Hybrid Renewable Energy System Optimization is Lacking Consideration of System Resilience and Robustness: An Overview

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***Abstract*—This paper reviews existing literature that focuses on optimizing Hybrid Renewable Energy System (HRES) regarding their incorporation of resilience and robustness properties and gives an overview of commonly used techniques in the field. HRES are energy systems consisting of renewable energy sources, as well as traditional fuel based generators as backup. In the current transformation phase of energy generation, it is important to size those systems large enough but as small as possible. Today, a plethora of optimization goals and techniques, as well as approaches to model and simulate the systems are known to researchers. Since no common definition of resilience and robustness exists for cyber-physical systems like HRES, different definitions are compared and explained. The review shows that a research gap exists in taking resilience and robustness into account when optimizing HRES. An outlook on how to address this research gap using Adversarial Resilience Learning (ARL) is also given.**

***Keywords*—HRES; optimization; resilience; robustness; ARL.**

I. INTRODUCTION

In order to reach the climate targets defined in the Paris Climate Agreement [1], the supply of electrical energy needs to be shifted from fossil to renewable sources. This often requires a redesign of the power grid as renewable energy sources are less dependable and therefore require ways of storing energy not necessarily needed before. At this point, the question of how to transform energy systems arises. This transformation will most likely not happen over night, which results in an intermittent state. The mix of renewable energy sources, energy storage and fossil sources as backup forms a Hybrid Renewable Energy System (HRES) [2]. Those systems can be built with a connection to the energy grid [3][4], or as standalone systems that provide electricity with low dependence on fuel in remote areas [5][6].

In order to design efficient and reliable HRES, a lot of research has been done on HRES optimization. Often, the optimization focuses on economical and technical aspects of the system like the cost of the generated energy or the system's ability to meet the energy demand. Recently, environmental and socio-political goals such as CO_2 emission of the system and impact on the local community have been scrutinized as well [7].

Renewable energy systems are often highly distributed and thus require extensive communication between components [8]. This leads to more and more digitization, effectively making the energy grid a large cyber-physical system [9], which poses different challenges. The recent blackout in the Ukraine [10] for example was caused by a cyber attack on the energy infrastructure. Other unpredictable events like the overloading of a substation in Europe in 2021, which lead to a system separation [11] or the increasing amounts of natural disasters like earthquakes, storms and floods show that energy grids can be disrupted in unforseeable ways [12][13]. In order to withstand such challenges, HRES must be resilient and robust, which begs the question whether resilience and robustness are considered in HRES optimization. Therefore, this paper gives an overview of HRES optimization, explains common techniques and reviews them regarding their incorporation of resilience and robustness.

Since no common definition of resilience and robustness exists, in Section II, we first compare existing definitions and decide on how we use the terms in this paper. In Section III, HRES components are introduced and their function is clarified. We describe optimization problems in general in Section IV, and methods used in HRES optimization in Section V. After that, in Section VI, common simulation techniques are explored. Section VII explains frequent optimization goals and reviews their consideration of resilience and robustness properties. Those findings are combined in Section VIII to identify a research gap. Finally, in Section IX a summary is given, as well as an outlook on how the research gap will be addressed.

II. ENERGY GRID RESILIENCE AND ROBUSTNESS

Throughout the literature exists no commonly agreed upon definition of resilience of cyber-physical systems. Arghandeh et al. [14] define cyber-physical resilience as

Definition 1. *The resilience of a system presented with an unexpected set of disturbances is the system's ability to reduce the magnitude and duration of the disruption. A resilient system downgrades its functionality and alters its structure in an agile way.*

The Presidential Policy Directive 21 [15] of the United States of America defines it as

Definition 2. *The ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.*

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The definitions show, that resilience of cyber-physical systems is concerned with the handling of unexpected disturbances. In order to remain functional, a resilient system downgrades its functionality and recovers back to the regular operating mode quickly. In energy grids the downgrade of functionality might mean shutting down subgrids in order to keep the rest of the grid stable. Resilience often gets confused with robustness. Arghandeh et al. [14] define cyber-physical robustness as

Definition 3. *Robustness is the ability of a system to cope with a given set of disturbances and maintain its functionality.*

The main difference is that a robust system maintains it's functionality, while a resilient system can downgrade and recover it's functionality. In energy grids robustness is, e.g., achieved with control energy [16]. Control energy is used to level frequency deviations that occur when energy demand and generation are not equal.

III. Hybrid Renewable Energy System Components

Hybrid Renewable Energy Systems are built from different components. They combine renewable energy sources like photovoltaic and wind turbines with traditional fossil fuel based generators to provide energy locally without high dependence on fossil fuels [17]. Traditionally, HRES are built for specific use cases like power sources for cities [18], small villages [19] or even buildings [20]. They can exist as standalone systems to provide power in remote areas [5] [6], or can be connected to the power grid [3] [4] in areas, where electricity is available anyways. This section explains commonly used components of HRES and describes their function.

A. Photovoltaic

Photovoltaic (PV) cells generate electricity by absorbing light. They consist of semiconductor material that forms an electric field. Once light hits the cell, electrons are knocked loose from the semiconductor's atoms. The electrons flow between the positive and negative side of the electric field, which creates a current and thus electricity. PV cells are usually connected and mounted to form PV modules, which can then be installed to harvest energy [21].

B. Wind turbine

Wind turbines convert the kinetic energy of wind into electricity. They achieve that by capturing the wind energy with rotor blades that make the rotor turn. The rotor is connected to a generator that turns the kinetic energy of the rotating motion into electricity. Usually, the rotor and generator are mounted on a tower to allow for large rotor diameters and thus a higher energy output [22].

C. Battery

Batteries are a form of energy store. They can store electrical energy as chemical energy. Batteries are composed of two electrodes, called anode and cathode, that are submerged in an electrolyte. When discharging a battery, a reduction-oxidation reaction occurs at the electrodes. At the anode, electrons are set free, which flow through the electric circuit attached to the battery to the cathode, thus creating a current. To balance that, positively charged ions move from the anode through the electrolyte to the cathode. If the right electrode material is used, batteries can be recharged by attaching an electricity source to the battery, which reverses the aforementioned process. Batteries can be used to store energy created by whether dependent energy sources if supply is higher than demand [23].

D. Diesel generator

Diesel generators are diesel engines that are connected to a generator. By compressing air and combusting diesel fuel, pistons in the engine move up and down cylinders. This motion is converted into a rotation of the crankshaft via connecting rods that connect the crankshaft to the pistons. The rotation powers a generator that transforms the kinetic energy to electrical energy [24]. The generator operates on the same principle as the generator in a wind turbine. The difference between a diesel generator and a wind turbine is the creation of the rotation.

E. Gas turbine

Gas turbines burn gas to create a rotating motion. The turbine compresses an air and gas mixture with rotating blades attached to a center shaft. The mixture is then ignited and the hot gases spin blades connected to the same shaft. The rotation is used to compress air on the compressor side and to power a generator similar to the generators used in wind turbines or diesel generators. An added benefit is the usage of the hot gas mixture for heating purposes, which allows for very efficient operation of gas turbines [25].

F. Hydrogen fuel cell

Hydrogen fuel cells use hydrogen and oxygen to create electricity. Although they are not energy stores, but rather energy converters, they work similarly to batteries. They consist of anode, cathode and electrolyte membrane. Hydrogen is passed through the anode and oxygen through the cathode. The hydrogen is split into electrons and protons. As in a battery, the electrons go through the attached circuit and the protons go through the electrolyte membrane. At the cathode, the electrons, protons and the oxygen combine again to form water, which is the only byproduct of this reaction apart from heat. Fuel cells differ from batteries in that they need a constant flow of hydrogen and oxygen, which is why fuel cells are not considered energy stores by themselves [26].

G. Hydrogen storage

Hydrogen is often stored in tanks. In order to maximize the amount of hydrogen that can be stored in a given tank, it is often compressed or liquefied. Pressures can reach up to 700 bar and in order to liquefy hydrogen it has to be cooled to -253°C. Compressing and liquefying hydrogen to store it adds costs to hydrogen handling. Liquefying for example, can use up to 30 % of the energy contained in the liquefied hydrogen [27].

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H. Hydrogen Electrolyzer

Hydrogen electrolyzers use electricity to split water into hydrogen and oxygen. They can therefore be used to create hydrogen to power fuel cells. Electrolyzers work similarly to fuel cells. They also consist of an anode, cathode and electrolyte. At the anode, water is split into oxygen and positively charged hydrogen ions. The electrons from this reaction flow through an external circuit, which powers the electrolyzer and the hydrogen ions travel through the electrolyte to the cathode. At the cathode, electrons from the external circuit and the positively charged hydrogen ions form hydrogen gas, which can then be extracted. Electrolyzers can be used to store energy in conjunction with hydrogen storage, if energy created by, e.g., a wind turbine is not currently needed [28].

IV. Optimization problems

The goal of optimization is generally to tune parameters of a system in a way, that makes the resulting system optimal. In order to know what is optimal, an optimization goal needs to be defined, which measures the performance of a certain set of parameters. Formally, an optimization problem can be described as [29]:

$$Minimize/Maximize: \quad F(x) \tag{1}$$

$$subject\ to: \quad g_j(x) \leq 0;\ j = 1, 2, ..., m\ , \tag{2}$$

where $F(x)$ is the target function representing the optimization goal and x is the parameter vector. The problem might be subject to a total number of m constraints $g_j(x)$ that limit the solution space.

Commonly used optimization goals and techniques in HRES optimization will be explained later in this paper.

A. Multi-Objective optimization

In order to incorporate multiple optimization goals into the optimization process, multi-objective optimization is often used. It also finds usage in HRES optimization frequently [3]–[5] [30]–[32]. Multi-objective optimization allows for goals to be combined and aims to find solutions that are good compromises regarding different targets.

In general, a multi objective optimization problem can be described as [33]

$$Minimize/Maximize: \quad F_{mo}(x) = [F_1(x), F_2(x), ..., F_k(x)] \tag{3}$$

$$subject\ to: \quad g_j(x) \leq 0;\ j = 1, 2, ..., m\ , \tag{4}$$

where $F_{mo}(x)$ is the multi objective function to be optimized, containing k single objective functions $F_k(x)$ and $g_j(x)$ the constraints like above.

There are two main approaches to multi-objective optimization. One combines the different objective functions into a weighted sum [33]

$$F_{mo} = \sum_{i=1}^{k} w_i \cdot F_i\ , \tag{5}$$

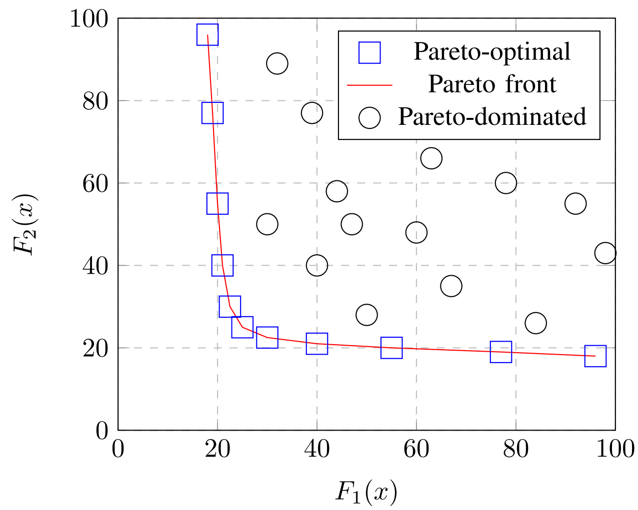

Figure 1. Example of Pareto front for 2 dimensional minimization problem

where w_i is the weight or importance of objective i and $F_i(x)$ is the ith objective function. In order to make this work, the different objective functions must either all be minimized or all be maximized. This can be achieved by multiplying objective functions by -1 to get the desired direction. The individual objective functions might also be normalized to allow the weight choice to directly represent an objectives importance without taking range of values into account [30]. For the other approach, each single objective function is evaluated separately. A set of solutions is retained, within which each solution is Pareto optimal. Pareto optimality is based on the hypothesis that solutions cannot be compared if one is better at one objective and the other at another. A solution is only better if it is better for at least one objective and at least equally good on all other objectives. In this case, the better solution Pareto-dominates the other solution. Formally a solution x Pareto-dominates a solution x' in a minimization problem if and only if

$$\forall i \in 1, ..., k : F_i(x) \leq F_i(x'),$$
$$and\ \ \exists j \in 1, ..., N : F_i(x) < F_i(x') \tag{6}$$

Figure 1 shows an example of Pareto-optimal and Pareto-dominated solutions and the Pareto front for a 2 dimensional minimization problem.

The set of solutions contains only solutions that are Pareto-optimal, meaning that all solutions within the set are not comparable and they Pareto-dominate every other solution. This set is called Pareto-optimal set or Pareto front [34].

This approach does not result in one best solution, but a set of solutions, from which a human can choose a suitable solution for the underlying problem. It is also regularly used in the context of HRES optimization [3][32][35].

V. Optimization methods

A. Evolutionary Algorithms

Evolutionary Algorithms (EAs) are optimization algorithms inspired by evolution theory. They use a combination of recombination, mutation and selection operators to find good solutions in the search space. In general, EAs first create an initial set of solutions, called population. For each iteration of the algorithm, solutions undergo the aforementioned steps. First, individuals recombine, which combines parts of two or more individuals into one or more so called offspring solutions. Those are then mutated, which adds random changes. From the old population, called parents and the new offsprings, a new population is selected, which is the new generation of parents for the next algorithm iteration. Selection is done by comparing the fitness of individuals, which is measured with objective functions such as those described in the previous section. They also work well on multi-objective optimization problems [29].

EAs are used frequently to optimize HRESs [32][36]–[38].

B. Particle Swarm Optimization

Another common technique in HRES optimization is Particle Swarm Optimization (PSO) [5][30][35][39]. It is inspired by the behavior of biological swarms and was first introduced by Kennedy and Eberhart [40]. Similar to EAs, PSO uses multiple individuals to carry out the search. In this case the population is called swarm, and the individuals particles.

Each particle in the swarm has knowledge about it's personal best and the global best solution that was previously found, as well as a velocity of it's movement through search space. This velocity depends on the distance to the current personal and global optima. It is lower, the closer the current solution is to the optima and higher, if it is further away. This encourages exploitation close to and exploration far from known optima.

In an iteration of the algorithm, the particle positions are updated by adding the velocity to their current position. Next, the fitness values of the particles are evaluated and the current personal and global optima are updated. Finally, the new velocities are calculated [29].

C. Other optimization methods

Less popular optimization methods used for HRES optimization include *Honey Bee Mating Optimization* [3], *Ant Colony Optimiztion* [41], *Harmony Search* [42], *Sampling Average Method*[31], *Simulated Annealing* [43] and *Tabu Search* [44]. This is not an exhaustive list, since in theory every optimization technique is usable in HRES optimization. Hybrid optimization methods that combine those algorithms are also investigated [45][46].

D. Software Solutions

Many software solutions exist for modeling, simulating and also optimizing HRES. Their main advantage is allowing optimization of HRES for users without algorithmic and programming skills. They also include modeling and simulation, which makes it possible to optimize and evaluate with one single program. Cuesta et al. [47] recently carried out a study of those software solutions.

The most popular HRES tool is *HOMER*. It allows optimization of systems regarding the Net Present Cost (NPC) [47]. Although this is the only possible optimization goal when using HOMER, it is frequently used for HRES optimization [4][48]–[50].

According to the study of Cuesta et al. other software capable of optimization are *DER-CAM*, *iHoga* and the open source *Calliope*. Calliope allows only optimization regarding Cost of Energy generation (COE), DER-CAM COE and CO_2 emissions, iHOGA NPC, CO_2 emissions, loss of load, human development index, and job creation. DER-CAM and iHoga can make use of multi objective optimization, iHOGA even allows for Pareto-optimization. From those tools only iHOGA is used somewhat regularly in HRES optimization [49][51].

VI. Simulation methods

A very important part of HRES optimization is the simulation of solutions. In order to calculate the target functions of the optimization, the performance of solutions must be evaluated. Since it is usually not feasible to build the proposed HRES and measure it's performance in real life, simulation is often employed.

In order to be able to simulate a HRES, energy demand and generation need to be modeled. Demand is modeled by load profiles. The energy generation of photovoltaic systems and wind turbines mainly depends on the weather. Because of that, sun radiation and wind speed profiles are important to calculate the output of those components. Practically, all of the surveyed work relies on those profiles to simulate HRES performance.

One common way to simulate the system is using mathematical models of the HRES components to calculate their output [5][30][32][35]–[37]. For every simulation step, the generated energy of renewable sources is calculated with equations that depend on the sun radiation or wind speed, as well as efficiency of the device. This generation is then compared to the load. If there is a surplus of energy, it is stored in the respective storage device of the system. Since those processes are not 100 % efficient, equations are used to calculate the stored energy depending on input and device efficiency. For electrolyzers, the amount of created hydrogen is calculated here. If not enough energy to meet the load is generated by the renewable sources, the stored energy is usually used first. Depending on the storage device it is calculated how much the storage has to be drained to supply the necessary load. In case the renewable and stored energy is not enough to supply the load, fallback solutions like diesel generators and gas turbines have to be used. The fuel consumption needed to supply the load can then be calculated by mathematical models as well.

Many different equations exist for modeling HRES components, which will not be discussed in detail here, because of varying complexity and accuracy. The review by Bhandari et al. [52] provides a good overview.

HRES tools such as the previously mentioned HOMER, DER-CAM and iHOGA include simulations of the created systems [47]. This is a key aspect of what makes these tools popular since no own implementation of the mathematical models is required.

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Failures of components or other disturbances could be included into the simulation e.g, by deactivating certain energy sources for some time in the simulation run. This would mimic real life failures in the system and allow for the investigation of the systems robustness and resilience. For resilience testing, further logic would need to be implemented into the simulation models that allows for the downgrading of functionality by e.g, cutting power to certain loads or by removing the connection to parts of the system in order to stabilize the system as a whole. Of the reviewed publications, none have incorporated system disturbances or the ability to downgrade into their simulations and thus did not challenge the robustness or resilience of the system.

VII. Optimization goals

Optimization goals are used as target functions for optimizing HRESs. Different configurations can be compared by comparing those target functions. This section gives an overview of commonly used goals in HRES optimization and evaluates their incorporation of robustness and resilience properties.

A. Economic optimization goals

A common economic optimization goal for HRESs is the COE [4][5][36]. The COE describes how expensive the average annual energy creation of a system is per unit of energy and is often given in $\mathrm{USD/kWh}$. Similarly, the Levelized Cost of Energy generation (LCOE) describes the average energy creation cost per unit over the entire project lifespan [30]. The LCOE can be calculated as [30][53]

$$LCOE = \frac{TPV}{E_L} CRF \quad [\mathrm{USD/kWh}] \ , \tag{7}$$

where the Total Present Value (TPV) depends on the components of the system:

$$TPV = \sum_{d=1}^{k} C_d \quad [\mathrm{USD}] \ , \tag{8}$$

where d is the device of k total devices and C_d are the costs associated with said device calculated as:

$$C_d = Init_d + C_{O\&M_d} \quad [\mathrm{USD}] \ , \tag{9}$$

comprised of initialization costs $Init_d$ and operation and maintenance costs $C_{O\&M_d}$, which also include replacement costs if necessary.

In equation 7, E_L $[kWh]$ is the total load over the simulation period. Capital recovery factor (CRF) takes the interest rate into consideration and is calculated as:

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \ , \tag{10}$$

where i $[\%]$ is the nominal interest rate and n $[years]$ is the system life.

The Net Present Value (NPV) is the difference between the present value of cash inflow and the present value of cash outflow of a system over a period of time and therefore a measurement for the return of investment [54]. In the context of HOMER (see Section V-D), the NPV is called NPC [55] and is used under that name in several publications [4][31].

Using the notation from above, it can be calculated as

$$NPV = (E_L - TPV) \ CRF \quad [\mathrm{USD}] \ . \tag{11}$$

The LCOE is the selling price needed to yield a NPV of 0 [56].

The aforementioned measurements take into account costs and earnings. Goals focused exclusively on the costs of a system are also used in the context of HRES optimization.

One such approach is the Annualized Cost of System (ACS), which annualizes all costs of the entire system [32] and can be described as

$$ACS = \sum_{d=1} C_{ad} \quad [\mathrm{USD}] \ , \tag{12}$$

where C_{ad} are the annualized costs of a device that occur over the project's lifespan. A similar approach is the Life Cycle Cost (LCC). It sums all costs over the project but does not annualize them [37].

The Initial Capital Cost (ICC) measures how high the initial investment of a system is. This can be useful in situations with limited initial budget and calculated as [37]

$$ICC = \sum_{d=1} Init_d \quad [\mathrm{USD}] \ . \tag{13}$$

None of the presented economic optimization goals measure the robustness or resilience of the system. Since they are concerned with the cost of the system or the generated energy, they rather work contradictory to the idea of a robust and resilient system. Enabling a system to be able to handle disturbances usually means adding redundancies, which in turn increases costs. Balancing those opposing objectives would be a key challenge when robustness and resilience should be implemented into HRES optimization.

B. Technical optimization goals

Technical optimization goals aim to formulate target functions that measure service security and reliability of the system. A widespread technical optimization goal is the Loss of Power Supply Probability (LPSP) [5][30][32][39][57]. Some publications refer to it as Loss of Load Probability (LLP) [31][36]. It measures the probability of the system being unable to supply enough power to satisfy the energy demand at any given time and can be calculated as [58]

$$LPSP = \frac{\sum_{t=1}^{T} E_{DE}(t)}{\sum_{t=1}^{T} E_L(t)} \quad [\%] \ , \tag{14}$$

where t is the current time step of T total time steps of the simulation, $E_{DE}(t)$ the energy deficit at time step t and $E_L(t)$ the total load at time step t.

Apart from the usage as a regular optimization goal, the LPSP is often used as a constraint. In that case, solution candidates must achieve a LPSP under a chosen constant to

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even be considered. This is done to ensure a certain level of reliability while optimizing other aspects of the system.

The LPSP could be a measure of the system's robustness and resilience, **if** the system is exposed to disturbances. If the system was exposed to threats, the LPSP would be improved if the system was robust enough to withstand the threats. If the HRES also had the ability to downgrade it's functionality, the LPSP would increase less than in the case of a total collapse, which would then be a measure of resilience. In the reviewed publications that use it, the system is not exposed to such events and therefore the LPSP only measures the reliability in regular operation.

The minimization of power losses aims to improve the efficiency of a HRES [3]. It can be described as

$$Loss_P = \sum_{t=1}^{T} \sum_{i=1}^{N_{br}} (R_i \cdot |I_i|^2 \cdot \delta t) \quad [\mathrm{W\,h}] \ , \qquad (15)$$

where i is the current branch, N_{br} is the total number of branches, R_i is the resistance of branch i, I_i is the actual current of branch i and δt is the time step in the simulation.

While the minimization of power losses is an important goal for creating an effective system, it has no direct impact on the robustness and resilience of the system.

C. Environmental optimization goals

One of the most present goals in HRES optimization is the reduction of emissions. The direct emission of CO_2 from the combustion processes within a diesel generator or gas turbines over the course of the project or a year is often used as a target function [31][32]. It can be calculated as [35]

$$Emission = \sum_{d=1}^{D} \sum_{t=1}^{T} cons_d(t) \cdot EF_d \quad [\mathrm{kg}] \ , \qquad (16)$$

where $cons_d(t)$ is the fuel consumption of device d at time t and EF_d is an emission factor that is specific to the device's and the fuel's characteristics. The emission factor usually ranges from 2.4 to 2.8 kg/l [59].

Other approaches try to incorporate all CO_2 emissions of a device over it's entire lifetime [30]. This includes emissions from harvesting the used materials, manufacturing, transporting, installing, operating and maintaining the device, as well as disposing it [60]. By dividing the emissions by the amount of generated energy, the Carbon Footprint off Energy (CFOE) can be calculated. It quantifies the emission of equivalent CO_2 mass per kWh of produced energy and can be described as [30][61]

$$CFOE = \frac{\epsilon_{sys}}{E_L} \quad [\mathrm{kg}CO2_{eq}/\mathrm{kWh}] \ , \qquad (17)$$

where ϵ_{sys} are total the emissions of the entire system:

$$\epsilon_{sys} = \sum_{d=1}^{D} \epsilon_d \quad [\mathrm{kg}\, CO2_{eq}] \qquad (18)$$

and ϵ_d the total emissions of device d, which can be broken down into

$$\begin{aligned} \epsilon_d = {} & \epsilon_{mat} + \epsilon_{man} + \epsilon_{trans} + \epsilon_{inst} \\ & + \epsilon_{o\&m} + \epsilon_{disp} \quad [\mathrm{kg}\, CO2_{eq}] \ , \end{aligned} \qquad (19)$$

which are the emissions for material gathering, manufacturing, transporting, installing, operating and maintaining and disposing the device.

The Renewable Energy Ratio (RER) is the ratio of energy created by renewable sources vs. conventional sources an is used as a environmental optimization goal [31]. It can be calculated as

$$RER = \frac{E_{ren}}{E_{conv}} \ , \qquad (20)$$

where E_{ren} and E_{conv} are the amounts of energy created by renewable and conventional sources respectively.

A similar approach is the Renewables Factor (RF) [30] calculated as

$$RF = 1 - \frac{E_{conv}}{E_{ren}} \ . \qquad (21)$$

None of the described goals measure robustness and resilience or directly impact those properties.

D. Socio-Political optimization goals

Recently, socio-political optimization goals are being scrutinized, since HRES impact communities in which they are installed beyond technical or environmental criteria, e.g., by creating jobs or shaping the landscape [47].

Eriksson et al. [30] have proposed a way to quantify the socio-political impact of a HRES to include it into the optimization process. The approach incorporates qualitative and quantitative factors to create an index-based measurement that represents the expected public satisfaction of a HRES. The used parameters are:

- **Aesthetics:** Acceptance of visual appearance, noise disturbance etc.
- **Employment:** Employment opportunities
- **Perceived hazard:** Potential hazard risk
- **Land requirement and acquisition:** Public resistance to land acquisition
- **Perceived local environmental impact:** Impact such as eco-system disturbances
- **Local ownership:** Ratio of local ownership in the proposed system
- **Local skills availability:** Availability of local workforce suitable for the project
- **Local resource availability:** Availability of local resources needed for the project
- **RF:** Penalty for reliance on non-renewable energy
- **Perceived service ability:** Level of improved service ability, such as improved availability of social electricity services

A score is assigned to each parameter ranging from 1 to 5 in order to rate a system or component. The scores are weighed

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to represent their importance on the given project, since every project has different priorities and different factors are important to the community. The weighed scores are then summed to give a single score named *Socio*. The perceived service ability parameter of the socio is impacted by a robust or resilient system, since the availability of the electrical services rises with robustness and resilience. Since no disturbances were used in it's original publication, that potential metric of robustness and resilience is yet unused.

VIII. Research gap

Some work has been done on resilience of HRES without specifically targeting optimization. Kosai et al. [62] proposed a method to analyze system resilience regarding batteries. They measure resilience of a HRES by assessing how much of the batteries can fail for how long throughout a day without impacting self sustainability of the system. Using those two performance indices, the authors size batteries of HRES to have sufficient resilience at minimal cost. Approaches like these only mimic failures and downgrading of certain components and cannot sufficiently evaluate the entire systems vulnerability to attacks or disasters due to this.

Currently, robustness and resilience is not considered in HRES optimization, as we have explained in the previous sections. Some of the optimization goals like the LPSP (see Section VII-B) and the *Socio* (see Section VII-D) have the potential to measure robustness and resilience of the system. In the reviewed publications, they could not fulfill that potential, because no disturbances were incorporated while simulating system performance. Also, none of the systems had the ability to downgrade their functionality (see Section VI), which is the key part of a resilient system according to the definitions we showed. Recent cyber attacks, e.g., the blackout in Ukraine [10] and the increasing amounts of natural disasters like earthquakes, storms and floods, as well as disturbances due to system overloads [11] show that energy grids can be disrupted in unforseeable ways [12]. Because of this, it would make sense to include resilience and robustness against such events into HRES optimization by challenging the systems with these occurrences.

In summary, a research gap exists in scrutinizing HRES robustness and resilience by confronting them with disruptions. Also, no distinct measures of system resilience or robustness against such disruptions have been used in HRES optimization.

IX. Conclusion

This paper provided an overview of HRES optimization by explaining frequently used techniques to optimize and simulate HRES. Since no commonly agreed upon definition exists for resilience and robustness of cyber-physical systems, a selection of definitions from literature was presented and applied to the energy grid and in extension HRES in Section II. We explained common optimization goals and techniques in Sections V-VII, which are summarized in tables I and II and highlighted a lack of consideration of robustness and resilience against unexpected disruptions in literature.

TABLE I
SUMMARY OF OPTIMIZATION GOALS

Goal	Formula
Economic optimization goals	
LCOE	$LCOE = \frac{TPV}{E_L} CRF$ [USD/kWh]
NPV	$NPV = (E_L - TPV)\ CRF$ [USD]
ACS	$ACS = \sum_{d=1} C_{ad}$ [USD]
ICC	$ICC = \sum_{d=1} Init_d$ [USD]
Technical optimization goals	
LPSP	$LPSP = \frac{\sum_{t=1}^{T} E_{DE}(t)}{\sum_{t=1}^{T} E_L(t)}$ [%]
Power loss	$Loss_P = \sum_{t=1}^{T} \sum_{i=1}^{N_{br}} (R_i \cdot \lvert I_i \rvert^2 \cdot \delta t)$ [W h]
Environmental optimization goals	
CO_2 emission	$Emission = \sum_{d=1}^{D} \sum_{t=1}^{T} cons_d(t) \cdot EF_d$ [kg]
CFOE	$CFOE = \frac{\epsilon_{sys}}{E_L}$ [kg$CO2_{eq}$/kWh]
Socio-Political optimization goals	
Socio	Weighted score of multiple parameters

TABLE II
SUMMARY OF OPTIMIZATION AND SIMULATION METHODS

Optimization method	Possible goals	Simulation method
EA	All	Mathematical modeling
PSO	All	Mathematical modeling
HOMER	NPC	Internal simulation
Calliope	COE	Internal simulation
DER-CAM	COE CO_2 emission	Internal simulation
iHOGA	NPC CO_2 emission LLP	Internal simulation

In order to address this research gap, we will develop optimization goals that measure system reliability and robustness in future work. The main concept used for this will be Adversarial Resilience Learning (ARL) [13][63][64]. It allows two agents to compete on the same environment. In the context of ARL, those agents usually take the role of attacker and defender and one key showcase of the concept is the energy grid. Here, the attacker tries to destabilize the grid and the defender tries to keep the grid in a stable state. It is possible to use many different types of agents such as rule based, learning or random agents. The defender could be realized as a multi-agent system, as those have been frequently used in smart grid management applications [65]–[70]. Learning agents can be used to uncover vulnerabilities of the underlying environment by learning attack strategies in the attacker agent. This approach could be expanded to HRES optimization by using proposed HRES configurations as environments and analyzing how easy the attacker agent could disrupt it. Possible measures in terms of optimization goals could be the time needed to disrupt the system, the amount of successful disruptions over multiple experiments, the ability of the system to downgrade and recover from those attacks or the time needed to fully recover. This could be integrated nicely into an optimization loop with the python framework *palaestrai* [64][71]. Palaestrai allows for easy setups of ARL experiments from configuration files, which is well suited for changing environments (changing configuration of HRES).

With this new approach robustness and resilience could be considered in HRES optimization, which would improve reliability of those systems in the future.

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