously), local balancing of generation and demand, and the capability to operate fully independently over extended periods [36–39].

Assessing islanding capability requires a precise definition of critical infrastructure (CI) load profiles. Unlike standard commercial consumers, facilities such as hospitals, water treatment plants, and data centers are characterized by strict multi-vector energy demands [40]. Maintaining the so-called functional minimum during a crisis is not limited solely to maintaining the power supply [41,42]. Reports on medical infrastructure failures and the analyses of García-Vera et al. show that hospitals require an uninterrupted and simultaneous supply of heat, cooling, and process steam to maintain critical functions, including sterilization and autoclave operation [43,44]. In addition, such facilities often generate dynamic loads with high inrush currents from pumps and compressors [45].

The traditional and most used solution for emergency power supply is diesel-powered generators [46]. From an engineering perspective, they offer high power density, relatively low CAPEX, and a mature market and service base [47]. However, under long-duration autonomous operation (e.g., 72 h), diesel generators face important operational limitations. A key problem is standby operation: regular low-load testing (below 30–40% of rated power) promotes wet stacking, i.e., the accumulation of unburned fuel and soot in the exhaust system, which reduces mechanical reliability and increases the risk of fail-to-run events after a sudden full-load demand during an outage [48–52]. Moreover, ensuring full-power operation for 72 h requires large on-site fuel storage, which creates significant space constraints and raises the risk of diesel fuel degradation during long-term storage [34,53,54]. As Ouyang points out in his work, reliance on continuous tanker-based fuel delivery is also problematic during HILP events, when external logistics chains may themselves be disrupted [55].

As an alternative, the literature considers zero-emission hybrid microgrids based on renewable energy sources (RESs) and battery energy storage systems (BESS). Their main advantages are independence from external fossil fuel supply chains, which can, in principle, support long-term autonomy, and the elimination of direct emissions in line with decarbonization goals [56–58]. However, scaling RESs + BESSs to support critical infrastructure remains constrained by major physical and economic barriers. Zakeri and Syri show that sizing lithium-ion storage to cover a hospital's multi-megawatt demand for 72 h in winter requires extremely high CAPEX and space that is often unavailable in dense urban areas [54,59,60]. In addition, inverter-based BESSs and PV systems have limited capability to supply short-circuit and inrush currents, which, in facilities with heavy motor loads, may require substantial and costly oversizing of power electronics [61–63].

Given the limits of both diesel-only and BESS-only approaches, the recent literature increasingly points to multigeneration technologies that can provide continuous operation while meeting multi-vector demand [40,56,64,65]. For data centers, Stoll (2025) and Keskin et al. (2025) show that CHP with heat recovery for absorption cooling improves PUE, reduces electric chiller demand, and enables seamless islanded operation by allowing the microgrid to operate as a primary source [66–68]. Similar benefits have been confirmed by subsequent studies. In their review of energy storage systems integrated with CHP, Aslam et al. (2025) demonstrated improved resilience metrics alongside a reduction in ENS [69].

Yin et al. (2025) show that CCHP dispatch accounting for renewable uncertainty improves stability and reduces operating costs [70]. Castañeda-Arias et al. (2025) further indicate that CHP significantly increases the resilience of critical loads in multi-microgrid systems [71]. According to research by Macmillan et al. (2024) and Hemmati et al. (2025), combining CHP with local fuel storage (such as solid biomass or biogas) removes reliance on external supply chains and SCADA systems' single points of failure [72,73].

Shareef et al. (2026) showed that in a biomass-anchored hybrid microgrid (biomass + PV + wind), biomass provided most of the annual generation and enabled full islanded operation even when solar and wind resources were unavailable [74].

Rico-Riveros et al. showed that a hybrid PV + biomass + BESS can outperform diesel-based supply in both environmental and operational terms, with biomass from local waste providing a cheaper and more stable source of energy, particularly at night and during prolonged outages [75].

Wang et al. (2025) demonstrated in an optimization model for a biomass hybrid microgrid with CHP and energy storage that BCHP (biomass CHP) integrated with storage reduces energy waste and improves fuel efficiency. Systems using wood pellets or waste biomass achieved a total efficiency of 80–90%, while ensuring long-term off-grid autonomy through simple solid fuel storage [76].

Studies by Dobre et al. (2024/2025), Anvari et al. (2025), and Seiler et al. (2025) indicate that biomass-based CHP integrated with PV and storage can outperform diesel in emissions, support islanded operation, and improve both cost performance and resilience through the use of locally available fuel [77–79]. It should be noted that the operational benefits of CHP/CCHP and biomass-based systems are not unconditional. Black-start restoration in distributed-generation microgrids remains technically demanding, requiring careful evaluation of DG black-start capability and coordinated parallel restoration strategies. Biomass supply chains also carry documented disruption risk, requiring dedicated decision-support systems to manage feedstock and logistics interruptions. Maintenance burden is a further trade-off: reliability and maintenance-prioritization analyses of CCHP systems show that component-level failure rates and servicing requirements significantly affect overall system availability, with critical components requiring more frequent intervention than in simpler standby generator configurations. Finally, solid biomass combustion is a substantial contributor to ambient PM_{2.5}, with urban case studies attributing a large share of wintertime particulate concentrations directly to biomass burning [80–84].

Despite the extensive literature confirming the operational and environmental benefits of cogeneration systems and hybrid microgrids, their reliable evaluation and comparison with conventional systems remains a challenge. In power systems engineering, multi-criteria decision-making (MCDM) methods are most commonly used to evaluate competing technological options. As literature reviews indicate, techniques such as AHP (analytic hierarchy process), TOPSIS, and PROMETHEE are commonly used to balance technical, economic, and environmental parameters [85–88]. Existing MCDM-based studies in the energy sector remain limited from a resilience perspective. Most models optimize microgrids for grid-connected operation, focusing on LCOE minimization, price arbitrage, or emission reduction [89–91]. Even when these models account for island operation, it is typically treated as a transient state lasting from a few to several hours.

Meanwhile, the requirement for 72 h of full autonomy for critical infrastructure—as defined by modern regulations such as Finland’s CER Act (2025)—completely reshapes the hierarchy of evaluation criteria. Under extreme high-impact events (HILP) and widespread power outages, traditional metrics such as return on investment (ROI) or emissions reduction give way to parameters determining the physical survival of the facility. These include, above all: the source’s start-up readiness, the spatial density of energy carrier storage, the fuel’s chemical stability over time, logistical independence from external supply chains, and the system’s ability to simultaneously meet the minimum functional requirements for both electricity and heat [34,35,42].

The main research gap is the lack of transparent engineering frameworks for comparing multigeneration systems (CHP/CCHP and BESS-based hybrids) with diesel generators under multi-vector loads and continuous 72 h islanded operation. Existing studies often rely on complex heuristic or AI-based methods that obscure the basic physical and operational parameters most relevant to critical infrastructure design [35,42,91–93]. In response to the identified gap, this article aims to propose and test a classical evaluation methodology based on hard operational and logistical parameters. This will allow for an objective assessment of the ability of individual technologies to maintain the functional minimum of selected critical infrastructure profiles (a hospital and a data center) under a 72 h power outage.

3. Methodology

3.1. Assumptions and Methodological Scope

The methodology proposed in this paper is intended for prequalification and is geared toward preliminary screening. Its purpose is not to identify the least expensive technology,

but to determine which of the available energy solutions are realistically capable of sustaining the minimum operational requirements of a critical infrastructure facility during outages and prolonged disruptions in energy supply. In this sense, the methodological framework is based on the logic of resilience: the priority is the ability to absorb failures, switch to island operation, perform a black start, and maintain the facility's critical services with limited external support. The method is intended to serve as an initial engineering filter, preceding detailed design, simulation, or optimization modeling for a specific facility.

The analysis is grounded in the realities of Poland and Central Europe. This means that the assessment of the technology considers not only technical parameters but also the local availability of fuels, the logistics of their storage, implementation readiness, safety requirements, spatial constraints, and the organizational capabilities of local operators. This location is methodologically significant because a solution that is theoretically attractive may prove to be operationally unreliable if it requires fuel or maintenance that is unavailable in a crisis scenario. For this reason, full economic optimization has been intentionally omitted at this stage. Parameters such as CAPEX, OPEX, and LCOE may be introduced at a later stage of the study, after some technologies have been eliminated for failing to meet basic resilience requirements.

In practice, this means that the evaluation hierarchy here is reversed compared to traditional energy analyses: priority shifts to ensuring the continued operation of critical functions, while cost optimization is treated as a secondary consideration rather than the primary selection criterion.

3.2. Reference Object, Functional Minimum Requirements, and Disruption Scenarios

A hospital was chosen as the reference facility because it represents one of the most demanding categories of civilian critical infrastructure. Unlike standard facilities, this type of facility requires an uninterrupted supply of electricity, heat, cooling, hot water, and process steam. For methodological purposes, the hospital is treated as a model facility rather than a fully parameterized specific design case. Thanks to this approach, the proposed framework can also be easily applied to other classes of critical infrastructure facilities, such as water treatment plants or government data centers.

Consequently, the functional minimum has been defined in operational terms as a set of services and corresponding energy flows that must be maintained for the facility to perform its critical functions under disruptive conditions (Table 1). At the screening stage, it is not necessary to specify a particular design load—it is sufficient to assume a realistic range of load values. Additionally, it is necessary to verify whether the given technology is capable of meeting the required demand profile.

Table 1. Operational classification of the functional minimum of a CI object.

Class	Operational Meaning	Illustrative Loads	Permissible Reduction
A: Life-critical	Non-interruptible functions directly linked to safety and security	ICU, operating theaters, ventilators, core medical equipment, safety systems	None; continuous supply required
B: Mission-critical	Functions required to maintain medical and technical activity	Sterilization, IT systems, hospital pharmacy, pumping systems, ventilation of critical zones	Limited reduction or short interruptions only
C: Support-critical	Support functions needed for crisis-mode operation	Parts of administration, non-essential lighting, selected support service	Partial reduction acceptable

The reference disruption scenario assumes a complete blackout. This situation is defined as a loss of external power supply combined with limited logistical and maintenance support. Winter conditions were chosen as the baseline scenario because energy demand is highest during this time. Additionally, winter conditions much better illustrate the danger of a crisis to society and to people's health and lives. The analysis considered three time horizons for autonomy: 24, 48, and 72 h. The 48 h horizon was set as the functional minimum for initial qualification in the selection process, while the 72 h horizon corresponds to a rigorous resilience target, in line with current international trends in crisis management. The scenario also assumes the risk of interruptions in grid gas supply, a lack of external fuel supplies, limited availability of technical personnel, and the need for an automatic or semi-automatic transition to island operation.

3.3. Technology Portfolio and Two-Stage Qualification Process

To avoid prematurely rejecting less common technologies and to ensure a comprehensive review, the procedure begins by defining a broad technology pool (Table 2). Qualification takes place in two stages. Stage I is a Go/No-Go filter (Table 3 and Figure 2), which eliminates technologies that do not meet basic boundary conditions (minimum 48 h autonomy, appropriate order of magnitude of power, multi-vector profile, feasibility of implementation).

Table 2. Technology portfolio for Phase I (prequalification).

Technology Group	Scope of Solutions	Role in the Methodology
Gas-engine CHP	Units fired by natural gas or dual-fuel configurations	Mature, high efficiency; fuel-dependent
Microturbines and gas turbines	Systems from tens of kW to several MW	For facilities that require a stable, high-power supply
Biogas CHP	Systems integrated with wastewater plants or local biogas production	Highly attractive, with local fuel autonomy
Biomass CHP	Solid biomass CHP, boilers with cogeneration, or gasification-based systems	Strong candidates for longer autonomy, with complex logistics
CCHP with absorption cooling	CHP integrated with absorption chilling	For critical continuity cooling requirements
Hybrid CHP/BESSs	CHP or CCHP supported by electrical storage	Improves black-start capability and flexibility
RESs + BESS	PV or other RES supported by storage	Supporting option; rarely sufficient for multi-day autonomy
Diesel generators	Conventional standby generators	Comparator and fallback option

Table 3. Phase I—threshold criteria (Go/No-Go).

Criterion	Verification Question	Threshold	Decision
Power adequacy	Does it meet the facility's functional minimum load?	Yes/No	Go/No-Go
Multi-vector capability	Does it provide multi-vector (power + heat/cooling) coverage?	Yes/No	Go/No-Go
Islanding capability	Is it capable of islanded or off-grid operation?	Yes/Conditional/No	Go/No-Go
Fuel autonomy	Can it sustain 48 h of operation without external fuel?	Yes/No	Go/No-Go
Implementation feasibility	Does it meet typical space, safety, and operational constraints?	Yes/No	Go/No-Go

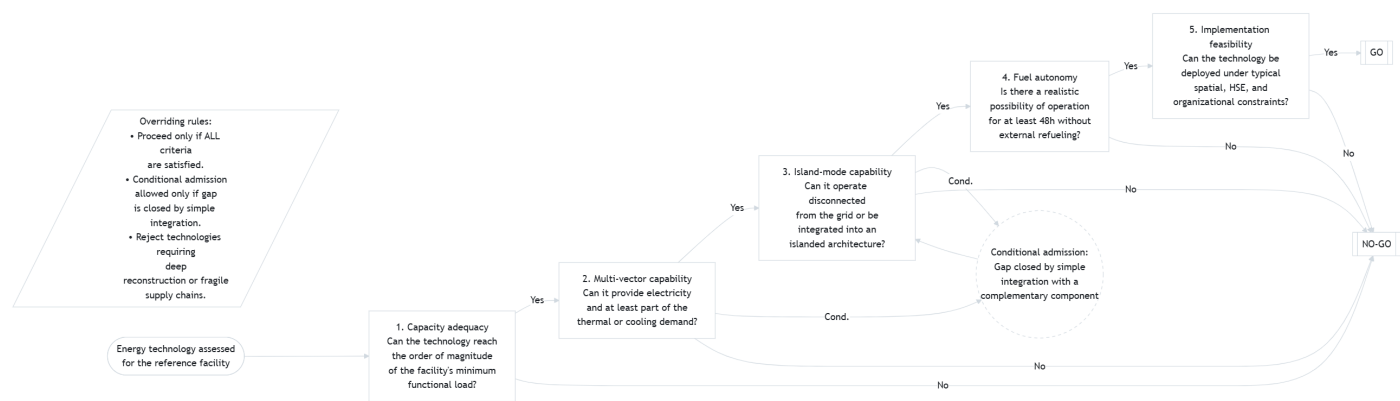


Figure 2. Sequential decision tree for Go/No-Go qualification of distributed energy resources.

Stage II involves scoring the solutions that passed the initial screening (Table 4 and Figure 3). This sequence is methodologically crucial: there is no point in scoring and comparing a technology that cannot operate in off-grid mode, does not cover the required energy sources, or lacks a reliable fuel supply chain in a crisis.

In this context, Go' denotes that a given technology satisfies the corresponding threshold criterion and is admitted to the next evaluation stage, while 'No-Go' denotes that the criterion is not met and the technology is excluded from further consideration. To formalize the Stage I logic, an architecture is admitted to Stage II if, and only if, all threshold criteria in Table 3 return a "Go" response:

$$D_i = c_{i,1} \text{ AND } c_{i,2} \text{ AND } c_{i,3} \text{ AND } c_{i,4} \text{ AND } c_{i,5}, \quad (1)$$

where $c(i,k) \in \{0,1\}$ is the binary Go/No-Go result for criterion k (Table 3), and $D_i = 1$ indicates advancement to Stage II.

Table 4. (a) Phase II—proposed scoring criteria and assigned weights. (b) Scoring rubric: reference definitions for scale endpoints (1 and 5).

(a)			
Criterion	Interpretation	Scale	Default Weight
Islanding readiness	Stable island operation and ease of integration with ATS/SZR logic	1–5	0.20
Fuel autonomy	Ability to sustain operation for 24/48/72 h using local or stored fuel	1–5	0.20
Black-start readiness	Ability to restart without support from the main grid	1–5	0.15
Multi-vector coverage	Simultaneous coverage of electricity, heat, and cooling	1–5	0.15
Reliability and maturity	Market experience, serviceability, and operational stability	1–5	0.10
Scalability and modularity	Ability to match the object and build N + 1/N + 2 configurations	1–5	0.05
Implementation feasibility	Space, safety, and local-operability requirements	1–5	0.10
Operational safety	Fuel, fire, environmental, and organizational risk profiles	1–5	0.05

Table 4. Cont.

(b)		
Criterion	Score 1	Score 5
Islanding readiness	No islanding capability	Fully automatic transition, no operator intervention
Fuel autonomy	On-site fuel reserve <24 h	On-site fuel reserve ≥ 72 h, no external resupply required
Black-start readiness	Requires external grid support to restart	Fully autonomous restart without grid support
Multi-vector coverage	Covers only one energy vector	Covers all required vectors (electricity/heat/cooling)
Reliability and maturity	Pilot-stage technology, no reference installations	Mature technology, extensive commercial track record
Scalability and modularity	No expansion capability	Full N + 1/N + 2 modularity
Implementation feasibility	Requires major facility reconstruction	Deployable without spatial/safety constraints
Operational safety	High fire/emission risk	Minimal risk, no additional organizational requirements

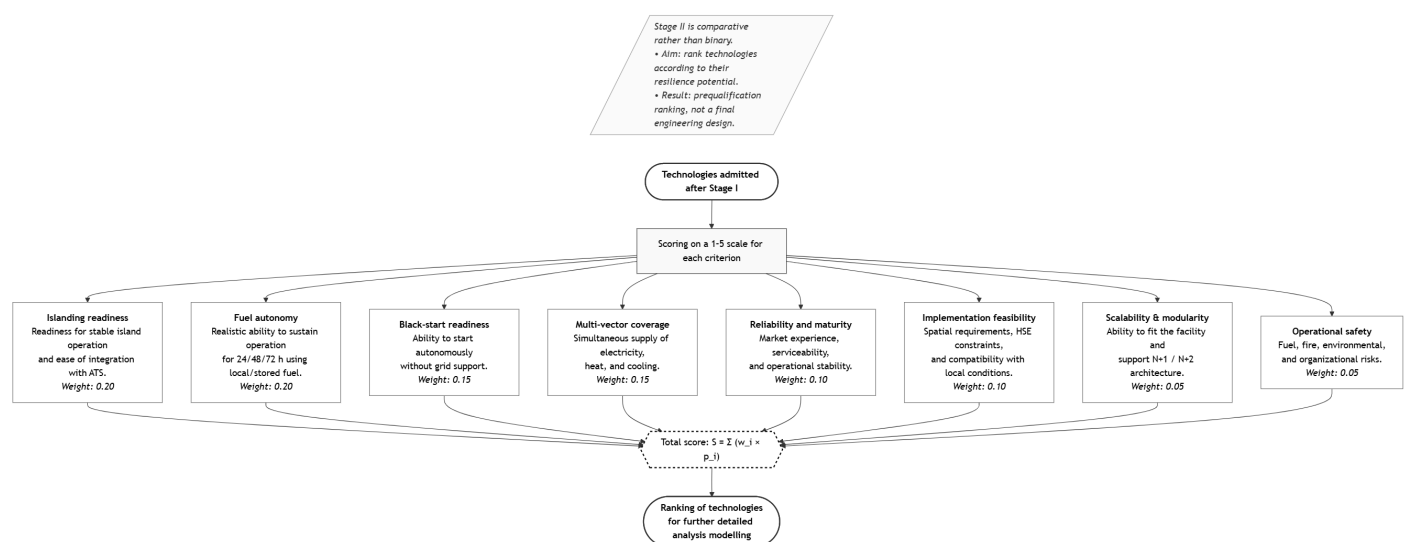


Figure 3. Block scheme of methodology in Stage II (with weights and scoring scale).

Stage II applies an ordinal 1–5 scoring scale with weights prioritizing islanding readiness, fuel autonomy, black-start capability (the ability of a generation unit to restart and re-energize a de-energized system without external grid support), and multi-vector coverage (the simultaneous requirement for more than one energy carrier (e.g., electricity, heat, and/or cooling from a single facility or architecture), alongside reliability, scalability, implementation feasibility, and operational safety. Simple engineering indicators are used throughout to maintain interpretability:

- A power adequacy index ($GAI = P_{avail}/P_{min}$);
- A thermal adequacy index ($TAI = Q_{avail}/Q_{min}$);
- A cooling adequacy index ($CAI = C_{avail}/C_{min}$);
- A fuel autonomy index ($FAI = t_{aut}/t_{req}$).

Values below 1.0 indicate a shortfall; values at or above 1.0 indicate that the minimum requirement is met.

To improve reproducibility, each criterion in Table 4 is anchored at the extremes of the ordinal scale (1 and 5); intermediate values (2–4) represent a proportional transition between these reference points.

Stage II aggregates these ordinal scores using a weighted sum model (WSM), a standard additive multi-criteria decision-making technique. The total score of architecture i is given by:

$$S_i = \sum (w_j \times s_{ij}), \text{ for } j = 1 \text{ to } n. \quad (2)$$

3.4. Reporting of Results and Methodological Limitations

The direct output of the proposed methodology is not a final installation design, but a technology-matching matrix that combines technology class, facility requirements, and operational constraints. The results should be reported in a standardized technology-card format, covering power range, supported energy carriers, islanding capability, black-start capability, estimated fuel autonomy, spatial requirements, organizational framework, and the final screening result.

The methodology is intentionally simplified compared to full MILP (mixed-integer linear programming) analyses, Monte Carlo models, or metrics such as EENS/LOLE (expected energy not served/loss of load expectation). Its main limitation—and, at the same time, its goal—is to offer a transparent front-end engineering tool that streamlines the decision-making process aimed at improving resilience and serves as a coherent bridge between a literature review and a subsequent, dedicated case study. While GAI, TAI, CAI, and FAI provide deterministic proxies for physical adequacy, they are not substitutes for probabilistic resilience metrics (e.g., EENS, LOLE); their integration is identified as a priority direction for the subsequent dynamic-modeling stage. It should also be noted that hybrid CHP + BESS architectures (V4–V6) require careful control-level coordination between inverter-dominated (BESS) and synchronous-machine-dominated (CHP) subsystems during islanded operation—a well-documented challenge in microgrid control involving virtual synchronous generator (VSG) strategies and fault-tolerant coordination [94]. This control-design dimension lies outside the scope of the prequalification screening, and is identified as a necessary component of the subsequent dynamic-modeling stage (Section 6).

4. Case Study and Input Data

4.1. Scope and Limitations of the Input Data

The input dataset comprises two streams: (i) an hourly electricity profile for 2025 covering the hospital's three metering points, and (ii) monthly district heat consumption for 2024–2025 together with information on the main heat source and network parameters. Hourly heat data, cooling data, process steam data, and a decomposition of loads into A/B/C criticality classes are not available. Accordingly, the analysis remains fully consistent with the methodological assumptions of the article: this is a prequalification exercise, not a final design balance. The monthly electricity and heat data used in the screening analysis are summarized in Appendix A.

4.2. Step I—Reconstruction of the Facility Energy Profile

4.2.1. Electricity

Total electricity consumption in 2025 amounted to 1148.0 MWh (1.148 GWh), which corresponds to an average load of 131.1 kW. The maximum recorded hourly energy, interpreted as the average hourly power, was 219.6 kW. The 95th percentile of the hourly load was 171.8 kW, while the 5th percentile was 101.3 kW. This shows that even after excluding

non-critical end uses, the hospital remains a facility with a stable, high base load around the clock.

4.2.2. Heat

Heat consumption in 2025 amounted to 6277.6 GJ, i.e., 1743.8 MWhth. The main source is the Veolia district heating network, and the installed/contracted capacity on the substation side equals 1060 kW. The average monthly heat uptake in winter reached roughly 0.39–0.42 MW, while the heat-to-electricity energy ratio in January and February was approximately 3:1. This profile shows that purely electrical resilience architectures are insufficient for the analyzed hospital; a multi-vector configuration with a thermal component is required. The key input parameters used throughout the case study are summarized in Table 5.

Table 5. Key input parameters used in the case study.

Electricity in 2025	Heat in 2025	P _{peak,h}	Adopted P _{min}
1148.0 MWh (1.148 GWh)	6277.6 GJ (1743.8 MWhth)	219.6 kW	153.7 kW

The screening interpretation of these values is presented in Table 6.

Table 6. Screening interpretation of the reconstructed demand profile.

Indicator	Value	Screening Interpretation
Annual electricity consumption	1148.0 MWh	Stable year-round profile with no clearly “empty” months.
Annual heat consumption	6277.6 GJ	Pronounced thermal component; the facility cannot be assessed like a standard commercial building.
Maximum hourly electric load	219.6 kW	Reference point for estimating the electrical functional minimum.
95th percentile of hourly load	171.8 kW	Represents a realistic sustained high-load level rather than a single outlier peak.
Heat-side capacity (substation)	1060 kW	Upper bound for the order of magnitude of the facility’s thermal needs.

The monthly electricity and heat consumption profile is illustrated in Figure 4.

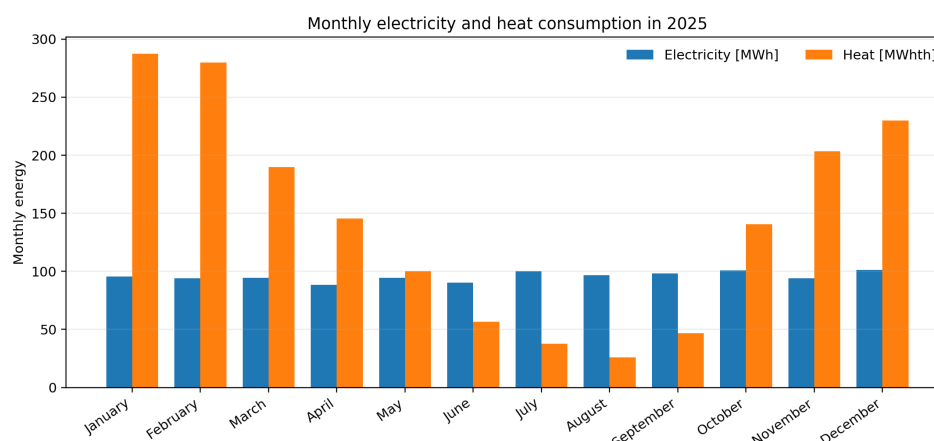


Figure 4. Monthly electricity and heat consumption in 2025 for the analyzed hospital.

The corresponding load–duration curve, together with the adopted functional minimum level, is shown in Figure 5.

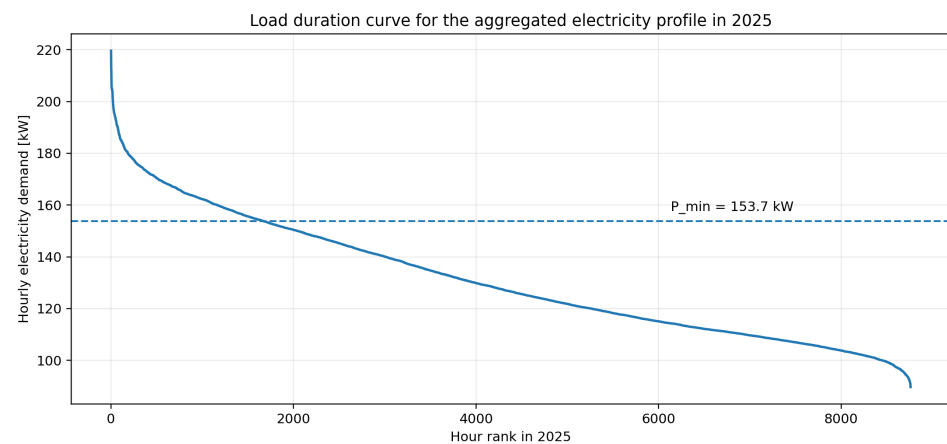


Figure 5. Load–duration curve of the aggregated electricity profile in 2025 and the adopted baseline functional minimum level $P_{\min}$.

4.3. Step 2—Definition of the Functional Minimum and Disruption Scenario

Functional minimum on the electricity side. Because the loads are not split into A/B/C classes, a simple and transparent screening proxy was adopted: $P_{\min} = 0.70 \times P_{\text{peak},h} = 153.7 \text{ kW}$. While a formal A/B/C load breakdown was not available for the analyzed facility, the adopted $P_{\min} = 70\%$ of $P_{\text{peak},h}$ is qualitatively consistent with the operational classification in Table 1: Class A loads (ICU, operating theaters, safety systems) are assumed to represent the non-reducible core, Class B loads (sterilization, IT, critical pumping) constitute the dominant share of the remaining coverage, and Class C loads (administration, non-essential lighting) are treated as curtailable. This illustrative allocation does not alter the numerical results of Sections 5.1 and 5.2 but clarifies the operational logic underlying the adopted screening proxy.

The 70% assumption represents the preservation of Class A functions together with the dominant share of Class B functions while selected support loads are curtailed. A sensitivity interpretation was additionally carried out for the interval 60–80% of $P_{\text{peak},h}$.

Functional minimum on the heat side. In the absence of an hourly heat profile, a baseline level of $Q_{\min} = 0.50 \text{ MWth}$ was adopted. This value lies above the average winter heat uptake, yet well below the 1.06 MW capacity available at the substation. It therefore provides a conservative but defensible approximation of a crisis-mode minimum covering space heating, DHW, and essential technical functions. A qualitative sensitivity range of 0.45–0.60 MWth was also considered.

Disruption scenario. In line with the article methodology, the reference case is a winter blackout with loss of external electricity supply, limited service availability, and a logistic risk of interruption in grid-gas delivery. As mentioned earlier, the 48 h horizon serves as the initial qualification threshold, while 72 h represents the target resilience level. In terms of the adopted functional minimum, this translates to an energy demand of 7.38 MWh of electricity and 24 MWhth of heat over 48 h, and 11.07 MWh of electricity and 36 MWhth of heat over 72 h. These assumptions, together with their sensitivity ranges, are summarized in Table 7.

Table 7. Assumptions used to define the functional minimum and the disruption scenario.

Parameter	Base Case	Sensitivity Range	Justification
$P_{\min}$	153.7 kW	0.60–0.80 $P_{\text{peak, h}}$	No A/B/C decomposition available; a percentage share of peak load was used as the screening proxy.
$Q_{\min}$	0.50 MWth	0.45–0.60 MWth	No hourly heat data; the range is anchored between the average winter load and the substation capacity.
Screening autonomy horizon	48 h	72 h as target	Consistent with the adopted technology-qualification logic.
Fuel scenario	Risk of interruption in grid-gas supply	Local fuel storage rewarded	Consistent with a resilience-oriented HILP framework.

4.4. Step 3—Portfolio of Analyzed Technology Architectures

This case study does not compare vendor catalogs but technology architecture classes. Each option is specified at the order-of-magnitude level required to test consistency with the demand profile of the analyzed facility. Where the methodology allows “simple complementary components”, a BESS and/or a peak-heat source were used to close a limited functional gap without deep reconstruction of the hospital. The six architectures subjected to preliminary qualification are listed in Table 8.

Table 8. Technology architectures subjected to preliminary qualification.

Code	Architecture	Adopted Screening Configuration	Comment
V1	Diesel generator	250 kWe	Reference only; not own heat supply.
V2	RES + BESS	300 kWp PV + 2 MWh/ 250 kW BESS	Short-term backup; unsuitable for multi-day winter use.
V3	Gas-fired CHP	200 kWe/240 kWth	Mature, but gas dependent.
V4	Dual-fuel CHP + BESS + boiler	200 kWe/240 kWth + 0.5 MWh BESS + 300 kWth peak-heat source	Hybrid, with local fuel storable.
V5	Biomass CHP + BESS + boiler	180 kWe/270 kWth + 0.5 MWh BESS + 300 kWth biomass boiler	High fuel autonomy, but space/logistics-intensive.
V6	Dual-fuel CCHP + BESS + boiler	200 kWe/240 kWth + 120 kWc absorption cooling + 0.5 MWh BESS + 300 kWth peak-heat source	V4 +cooling; justified only if cooling is confirmed as critical.

5. Results of the Methodology Application

5.1. Step 4—Stage I: Go/No-Go Screening

For each architecture, three simple engineering indicators were calculated. $GAI = P_{\text{avail}}/P_{\min}$ expresses electrical capacity adequacy, $TAI = Q_{\text{avail}}/Q_{\min}$ expresses thermal adequacy, and $FAI = t_{\text{aut}}/t_{\text{req}}$ expresses fuel autonomy against the required horizon.

Values < 1.0 indicate a shortfall. In Stage I, $TAI < 1$ avoids automatic rejection if the deficit can be covered by simple, non-invasive components. A value of 0.00 for TAI or FAI48 does not reflect a measurement or calculation artifact, but indicates that the architecture provides no thermal output, or no on-site fuel reserve sufficient for the 48 h autonomy horizon, respectively (e.g., diesel-only and RES + BESS variants inherently lack a thermal vector, while conventional natural-gas CHP lacks any local fuel stock under the assumed supply-disruption scenario). Consistent with the Boolean admission rule formalized in

Equation (1), an architecture is admitted to Stage II only if all three indices meet or exceed the 1.0 threshold, or where a shortfall in TAI can be resolved by a simple non-invasive component (e.g., an auxiliary peak boiler); a critical shortfall in any single index—such as $FAI_{48} = 0.00$ —is therefore sufficient on its own to trigger a No-Go outcome, regardless of adequate performance on the remaining indices. The resulting Go/No-Go verification for all six architectures is presented in Table 9.

Table 9. Stage I results—verification of architectures in Go/No-Go logic.

Code	Variant	GAI	TAI	FAI48	Result
V1	Diesel generator 250 kW _e	1.63	0.00	1.50	No-Go
V2	RES + BESS 300 kW _p + 2 MWh/250 kW	1.63	0.00	0.27	No-Go
V3	Gas-fired CHP 200 kW _e /240 kW _{th}	1.30	0.48	0.00	No-Go
V4	Dual-fuel CHP + BESS + peak boiler	1.30	1.08	1.50	GO
V5	Biomass CHP + BESS + peak boiler	1.17	1.14	1.50	GO
V6	Dual-fuel CCHP + BESS + peak boiler	1.30	1.08	1.50	GO

Stage I Screening Results

Variants V1 (diesel generator) and V2 (RES + BESS) were rejected due to the absence of thermal and cooling coverage; V2 additionally failed the multi-day fuel autonomy criterion in a winter scenario. Option V3 (gas cogeneration) was ruled out because, in the assumed scenario of gas supply disruptions, no realistic path to fuel self-sufficiency could be identified, despite its favorable technical parameters. Variants V4 (dual-fuel cogeneration + BESS + peak boiler) and V6 (dual-fuel cogeneration + BESS + peak boiler) met three out of three thresholds, providing full electrical and thermal profiles with the ability to start from zero and local fuel stock autonomy; Variant V6 additionally offers absorption cooling, contingent upon confirmed critical cooling demand. Variant V5 (biomass cogeneration + BESS + peak boiler) also passed the selection process, demonstrating high autonomy and full profile coverage, although its site feasibility rating is lower than that of variant V4.

Already at the boundary-filter level, it becomes clear that the demand profile of the analyzed hospital eliminates purely electrical architecture. The diesel generator remains a useful reference point and may protect part of the electric load, but it does not satisfy the multi-vector requirement. The stand-alone RES + BESS option does not achieve 48 h autonomy under winter conditions. Conventional natural-gas CHP is eliminated not because of efficiency, but because of the assumed fuel-risk scenario. Consequently, only hybrid solutions with locally secured fuel and a simple storage/start-up component pass to Stage II in a methodologically defensible manner. This assumption of grid-gas disruption risk reflects documented precedents of supply chain vulnerability in Central Europe, including the 2022 curtailment of gas flows following the Russian invasion of Ukraine and subsequent supply reallocation across the region; accordingly, natural gas is treated in this screening as a non-autonomous energy carrier under HILP conditions, consistent with the disruption scenario defined in Section 3.2.

5.2. Step 5—Stage II: Scoring of Admitted Solutions

Variants V4, V5, and V6 were ultimately selected for Phase II. The base weights specified in the methodology were applied: 0.20 each for readiness for island mode operation and fuel autonomy, 0.15 for readiness for cold start, 0.15 for multi-vector range, 0.10 for reliability and maturity, 0.05 for scalability and modularity, 0.10 for implementation feasibility, and 0.05 for operational safety. Although site-specific cooling load data were not

available, cooling is retained as a potentially critical function for the hospital case, consistent with the medical infrastructure requirements discussed in Section 2: air handling and filtration for infection-control zones, and refrigeration of blood products, organs, and temperature-sensitive pharmaceuticals (e.g., vaccines, insulin) all require uninterrupted cooling regardless of load magnitude. This qualitative criticality justifies including CCHP with absorption cooling (V6) in the technology basket, while the final decision on its necessity remains conditional on confirming actual cooling demand at the facility level, as already noted in Table 8. The resulting scoring assessment for the three prequalified architectures is shown in Table 10.

Table 10. Stage II results—scoring assessment of prequalified architectures.

Criterion	Weight	V4	V5	V6
Islanding readiness	0.20	5	4	5
Fuel autonomy	0.20	4	5	4
Black-start readiness	0.15	5	4	5
Multi-vector coverage	0.15	4	4	5
Reliability and maturity	0.10	5	3	4
Scalability and modularity	0.05	4	3	4
Implementation feasibility	0.10	4	2	3
Operational safety	0.05	3	3	3
Total weighted score	1.00	4.40	3.80	4.35

Scores were assigned using the anchor definitions in Table 4a; for example, V5 received a lower implementation feasibility score (2) due to the spatial and logistical demands of solid biomass fuel handling and storage, consistent with the qualitative characterization in Table 2. The final ranking of the three architectures is summarized in Table 11.

Table 11. Ranking of architectures after Stage II.

Rank	Code	Variant	Weighted Score	Conclusion
1	V4	Dual-fuel CHP + BESS + peak boiler	4.40	The most balanced option for the analyzed profile: strong islanding readiness, technical maturity, and complete electric and thermal coverage.
2	V6	Dual-fuel CCHP + BESS + peak boiler	4.35	A very strong option, but its added value becomes visible only when a critical cooling requirement is confirmed.
3	V5	Biomass CHP + BESS + peak boiler	3.80	The strongest fuel autonomy, but weaker local deployability and higher logistics complexity.

The weighted score for each architecture is calculated as the sum of its ordinal criterion scores (1–5, anchored per Table 4a), each multiplied by the corresponding weight from Table 4, in accordance with Equation (2). For example, variant V4 achieves its total score of 4.40 primarily through top ratings on the highest-weighted criteria— islanding readiness and fuel autonomy (weighted 0.20 each)—combined with strong-to-moderate scores on the remaining, lower-weighted criteria.

5.3. Step 6—Sensitivity Analysis and Interpretation of the Result

Decision stability. Within the range $P_{\min} = 0.60\text{--}0.80 P_{\text{peak}, h}$ and $Q_{\min} = 0.45\text{--}0.60 \text{ MWth}$, the Stage I result remains stable: V1, V2, and V3 still fail the boundary conditions, whereas V4–V6 remain prequalified. What changes is the margin between the admitted architectures. As the relevance of cooling increases, V6 becomes more attractive; in contrast, when stronger

emphasis is placed on fuel independence and lower dependence on external deliveries, the relative position of V5 improves.

Importance of the heat-to-electricity relation. The most important conclusion from the real-world data is that the analyzed hospital is not a facility for which extra electrical capacity alone is sufficient. In winter months, thermal energy is approximately three times larger than electrical energy. Therefore, the resilience architecture must combine islanded electrical operation with a credible local thermal source. This is precisely the factor that disqualifies simple diesel-only configurations as target solutions.

6. Conclusions, Limitations and Implications for Further Design

These findings confirm the value of inverting the traditional evaluation hierarchy for critical infrastructure emergency power: prioritizing survivability criteria ahead of economic optimization enables early, defensible elimination of technologies that would otherwise require costly and time-consuming techno-economic modeling before being ruled unsuitable. The hospital's real operating data confirm the validity of the adopted methodology: the demand profile itself eliminates part of the technology basket even before any economic optimization is attempted. For a facility with the analyzed profile, the most promising direction for further modeling is a hybrid CHP/CCHP architecture with energy storage, locally secured fuel, and a simple heat source for peak demand. The biomass CHP + BESS option remains very interesting from the perspective of 72 h autonomy, but before initiating a full feasibility study, it is necessary to verify site-specific spatial, organizational, and environmental constraints.

Moving from the preliminary selection stage to the FEED stage, a quantitative design model requires several additional inputs: an hourly heat demand profile, data on cooling and HVAC demand, the A/B/C load structure, information on existing backup generators, ATS/SZR systems, UPS systems, and the possibility of isolating the microgrid at the switchgear level. These data needs are closely tied to the methodological limitations of the present screening exercise, which deliberately excludes probabilistic resilience metrics (EENS, LOLE) and the control-level dynamics of parallel synchronous-inverter islanded operation, both identified in Section 3.4 as priorities for the subsequent dynamic-modeling stage. Such limitations do not undermine the value of the screening exercise as a prequalification tool, but they define its precise scope of validity and reinforce the necessity of the input data listed above before any final technology commitment.

Based on the present case study, it can be concluded that for the analyzed hospital, the methodology favors multi-vector and fuel-autonomous solutions. The first-choice option for detailed follow-up analysis is dual-fuel CHP + BESS + a peak-heat source, whereas biomass CHP + BESS should be treated as a strong resilience-oriented alternative, especially where local solid fuel security can be achieved. While these conclusions are grounded in a hospital case study, the underlying two-stage screening logic—and the boundary conditions it establishes for prequalifying multi-vector, fuel-autonomous architectures—is designed to be directly transferable to other critical infrastructure classes, such as water treatment plants or data centers, as noted in Section 3.2.

This study has several limitations. First, the screening framework relies on deterministic adequacy proxies (GAI, TAI, CAI, FAI) rather than probabilistic resilience metrics such as EENS or LOLE, which are identified as a priority for subsequent dynamic-modeling stages. Second, the case study input data are constrained to an hourly electricity profile and monthly heat consumption; hourly heat, cooling, and process steam data, as well as an ABC load decomposition, were not available and had to be approximated through screening proxies. Third, control-level coordination challenges between inverter-dominated BESS and synchronous CHP subsystems during islanded operation lie outside the scope of this

prequalification stage. These limitations do not undermine the framework’s validity as a pre-feasibility screening tool but define its precise scope of applicability ahead of detailed FEED-stage design.

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Abbreviations

The following abbreviations are used in this manuscript:

ATSSZR	Automatic Transfer Switch
BESS	Battery Energy Storage System
CAPEX	Capital Expenditure
CCHP	Combined Cooling, Heating, and Power
CER	Critical Entities Resilience
CHP	Combined Heat and Power
CI	Critical Infrastructure
DHW	Domestic Hot Water
EENSLOLE	Expected Energy Not Served/Loss of Load Expectation
ENTSO-E	European Network of Transmission System Operators for Electricity
FEED	Front-End Engineering Design
HILP	High-Impact Low-Probability
HVAC	Heating, Ventilation, and Air Conditioning
ICU	Intensive Care Unit
LCOE	Levelized Cost of Energy
LIHP	Low-Impact High-Probability
MCDM	Multi-Criteria Decision-Making
OPEX	Operational Expenditure
PUE	Power Usage Effectiveness
RES	Renewable Energy Sources
UPS	Uninterruptible Power Supply

Appendix A

Table A1. Monthly data used in the screening analysis.

Month	Electricity [MWh]	Heat [GJ]	Heat [MWhth]
January	95.386	1034.62	287.394
February	94.176	1007.55	279.875
March	94.292	682.73	189.647
April	88.424	524.52	145.700
May	94.290	360.88	100.244
June	90.325	203.48	56.522

Table A1. Cont.

Month	Electricity [MWh]	Heat [GJ]	Heat [MWhth]
July	99.996	136.25	37.847
August	96.815	93.20	25.889
September	98.293	168.28	46.744
October	100.746	506.62	140.728
November	94.095	731.77	203.269
December	101.166	827.73	229.925

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