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A Conceptual Framework to Determine the Economically Optimal Level of Microgrid Resilience

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Abstract

The increased frequency of electrical outages due to natural disasters in recent years has necessitated the enhancement of the resilience of the power grids. Microgrids are considered as one of the effective measures for the resilience enhancement due to their ability to island themselves during an outage and thus to ensure continuity of supply. While planning a microgrid for the purpose of resilience enhancement, it is important to evaluate the level of resilience possessed by the microgrid itself. Currently, there is no standard framework for resilience evaluation of a microgrid. The available resilience evaluation frameworks in the literature typically ignore the economic parameters which are important in the decision-making about investments in resilience enhancement. To bridge this gap, a methodology to evaluate the economically optimal level of microgrid resilience is proposed. The proposed new methodology is demonstrated by assuming a community microgrid model. An availability-based resilience evaluation framework is used for quantification of the resilience. That is, the resilience of a microgrid is quantified using the microgrid's availability during the islanded mode. Two resilience enhancement measures are evaluated: an increase in the amount of energy generation capacity from photovoltaics and an increase in the amount of energy storage by using a battery. The quantified resilience values are monetized using the Value of Lost Load economic indicator. The economically optimal resilience level for different combinations of loads is evaluated using the Net Present Value method. An increase in the amount of energy generation capacity from photovoltaics is found to be the most effective resilience enhancement measure giving maximum resilience and economic gains. The proposed methodology can be extended for determining the economically optimal resilience level for microgrids having different combinations of sources and loads.

Keywords: Resilience; Microgrid; Economic evaluation; Power outage.

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1 Introduction

Storms, hurricanes, floods, wildfires, and other natural disasters can lead to major disruptions of power supply. The increased frequency and severity of natural disasters in recent years has necessitated the enhancement of the resilience of the power grids. The losses due to electrical outages have a large negative economic impact. Hence it is important to mitigate these impacts in the future by a reasonable amount. In this context, the resilience of the power grid comes into the picture. The resilience of power grids is the ability of the grid to adapt and recover from extreme events.

Microgrids are considered as one of the most effective measures to increase the resilience during natural disasters because of their ability to isolate themselves from the main grid during the occurrence of an outage and maintain continuity of supply to the local load (Kezunovic and Overbye, 2018). Microgrids are a part of the power grid, having their own local distributed generation resources and being able to operate autonomously to supply the local loads and thus reducing the impact of the disaster. While planning a microgrid for resilience purposes, it is important to quantify the level of resilience of the microgrid to be able to evaluate its preparedness against extreme events. Since the enhancement of microgrid resilience involves significant capital investment, it provides useful to determine the economic value of the resilience in order to be able to take an informed and rational economic decision on the optimal level of resilience that a microgrid should possess. In the literature, there is no standard to measure the economic value of the microgrid resilience, which is one of the challenges when designing the microgrid for resilience enhancement purposes ("Unpacking the Value of Resiliency That Microgrids Offer," n.d.). The economic benefit of increasing microgrid resilience has also been discussed in (Stadler et al., 2016), but without providing a methodology for evaluation. Reference (Roege et al., 2014) provides a metric for resilience evaluation that is based on a subjective scale. In reference (Thomas and Henning, 2017), a methodology to calculate the economic value of a resilient power supply is given but it lacks a method to actually quantify the resilience level. Finally, in (Vugrin et al., 2017), a comprehensive approach is used to calculate resilience, and its economic value for the decision-making purpose, similar to our own research, but it focuses on the large scale electrical distribution systems and not particularly on microgrids.

This study aims at proposing a new methodology to evaluate the economically optimal level of resilience for a microgrid. Using the resilience quantification results, the economic benefits obtained from the increased resilience are compared with the investment cost for resilience enhancement and its economic value is evaluated using the net present value method. The benefits from feed-in tariff and self-consumption of energy are also considered. The optimum level of resilience for the microgrid is found out using the obtained results.

To demonstrate the methodology, a community microgrid model was considered. During the disaster, microgrids will isolate themselves from the main grid. Hence, the resilience of the microgrid is considered during islanded operation only. Different combinations of load patterns are compared to investigate their resilience levels. The effect of changes in the load pattern on the optimum resilience level is also analyzed.

This paper is structured as follows. Section 1 provides a general introduction. Section 2 proposes the methodology and reports on the theoretical background. Section 3 demonstrates the implementation of the methodology considering a community microgrid model. Results obtained are presented and discussed in section 4. Section 5 provides some conclusions and scope for future research.

2 Microgrid resilience evaluation

In the context of power systems, resilience refers to the ability of a power system to recover quickly following an unforeseen, potentially catastrophic shock event (in the following referred to as 'disaster'). In general, it is the ability to anticipate extraordinary and high-impact, low-probability events; rapidly recover and adapt operations and structure for preventing or mitigating the impact of similar events in the future. Adaptation refers to the long-term planning and operational measures taken to reduce the vulnerability to external sudden shocks (Panteli and Mancarella, 2015). A generally accepted definition of resilience is 'the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions' ("Presidential Policy Directive 21," n.d.). According to this definition, resilience can be interpreted as an attribute with four components (Kwasinski, 2016) listed in Table 1.

Table 1: Resilience Components

Component	Explanation
Withstanding capability	Capacity to sustain operation amid disaster / robustness
Recovery speed	How long does it take to recover for a given level of disruption (power outage)/ rapidity
Preparation / planning capacity	Ability to implement measures to reduce future potential outages / resourcefulness
Adaptation capability	Ability to react to conditions that could affect the power grid's performance / recovery

Microgrids are considered as an effective solution to enhance the resilience of the power grid, but the resilience of the microgrids itself needs further evaluation. It is important to investigate the resilience of microgrids from both a technical and an economic perspective. How much is it worth not to lose power when the grid goes down? Answering that question could mean the difference between a "yes" or a "no" for a company or a community considering investing in a microgrid ("What is the Economic Value of Microgrid Resilience," 2017). Currently, a standardized metric to measure the resilience of a microgrid does not exist. Most of the proposed metrics consider complex technical parameters to measure resilience. These technical resilience metrics cannot be translated to economic indicators used in the decision-making process.

There have been various methods proposed in the literature for the quantification of resilience in the context of electrical power grids. These methods can be broadly classified into

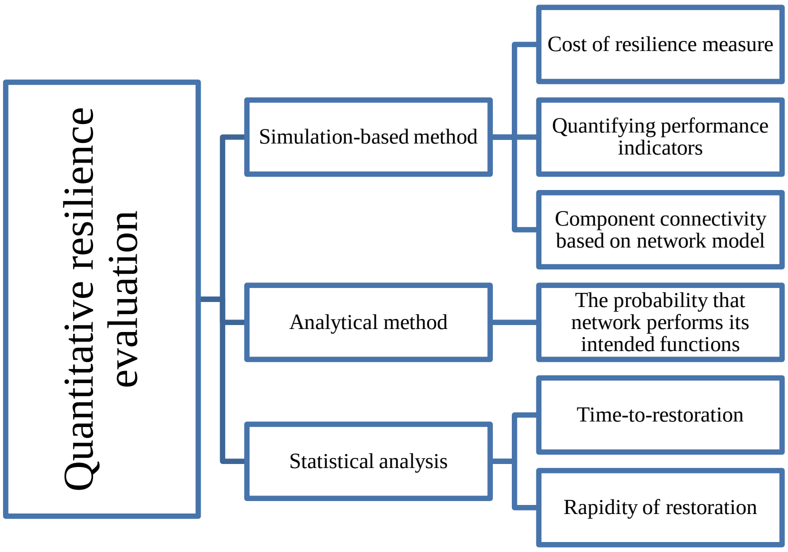


Figure 1: Summary of quantitative resilience evaluation methods. Source: (Bie et al., 2017)

two categories: qualitative resilience evaluation and quantitative resilience evaluation (Bie et al., 2017). Qualitative methods usually take into consideration different system aspects and different capabilities of the systems to evaluate resilience. System aspects can include attributes of the power system and other interdependent systems such as a communication system or a fuel supply chain. Capabilities take into consideration preparedness, mitigation response and recovery, which are evaluated using qualitative factors such as the existence of an emergency plan, personnel training etc. In contrast, quantitative methods focus on the evaluation of system performance and quantify it by defining a metric. Quantitative methods can be further classified into three categories: simulation-based methods, analytical methods and statistical analysis as shown in Figure 1.

Figure 2 summarize quantitative and qualitative methods of resilience evaluation (Bie et al., 2017)

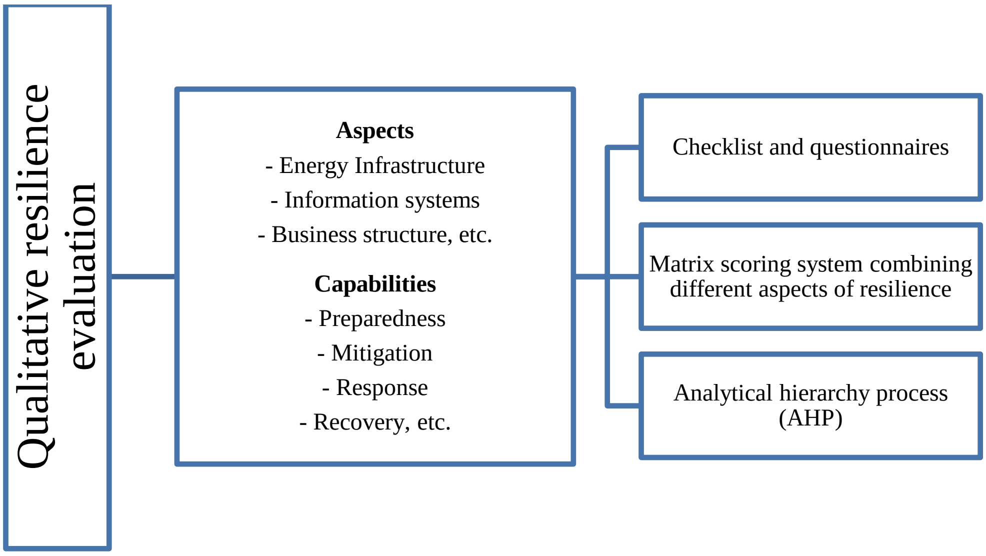


Figure 2: Summary of qualitative resilience evaluation methods. Source: (Bie et al., 2017)

For a comparison between the resilience of different scenarios to find an optimum scenario, it is important to have a quantitative measure. Therefore, quantitative resilience evaluation is used.

2.1 Availability based resilience quantification

This research uses the 'availability based resilience evaluation framework' for resilience quantification introduced in (Krishnamurthy and Kwasinski, 2016). Accordingly, resilience of the microgrid can be measured as a quantity corresponding to the availability. Hence, the resilience level R of the microgrid can be calculated as

$$R = \frac{T_U}{T_D + T_U}, \tag{1}$$

where T_U is the uptime and T_D is the downtime. The sum of T_D and T_U is the total resilience evaluation time T. The downtime T_D is related to the recovery speed, and it is influenced by both available infrastructure and human-related activities such as repairs and maintenance policies. The uptime T_U is directly dependent on the withstanding capability of the power grid to the given event. Its value is mostly related to infrastructure characteristics and grid design.

Although preparation / planning capacity and adaptation capability are not directly reflected in the resilience measurement, they influence the resilience metric indirectly.

For example, they will be reflected in the resilience values of two different scenarios. Scenarios may differ in the available generation capacity or storage capacity of the microgrid and will give two different values for resilience. This difference will indicate a change in resilience when adopting different technological or infrastructure improvements in the microgrid.

A comparison between the two resilience values will represent the part of the implementation of planning and adaptability on resilience. This quantifiable difference can be used in conjunction with cost analysis and probabilistic evaluation to decide about the priority setting, based on the resilience and cost of implementing different scenarios. Since this research aims to evaluate the resilience of a microgrid for various scenarios, this approach is perfectly suited. It also considers all the components of resilience attributes. Hence an availability-based resilience quantification framework is used to analyze the microgrid resilience in this research. The resilience of the microgrid in the context of this research is defined as the "resilience of the microgrid is the availability of the microgrid in the event of the disaster until the recovery of the parent network".

According to the considered definition, the resilience is evaluated only when there is an outage in the parent distribution grid and microgrid is supplying the loads through its own DERs, i.e., the microgrid is in the islanded mode. Hence, the resilience of the microgrid only during islanded operation is considered in this research. The resilience is calculated for the whole microgrid and not considered independently for individual consumers within the microgrid. Notice that the resilience evaluation methodology adopted does not consider any partial supply to the loads. Therefore, the microgrid consumers are either supplied to their full load demand or not supplied at all. The possibilities of load curtailment and demand-side management are not considered at this step in this research.

Let $G[t]$ be the fitness function indicating the ability of the microgrid to serve the load. At every time instance t, $G[t]$ measures the total difference between the capacity of microgrid resources (energy supply + energy storage) and the load demand. The $G[t]$ function for time interval t can be defined as

$$G[t] = X[t] + B[t] - L[t] \tag{2}$$

where $X[t]$ is the energy supplied by the source in time interval t, $L[t]$ is the load energy demand during time interval t, and $B[t]$ is the energy in the battery storage unit at time interval t. $G[t]$ indicates the ability of the energy source and the battery to serve the load at the time interval t.

If $G[t]$ is positive ($G[t] > 0$), it indicates that there is surplus energy in the grid. If $G[t]$ is negative ($G[t] < 0$), it indicates that there is an energy deficiency in the grid. If $f_{X[t]}$ is the probability distribution of $X[t]$, $f_{L[t]}$ is the probability distribution of $L[t]$ and $f_{B[t]}$ is the probability distribution of $B[t]$ at time t, then the probability distribution of $G[t]$, $f_{G[t]}$, can be calculated using eq. (3). The resilience of the microgrid $R[t]$ at the time instance t is given as,

$$R[t] = Pr(G[t] \geq 0) = \sum_{g \geq 0} f_{G[t]}, \tag{3}$$

i.e., resilience $R[t]$ equals to the probability that the microgrid resources can satisfy the load demand at the time instance t (probability of $G[t] \geq 0$). To find the probability distribution of $G[t]$, i.e., $f_{G[t]}$, the probability distributions of $f_{X[t]}$, $f_{L[t]}$ and $f_{B[t]}$ are required. The probability distribution of battery storage $f_{B[t]}$ depends upon the probability distribution of energy source and the load $f_{X[t]}$ and $f_{L[t]}$.

2.2 Deterministic computational model

The deterministic model evaluates resilience by calculating the availability of the microgrid. This method can be used to analyze the best- and worst-case scenarios. Figure 3 shows the algorithm developed for an example microgrid having a PV system and Li-ion battery storage as the only microgrid resources. This algorithm takes into account bidirectional energy flows and maintains a minimum state of charge in the battery during normal operation. The battery is allowed to discharge fully in the case of an outage. Since the deterministic approach provides a range of resilience values possessed by the microgrid (based on the best- and worst-case scenario), it has limitations and does not provide any generalized value that can be used directly in resilience planning and investment decisions. The computational model is simulated in a Python environment.

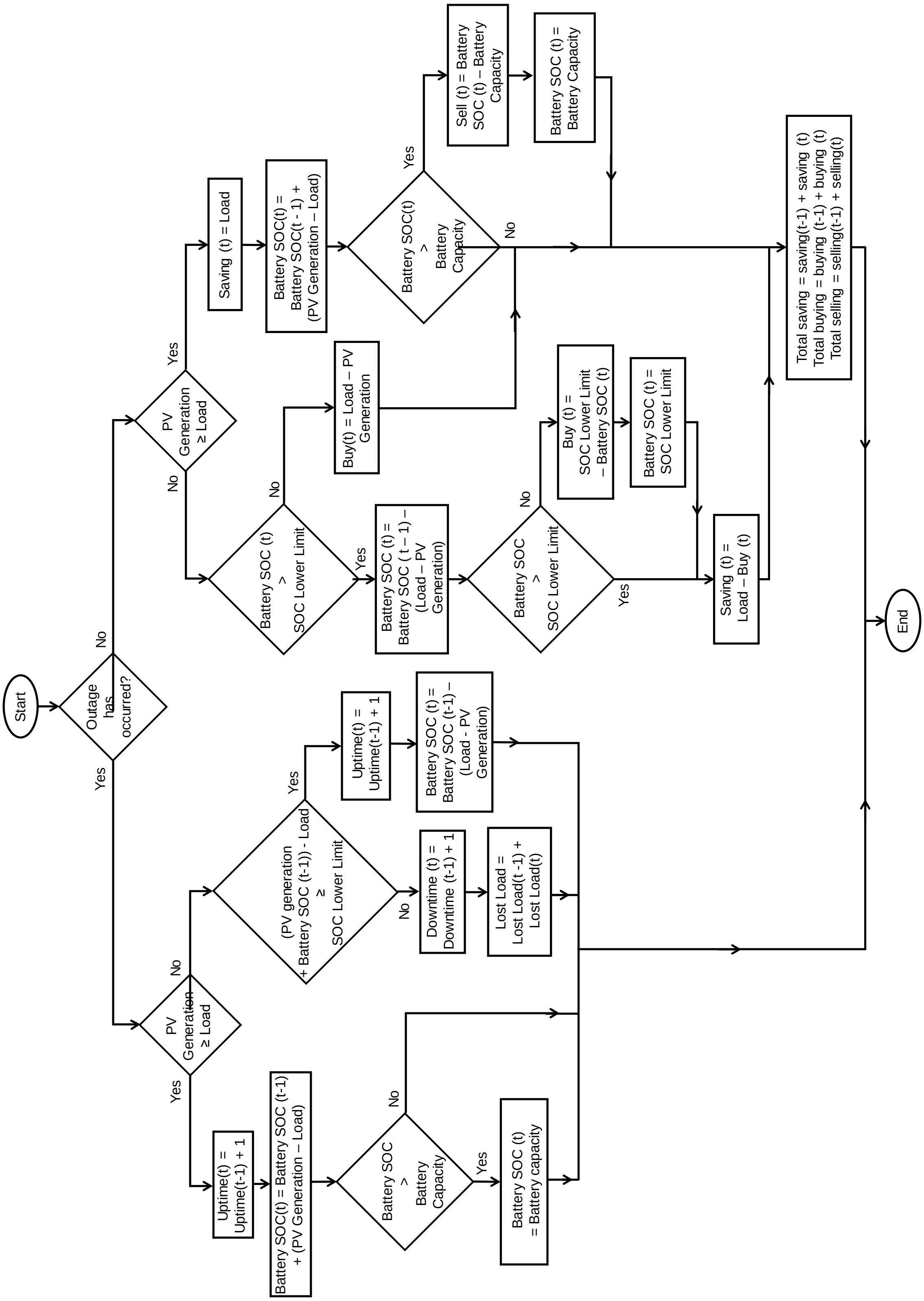


Figure 3: Flowchart of the computational model used for the microgrid resilience evaluation

2.3 Markov-chain-based probabilistic model

To overcome the imitations of the deterministic model and obtain generalized resilience values, a Markov-chain-based stochastic model was adopted. This section introduces this model.

In the microgrid, X_i be the power supplied by PV source i, then the total power of all the PV sources in a microgrid can be given as

$$X_r = \sum_{i \in S} X_i. \tag{4}$$

Let us consider the availability of the microgrid as A. The availability of the microgrid can be defined as the probability that a PV energy source is able to serve the load L. This probability can be given by the equation

$$A = P[X_r \geq L]. \tag{5}$$

Equation (5) is similar to eq. (3) which finds the probability that the fitness function is positive. Except for the battery energy level considered in eq. (2) both the energy source and the load terms are reflected in eq. (5). The Markov chain is modeled based on the battery energy level to consider its effect on the fitness function. In this research, the Markov chain is modeled considering the battery state of charge as the states of the Markov chain as proposed in (Song et al., 2013). The Markov chain used in this research is represented below.

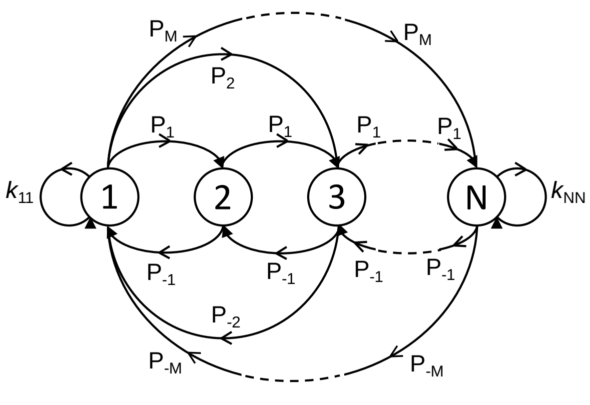


Figure 4: Markov-chain-based battery state transition diagram, based on (Song et al., 2013).

The energy capacity of the battery is divided into N discrete states. These 1 to N states can be also seen as the level of charge in the battery, state 1 representing no charge in the battery while N representing full charge. Hence the state space S_1 of the Markov chain states can be given as

$$S_1 = (1, 2, \dots, N). \tag{6}$$

The difference between the SOC of each state can be represented by the unit of energy **Δ.** The difference between PV generation and the load $(X_r - L)$ is the energy available for storage per unit time. It is assumed that there are M possible transitions from each state at each time instance. In the Markov chain shown in Figure 4 , K_{11} and K_{nn} indicate the probability of staying in the state 1 or state N in the next step.

The transition amongst various battery states is indicated with the probabilities P_i, where i represents the amount of energy charged or discharged into or from the battery per unit of time with respect to the unit of energy **Δ.** For example, P_1 is the transition to the adjacent state or adjacent level of charge with energy transfer of Δ happening per unit of time. Hence P_1 represents charging the battery by Δ units per unit time and transition in the battery SOC from state i to state j. P_2 is the transition probability of having an energy transfer of 2Δ per unit of time, i.e., charging the battery with 2Δ units per unit of time. While P_{-1} represents an energy transfer of Δ per unit of time in the reverse direction, i.e., discharging the battery by Δ units. The number of possible transitions as observed in the Markov chain can be given as

$$M = N - 1. \tag{7}$$

Considering all the possible transitions, the state space S_2 of (Xr - L) is given as,

$$S_2 = [-M\Delta, -(M-1)\Delta, \dots\dots, -2\Delta, -\Delta, \Delta, 2\Delta, \dots\dots, (M-1)\Delta, M\Delta]. \tag{8}$$

S_2 represents all the possible transitions from one battery energy state to the other due to charging or discharging of the battery by the energy, amounting to (Xr -L) during a time instance. It is assumed that the charging and discharging rates of the battery are the same and that the charging and discharging processes of the battery can be considered to be linear for simplicity reasons. Hence the capacity of the battery can be given as

$$C = (N - 1) \cdot \Delta. \tag{9}$$

If D is the total energy per unit of time transferred to the battery during total time T, then D can be given as,

$$D = \sum_{i \in \{1,M\}} \Delta \cdot i \cdot p_i - \sum_{i \in \{1,M\}} \Delta \cdot i \cdot p_{-i}. \tag{10}$$

Then the charging and discharging process of the battery can be represented by eq. (10) as

$$X_{t+1} = X_t + D_t, \tag{11}$$

where X_t is the energy level of the battery at time t and X_{t+1} is the energy level of the battery after one unit of time. This Markov chain can be represented as follows using the one-step transition probability matrix P:

$$P = \begin{bmatrix} k_{11} & p_1 & p_2 & \cdots & & & \\ k_{11} & 0 & p_1 & \cdots & & & \\ \tilde{p}_{-2} & p_{-1} & 0 & \cdots & & & \\ \vdots & \vdots & \vdots & \ddots & & & \\ & & & & 0 & p_1 & \tilde{p}_2 \\ & & & & p & 0 & k_{NN} \\ & & & & p_{-1} & p_{-2} & k_{NN} \end{bmatrix}_{N \times N} \tag{12}$$

The size of the matrix is N x N where N is the total number of states of the Markov chain. Elements of P are calculated as:

$$k_{11} = 1 - \sum_{i \in \{1,M\}} p_i \tag{13}$$

$$k_{NN} = 1 - \sum_{i \in \{1,M\}} p_{-i} \tag{14}$$

$$\tilde{p}_{-k} = 1 - \left(\sum_{i=1}^{k-1} p_{-i} + \sum_{i \in \{1,M\}} p_i \right) \tag{15}$$

$$\tilde{p}_{-k} = 1 - \left(\sum_{i=1}^{k-1} p_i + \sum_{i \in \{1,M\}} p_{-i} \right). \tag{16}$$

Equations (13)-(16) are calculated by using the Markov chain property that the sum of probabilities in each row of P is equal to 1, i.e.:

$$\sum_{j=1}^{m} p_{i,j} = 1, \quad for\ all\ i \tag{17}$$

The limiting probability or the steady-state distribution of the Markov chain indicate the probability of ending up at each state of the Markov chain as the stochastic process becomes steady (time instance $n \rightarrow \infty$). The steady-state probability distribution is indicated as

$$\pi = [\pi_1, \pi_2, \dots, \pi_N], \tag{18}$$

where

$$\pi_j = \lim_{n \to \infty} P(X_n = j), \; j \in S \tag{19}$$

The limiting probability can be found with eq. (20),

$$\pi = \pi P. \tag{20}$$

Equation (20) resembles the formula of eigenvalues and eigenvectors,

$$AX = \lambda X, \tag{21}$$

where X is the eigenvector of matrix A and λ is the eigenvalue of matrix A. Comparing (21) with (20), the limiting distribution is the eigenvector of matrix A when the eigenvalue is equal to unity.

The probability of the Markov chain being in a state such that it does not have enough energy to power the loads, also known as loss of load probability (LoLP) of the Markov chain, is the probability of having a power deficiency of i units of Δ**;** and the battery SOC is such that it is unable to meet this power deficiency because it would require the transition to the fully discharged state or beyond it. Hence the loss of load probability needs to consider the power deficiency of $i \times \Delta$ for i from 1 to M to consider all the mutually exclusive events in which power deficiency can be encountered. Since all the events of having power deficiency are mutually exclusive, it can be found as a sum of probabilities. Using the limiting probabilities, the loss of load probability π_E of the microgrid can be found as:

$$\pi_E = \sum_{i \in \{1,M\}} \left[p_{-i} \sum_{j \leq i} \pi_j \right]. \tag{22}$$

Once π_E is known, the availability A and resilience R can be calculated as

$$R = A = 1 - \pi_E \tag{23}$$

The procedure for forming a Markov chain and finding the availability of the microgrid can be summarized using the flow chart shown in Figure 5. The Markov chain-based model is simulated using MATLAB.

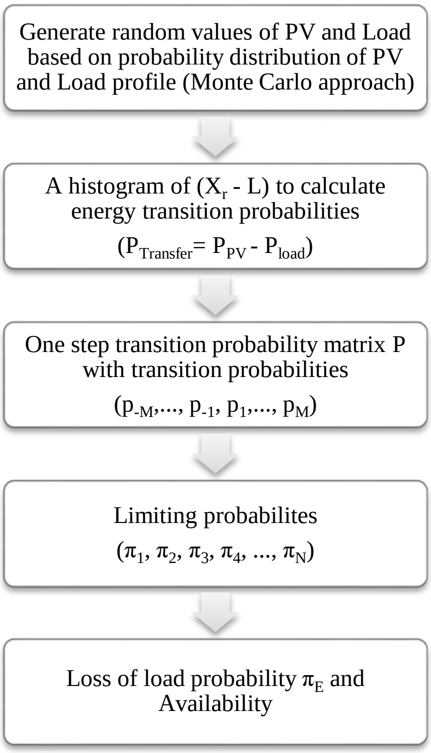


Figure 5: Summary of Markov chain-based availability evaluation

2.4 Monetizing the resilience

As discussed in the previous section, the metric used for resilience assessment is availability based in which the resilience of the microgrid is the fraction of time the microgrid can cater to the load during the total duration of the disaster. To translate this into economic value, it is important to see how much it costs for the consumer not to have electrical supply. The Value of Lost Load (VoLL) or outage cost in €/ kWh is one of the economic indicators used for this purpose. The VoLL quantifies the average cost of unsupplied electricity in monetary units per unit of electricity (kWh) (Praktiknjo et al., 2011).

2.4.1 Value of Lost Load

The Value of Lost Load is a monetary indicator expressing costs associated with the interruption of electrical supply (Schröder and Kuckshinrichs, 2015). It varies for different types of consumers (Praktiknjo et al., 2011);

- For residential customers, power outages lead to a loss of opportunity for leisure activities. The VoLL for them is associated with the opportunity costs.
- For commercial, industrial and agricultural consumers, electricity is the input factor for value addition in their products and services. For these sectors, the VoLL is calculated by dividing the value added of a sector by its annual electricity consumption.
- For estimating the VoLL for public administration, it is calculated by dividing total tax income by electricity consumption of public administration.

The VoLL as an economic indicator that enables to monetize resilience is complimentary to the availability-based resilience quantification framework. The greater the availability of the system, the lower is the economic impact due to lost load to the consumers, and vice versa. The VoLL-based economic evaluation of resilience is widely accepted (Anderson et al., 2018; Laws et al., 2018). Computation of VoLL for different sectors using electricity is beyond the scope of this work and the VoLL values of electricity consumers in Germany reported in (Praktiknjo et al., 2011) are directly used for our calculations.

2.4.2 Net Present Value

The investment in resilience will have a long-term economic impact. The net present value (NPV) approach is suitable for evaluating such investments. It is a discounted cash flow method considering the time value of the revenues and costs of an investment project ("Performance Measurement and Management for Engineers - 1st Edition," n.d.). This method assumes a perfect capital market with a constant rate of interest over the lifetime of the project (*Investitionsrechnung*, n.d.). The NPV is calculated by summing up discounted gains and losses for every period of the investment using a constant discount rate, to the date when an investment decision is made. The NPV can be computed by using the formula

$$NPV = \sum_{t=0}^{n} \frac{G_t - L_t}{(1+r)^t} \tag{24}$$

where n denotes the project lifetime; t is time; G denotes the gains and L represents the losses; r is the interest rate, and $(1 + r)^{-t}$ is the discount factor. The assumed project lifetime depends on the useful life of the asset considered. In the initial periods of the investment, the accumulated cash flows are negative due to the initial investment costs. The time resolution typically assumed is yearly (Vonsien and Madlener, 2019).

The investment should be accepted when the NPV is greater than zero. If the NPV is greater than zero, not only does the (discounted) revenues cover the investment costs and the desired capital return rate, but also the investment is profitable. The corresponding investment costs for a zero NPV is the break-even costs. In the case of a negative NPV, the investment costs and the capital return cannot be compensated by the revenues, and a loss occurs (*Investitions- und Wirtschaftlichkeitsrechnung für Ingenieure*, n.d.). While deciding among two different investments, the most optimal investment is the one with higher NPV. An investment with a higher NPV generates higher revenue (*Investitionsrechnung*, n.d.). In this research, the NPV is used as the main indicator to find the optimal level of investment in (microgrid) resilience.

2.4.3 Internal Rate of Return

The Internal Rate of Return (IRR) of an investment is that discount rate which, when used to discount an investment's future cash flows, makes the NPV equal to zero. IRR can be found out from the equation

$$NPV = \sum_{t=0}^{n} \frac{G_t - L_t}{(1 + IRR)^t} = 0 \tag{25}$$

The formula for finding IRR is the same as the formula for finding the NPV except that NPV is replaced by zero and the discount rate is replaced by IRR.

IRR indicates the exact rate of return that will be earned on the original investment. IRR is a useful tool for deciding whether to go ahead with an investment. If IRR exceeds the opportunity cost of capital (rate of return that can be earned elsewhere), then the project should be accepted. While comparing alternate investment options, investment with higher IRR shall be preferred. IRR is used along with NPV for investment evaluation. NPV numbers can vary for different investment amounts and might not be useful for comparing alternative investments. IRR shows project returns as a percentage value, and hence the IRR is more useful for relative comparison between alternative investments.

3 Methodology implementation

3.1 Microgrid model

A hypothetical community microgrid model is considered for this research. The modelling approach adopted is simple and intends to demonstrate the usefulness of the model rather than identifying the optimal investment choices for enhancing resilience of the said community microgrid.

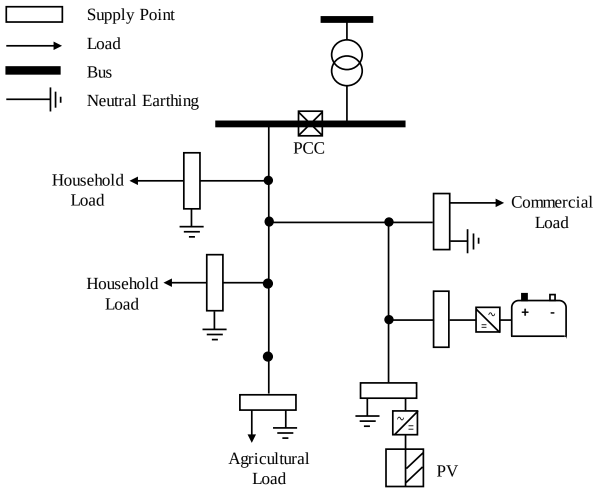


Figure 6: Community microgrid

During normal operation, the proposed microgrid sells the excess energy generated from the PV energy sources and gets remunerated by the feed-in tariff. It is assumed that electricity consumers have formed an energy cooperative. It has three types of consumers: residential consumers, commercial consumers, and agricultural consumers. It is assumed that the microgrid already has 20 kW_p rooftop photovoltaic system installed and has 20 kWh battery energy storage.[1] Because of regular power interruptions caused due to natural disasters, consumers are willing to increase the resilience of their microgrid. The peak load of the microgrid is assumed to be 50 kW_p. The schematic network model of a community microgrid is shown in Figure 6. Different load scenarios were considered, as shown in Table 2, in order to see the effect of resilience and impact on investment decision with the change in the load pattern.

[1] The battery energy storage size in Germany depends on the size of coupled PV system. The rule of thumb is the simple 1:1 ratio (Vonsien and Madlener 2019).

Table 2: Considered load pattern scenarios in the microgrid

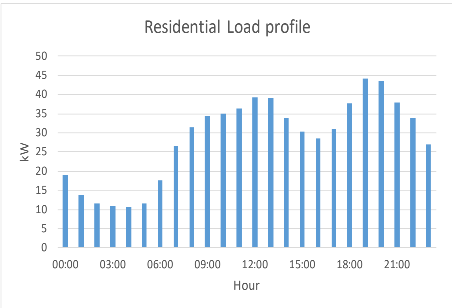
Scenario	Residential peak load [kW_p]	Commercial peak load [kW_p]	Agricultural peak load [kW_p]	Average load demand [kW]
Vbase	30	10	10	22.27
V1	30	20	0	22.30
V2	30	0	20	22.26

3.2 Load profiles

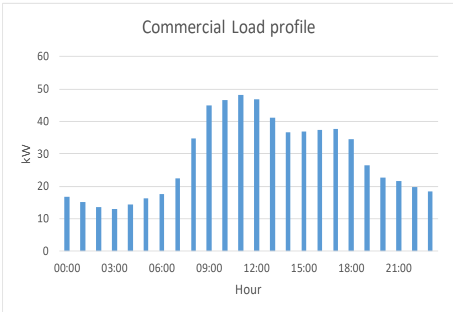
The load profiles considered for this model are obtained from the distribution grid's standard load profiles of Stromnetz Berlin GmbH for the year 2019. The standard load profiles correspond to the load profiles from the Bundesverband der Energie- und Wasserwirtschaft e.V. (BDEW, the German Association of Energy and Water Industries)[2] ("Grid user," n.d.). The available load profile resolution is 15 min.

The constructed load profile confirms with the general pattern observed in (Claridge et al., 2004; Mikulik, 2018). Figure 7 shows the average hourly load profiles for each type of consumer.

(a)



(b)



(c)

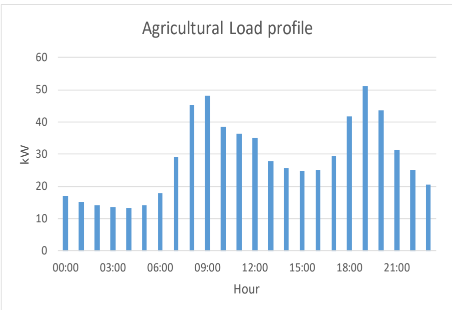


Figure 7: Yearly average standard load profiles for 2019, (a) Residential consumers, (b) Commercial consumers, (c) Agricultural consumers

[2] Customers who have annual energy usage less than 100,000 kWh are connected to the low voltage grid and charged according to their active power consumption. These customers are supplied according to synthetic standard load profiles. The standard load profiles completely cover the respective calendar year. Holidays and weekends are included. The standard load profiles are scaled such that the total annual consumption for each type of consumers amount to 100,000 kWh.

For further analysis in this research, the standard load profiles are scaled according to the peak load considered for each category given in Table 2.

3.3 PV generation profile

The generation profile for the rooftop PV system in Berlin is obtained from online ("PVWatts Calculator," n.d.). The photovoltaic generation profile obtained has an hourly frequency. It is available for the duration of a whole year. The hourly values are interpolated using cubic interpolation for a 15 min frequency. The power output for the PV system of size 20 kW (base case scenario) is obtained. The total output energy obtained in a year from a 20 kW_p PV system with the above parameters is 17,513 kWh. The monthly output for the solar system is shown in Figure 8. During further analysis, the output for other PV system sizes is calculated similarly using ("PVWatts Calculator," n.d.).

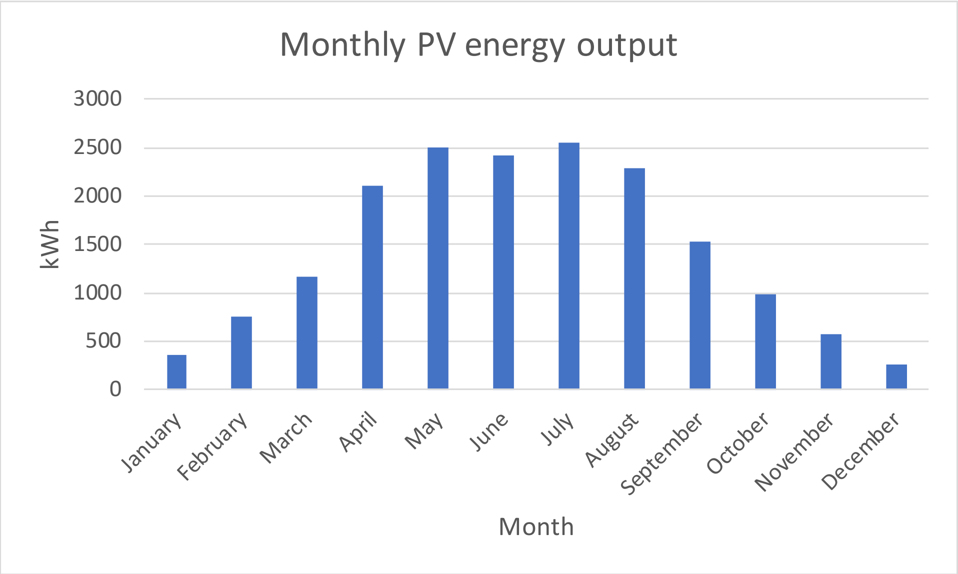


Figure 8: Exemplary monthly output of a 20 kW_p solar PV system, in kWh

3.4 Time duration of the disaster

Disaster time duration will vary according to the type and severity of the disaster, the time required for the restoration, the type and region of the distribution grid, the voltage level of the grid and other factors which influence disaster operational phases and restoration time. The resilience of the grid will be influenced by the time of the start of the outage, availability of the PV resources, the energy available in the battery storage at the beginning of the outage, etc. In this research, it is assumed that the said region frequently experiences an outage due to a natural disaster. For the planning of a resilient microgrid in the region, the average outage time values calculated by using historical data for the specific distribution grid can be used. Since the specific data is not available to us, the time duration for the outage is assumed to be 24 hours, i.e., the microgrid experiences on average one disruption per year for the duration of 24 hours.

3.5 Evaluation of resilience enhancement

Two measures were considered to enhance the resilience of the microgrid

1. Increase in the amount of distributed energy resources in the microgrid
2. Increase in the amount of energy storage in the microgrid

3.5.1 Resilience enhancement by increased PV generation

In addition to the 20 kW of already installed PV generation capacity in the microgrid, the PV generation capacity in the microgrids is increased in steps of 5 kW until the peak-load demand of the microgrid. (25 kW, 30 kW, 35 kW, …, 50 kW. By finding the PV generation data for each case, as explained in section 3.3, the resilience of the microgrid is calculated by using the deterministic model and Markov chain-based model. The effect on resilience and availability of the microgrid by increasing the amount of distributed PV generation capacity is recorded.

3.5.2 Resilience enhancement by increased energy storage capacity

In addition to the 20 kWh of installed energy storage capacity in the microgrid, the energy storage in the microgrid is increased in steps of 5 kWh similar to the increase in PV generation capacity just described. The change in resilience is recorded.

3.6 The total value of the lost load

As explained in subsection 2.4.1, the economic indicator Value of Lost Load is used to monetize resilience. The VoLL figures used in this research are adopted from (Praktiknjo et al., 2011). The VoLL values for different types of consumers are given in Table 3. The VoLL for agricultural consumers is the lowest among all the values, whereas VoLL for commercial consumers is the highest. In (de Nooij et al., 2007), The cost of power interruption has been calculated for the Netherlands, and similar VoLL are obtained for the residential and agricultural sectors.

To determine the revenue loss due to lost load for each load category in every case considered for resilience evaluation, the total lost load in every case is multiplied by the VoLL of the respective load category.

Table 3: VoLL for different types of consumers

Consumer type	VoLL [€/kWh]	Consumer type
Residential	**15.70**	**Residential**
Commercial	16.35	Commercial
Agricultural	2.34	Agricultural

In the case of a computational model for evaluating resilience, it is possible to get the exact values of the amount of load not served in the downtime instances for the assumed duration of an outage on a specific day in each category. Hence the total value of lost load for that specific outage can be calculated by multiplying the number of kWh not served for the respective load category with its VoLL. The total value of the lost load using the results from the computational method will be,

$$\begin{aligned} VoLL_{Total} = {} & VoLL_{Residential} \times Lost\ Load_{Residential} \\ & + VoLL_{Commercial} \times Lost\ Load_{Commercial} \\ & + VoLL_{Agricultural} \times Lost\ Load_{Agricultural} \end{aligned} \tag{26}$$

While using the Markov chain method, it is not possible to get the exact values of the lost load because the result from the Markov chain model is more general. The Markov chain model gives the availability of the microgrid as a result, considering the randomly generated generation and load data. Hence to get the total value of the lost load from the Markov chain model, the hourly average load values in kWh for each category of the load are used for each load pattern from Table 2. Hence the total lost load in each category is the load demand from the consumers during the downtime of the microgrid for the total duration of an outage. Hence the total value of the lost load that results from using the Markov chain model is used can be given as,

$$\begin{aligned} VoLL_{Total} = h \times (1 - R) \times (& VoLL_{Residential} \times Avg. Load_{Residential} \\ & + VoLL_{Commercial} \times Avg. Load_{Commercial} \\ & + VoLL_{Agricultural} \times Avg. Load_{Agricultural} \end{aligned} \tag{27}$$

The total value of the lost load is considered as the loss for the consumers due to the unavailability of the power supply.

3.7 Capital expenditures and operational expenditures

In the microgrid models considered for evaluation in this research, different types of consumers are considered. Different consumers will have a different cost structure for the installation of the PV system and energy storage based on various parameters such as land availability, access to capital, economies of scale etc. But for the ease of analysis, a single cost for the installation of the PV system and battery storage is assumed for all types of consumers in this research. This cost of system installation can be considered as the weighted average cost of the system. Since it is assumed that the microgrid is already present in the base case scenario, the cost of islanding, i.e., the cost of forming a microgrid, is not exclusively considered. The input parameters used for the economic evaluation are explained in the following.

3.7.1 Economic parameters considered for PV system

For considering the capital expenditures for the PV system, the cost of installation of the PV modules is considered as 1200 € per kWp (Kost et al., n.d.). The cost of the solar inverter is assumed at 170 € per kW_p (Hoppmann et al., 2014). System balance costs are assumed to be 640 € per kW_p (Hoppmann et al., 2014). The engineering procurement and construction costs are assumed to be 8% of the total system costs (Peters et al., 2011). The operational & maintenance of the PV system is assumed to amount to 1.5% of the total system costs per year (Hoppmann et al., 2014). Finally, the expected lifetime of the photovoltaic system is assumed to amount 25 years (Kost et al., n.d.).

3.7.2 Economic parameters considered for battery storage

For the battery storage system, the capital cost of investment in the lithium-ion battery storage unit is considered as 1000 € per kWh (Vonsien and Madlener, 2019). The lifetime of the battery storage is considered as 12 years and the cost of battery replacement is considered as 60% of the total capital expenditures (Kost et al., n.d.). Operation and maintenance cost of the battery storage system per year is considered at 1.8% of the capital investment in the battery storage unit (Vonsien and Madlener, 2019).

3.7.3 Present value calculation

The interest rate was assumed to be 0.5% (Vonsien and Madlener, 2019). The lifetime t of the project is assumed to be 25 years, which is equal to the lifetime of the photovoltaic system (Kost et al., n.d.). The operational expenses for the battery and PV system are considered as the per year losses. It is assumed that within the 25 years of the project lifetime, batteries and PV inverter are replaced once after the halftime of the expected lifetime of the system (Hoppmann et al., 2014; Kost et al., n.d.). Their replacement cost is accounted for in the 13^{th} year.

Benefits achieved due to an increase in resilience are considered as gains. The costs are only considered for the extra added capacity and the investments for the already installed capacity are excluded from the calculation of capital and operational expenditure. A similar approach is adopted to evaluate the gains due to an enhancement in the resilience. The gains for the different cases after adopting resilience enhancement measures are calculated as

$$G_{Resilience} = VoLL_{Total\,(base\ case)} - VoLL_{Total\,(resilient\ case)}, \quad (28)$$

where $VoLL_{Total\ (base\ case)}$ is the total value of the lost load in the base case scenario and $VoLL_{Total\ (resilient\ case)}$ is the total value of the lost load after adopting the resilience enhancement method. Hence $G_{Resilience}$ records the benefit of adopting the resilience enhancement measure in terms of the loss that consumers do not have to bear due to the loss of the load. It is assumed that the outage due to disaster occurs each year and consumers get benefited each year due to the gains from increased resilience. Hence resilience gains are considered as a gain per year while calculating the present value.

3.7.4 The feed-in tariff, buying the electricity from the grid and energy savings due to self-consumption

The microgrid is assumed to receive a fixed feed-in tariff on their sale of excess energy from the PV systems. The feed-in tariff received by the microgrids is assumed to be 0.1111 € per kWh (Wirth and Ise, n.d.). For the amount of energy bought from the grid, the price considered is 29.23 €-ct per kWh which is including VAT (Kost et al., n.d.). Since this is the average end-customers electricity price considering all types of consumers, this value is used for the purpose of analysis in this research.

The amount of energy considered as saved is the result of self-consumption from the PV system and energy stored in a battery energy storage unit. It is assumed that this energy is the energy that the microgrid does not have to buy from the utility grid. Hence the benefits of saving per kWh can be considered to be the same as the rate of buying electricity. But according to EEG (2017), the consumers who have a PV system of a size greater than 10 kW have to pay a portion of the EEG surcharge which is 40% of the total EEG surcharge for the self-consumed energy. The EEG surcharge in Germany including the VAT amounts to 7.62 €-ct per kWh. Since the size of PV systems considered for the microgrid is greater than 10 kW, the microgrid must pay 40% of the EEG surcharge which amounts to around 3 €-ct per kWh of self-consumed energy. Considering this, the benefit of self-consumption reduces to 26.23 €-ct per kWh.

4 Results and discussion

The results obtained from the research done are discussed in this section. We first discuss the results obtained from resilience quantification, followed by the results from the economic evaluation.

4.1 Resilience quantification results

Two different methods are used for the quantification of the microgrid resilience: a computational method and a Markov chain-based method. In the computational method, a randomly chosen summer day representing high PV generation, which is considered as the best-case scenario. Another randomly chosen day in winter represents low PV generation, which is considered as the worst-case scenario. The results for resilience obtained from the computational method can vary according to the randomly chosen day. To get more general results, the Markov chain-based resilience quantification model is adopted. Figure 9 shows the resilience of the microgrid for a randomly chosen day in summer and a random in winter along with the results obtained from the Markov chain-based method for the V_{Base} scenario.

(a)

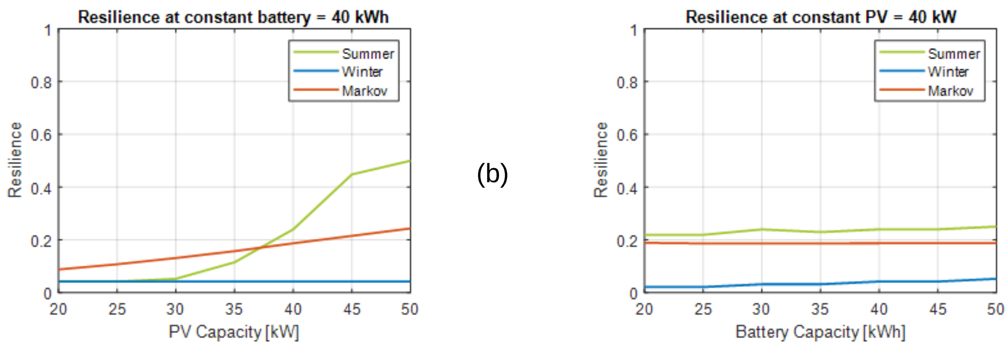


Figure 9: Resilience of the microgrid for a random day in summer, random day in winter and Markov chain-based model (a) Resilience with respect to change in PV system size, energy storage capacity = 40 kWh (b) Resilience with respect to change in energy storage capacity, PV system size = 40 kWp

It can be observed from Figure 9 that the resilience quantification values obtained from the Markov chain-based model are following the general pattern of the resilience values obtained for summer and winter. Therefore, the Markov chain-based model gives general results for resilience by considering all possible values for the PV generation profile and load. Hence these results are more useful while planning a microgrid. For further evaluation, the results obtained from the Markov chain model for resilience evaluation are used. The PV system size 40 kW_p and the energy storage capacity 40 kWh are used to show some general patterns observed in the results of the microgrid. Figure 10 depicts the resilience results obtained from the Markov chain-based model for various PV and battery values for the V_{Base} scenario.

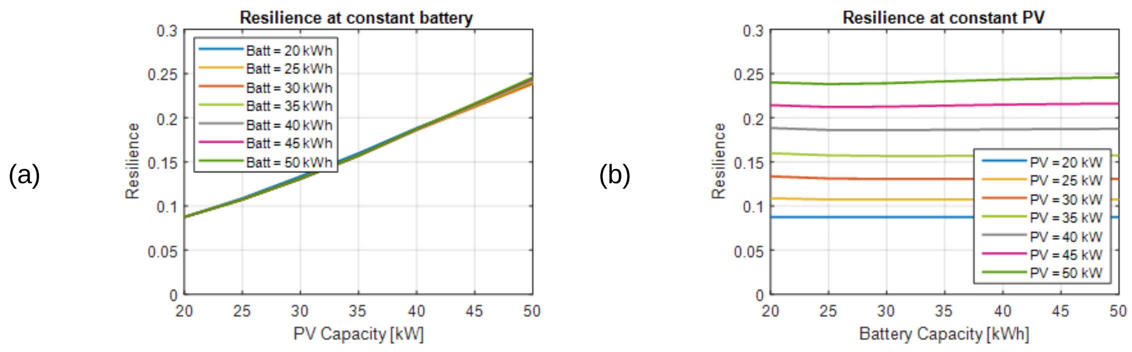


Figure 10: Resilience results obtained from the Markov chain-based model (a) Resilience with respect to PV system size for the V_{Base} scenario, (b) Resilience with respect to energy storage capacity for the V_{Base} scenario

Notice that resilience increases with the increase in energy storage capacity and PV system size. But while the increase in resilience with an increase in PV capacity is significant, an increase in the resilience with an increase in energy storage capacity is very small.

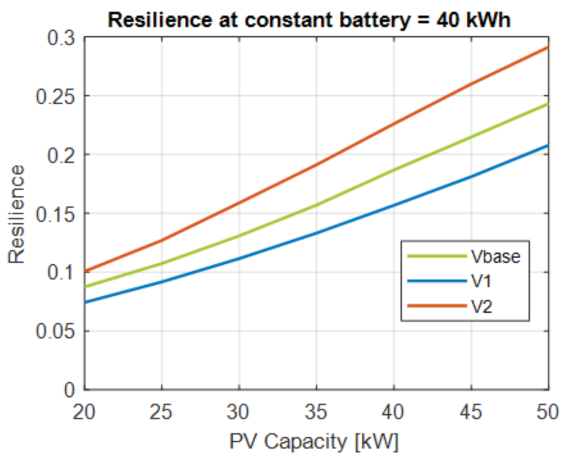


Figure 11: Resilience with respect to a change in PV system size for different load scenarios in the microgrid

In Figure 11 the resilience with respect to changes in the PV system size for three different load scenarios, V_{Base}, V_1, V_2 of the microgrid is shown. The energy storage capacity is kept constant at 40 kWh. In the microgrid, different load scenarios have different resilience values due to the complementary behavior of the considered load profiles. The

V_2 load scenario consists of residential loads and agricultural loads. It has the highest resilience among the three load scenarios considered. As observed in Figure 7, the load profile for agricultural and residential loads has a peak demand at different times during the day, due to which the available energy resources within the microgrid can sustain the load for a longer duration. The V_1 load scenario consisting of the residential and commercial loads has the lowest resilience. The residential and commercial load profiles both show a higher demand during the afternoon hours, and hence they are not complementary to each other, resulting in the lowest resilience among the three scenarios considered.

4.2 Economic evaluation results

Using the quantified resilience values, the total value of the lost load is determined for each scenario. The results of the economic evaluation for the microgrid (V_{Base} scenario) are presented in Table 4 (results for resilience, NPV and IRR for each case along the total amount of energy bought, sold, and saved).

Table 4: Economic evaluation results for the V_{Base} scenario

PV [kW]	Battery [kWh]	Resi-lience [-]	VoLL [€]	Buying [kWh]	Selling [kWh]	Saving [kWh]	NPV [€]	IRR [-]
20	20	0.09	6338	177414	0	17662	0	-
20	30	0.09	6340	177414	0	17662	-19884	-
20	40	0.09	6340	177414	0	17662	-39728	-
20	50	0.09	6340	177414	0	17662	-59572	-
30	20	0.13	6019	168583	0	26493	92455	0.22
30	30	0.13	6039	168583	0	26493	72131	0.13
30	40	0.13	6038	168583	0	26493	52309	0.08
30	50	0.13	6038	168583	0	26493	32475	0.04
40	20	0.19	5638	159777	0	35299	186029	0.22
40	30	0.19	5655	159777	0	35299	165792	0.17
40	40	0.19	5649	159777	0	35299	146085	0.13
40	50	0.19	5645	159777	0	35299	126341	0.11
50	20	0.24	5279	151792	712	43284	270268	0.22
50	30	0.24	5286	151476	389	43601	253540	0.18
50	40	0.24	5257	151298	208	43779	236210	0.16
50	50	0.25	5240	151202	98	43874	217729	0.13

4.2.1 Total value of lost load and resilience gain

Figure 12 shows the change in the value of lost load (ΔVoLL) with an increase in the PV system size for the V_{Base} scenario of the microgrid. The energy storage capacity is kept constant at 40 kWh. It can be observed that ΔVoLL decreases with an increase in PV system size as resilience also increases. The economic gain obtained from an increase in resilience is also depicted in Figure 12.

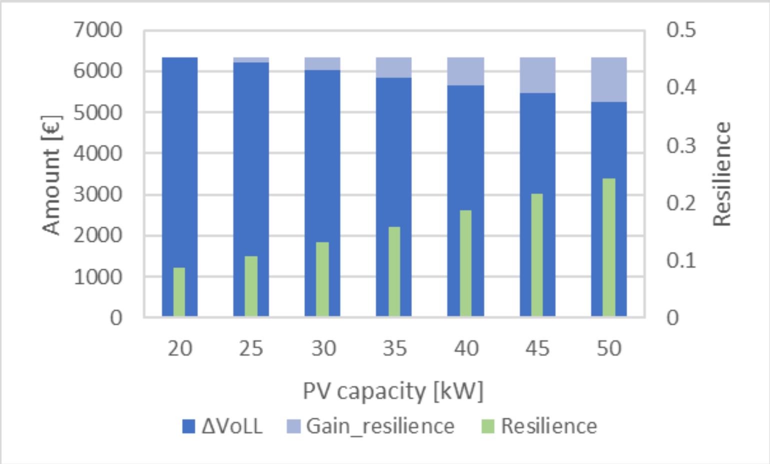


Figure 12: ΔVoLL with an increase in the size of the PV system for the V_{Base} scenario. Energy storage capacity = 40 kWh

Figure 13 shows the resulting NPV for all PV system values considered if only the gain obtained from the resilience is considered, and the gains from selling the energy and saving the energy and losses due to buying the energy are neglected. The energy storage capacity is again kept constant at 40 kWh. It can be seen that the NPV is negative for all sizes of the PV system considered. This is because the gain from resilience is less than the annual operation & maintenance costs. Hence the cost of the project will not be recovered if the gain from selling and self-consumption is not considered.

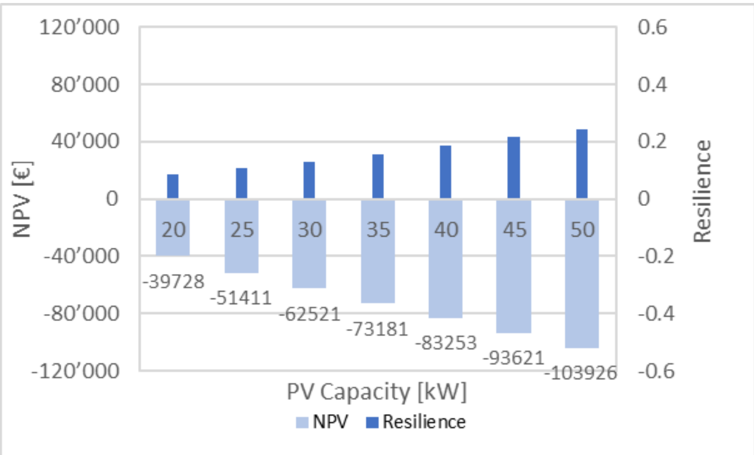


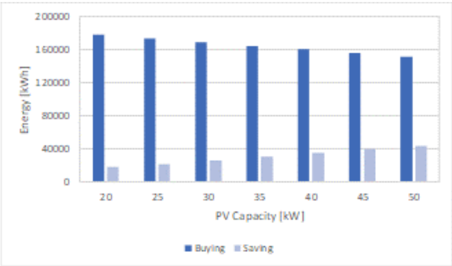
Figure 13: NPV when only the gain from resilience is considered for the V_{Base} scenario

4.2.2 Gains obtained through feed-in tariff and self-consumption

Figure 14 (a) shows the change in the total amount of energy bought and the total amount saved for an increase in the PV system size for the V_{Base} scenario. The energy storage capacity is kept constant at 40 kWh.

The total amount of energy bought from the grid is decreasing with an increase in the PV generation capacity.

(a)



(b)

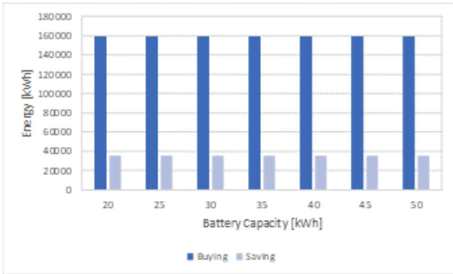
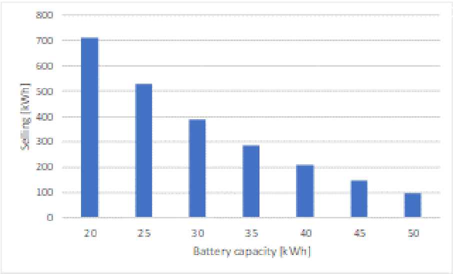


Figure 14: (a) Total amount of energy bought and saved with an increase in PV system size for the V_{Base} scenario, the energy storage capacity is kept constant at 40 kWh. (b) Total amount of energy bought and saved with an increase in energy storage capacity for the V_{Base} scenario, the PV system size is kept constant at 40 kW_p.

The total energy saved also increases with an increase in the PV system size. Figure 14 (b) shows the total amount of energy bought from the grid and the total energy savings with an increase in the energy storage capacity for the V_{Base} scenario. The PV system size is kept constant at 40 kW_p. From the graph, it seems that there is almost no change in the values of the total amount of energy bought and the total amount of energy saved. But it can be observed in Figure 14 (b) that the total amount of energy bought decreases with an increase in the energy storage capacity. However, the change in the values is insignificant. Similarly, the total amount of energy saved increases only by a very small amount with an increase in the energy storage capacity.

The increase in the size of energy storage capacity has no effect on the amount of energy bought and saved because the PV system does not provide any surplus energy that could be stored in the battery and consumed during the time of low PV generation. The reason is that the load demand is always greater than the PV generation for most of the cases considered. Hence even though the energy storage capacity is raised, the amount of energy stored in the battery remains almost the same.

(a) 

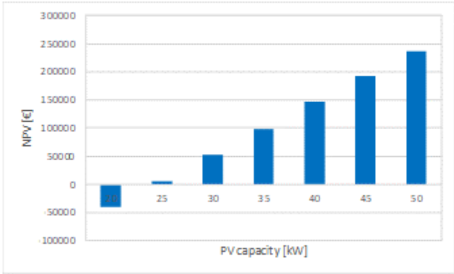
(b) 

Figure 15: (a) Total amount of energy sold to the grid with an increase in energy storage capacity V_{Base} scenario. (b) NPV with a change in PV system size for V_{Base} scenario.

Figure 15 (b) shows the amount of energy sold to the grid with an increase in the energy storage capacity for the V_{Base} scenario. The PV system size is kept constant at 50 kW_p. The amount of energy sold to the grid decreases with an increase in the energy storage capacity as the battery can accommodate more energy for self-consumption. It can be observed in Figure 15 that the total amount of energy sold to the grid is significantly smaller compared to the total amount of energy saved. For example, the amount of energy sold to the grid for the PV system size of 50 kW and the energy storage capacity of 20 kWh is 712 kWh. For the same case, the total amount of energy saved is 43,284 kWh. Hence the gain due to energy sales is insignificant and major gains are obtained from energy savings, i.e., from self-consumption of the self-generated energy.

When the gain from selling and saving the energy and the loss due to buying the energy from the grid is considered, the NPV increases with an increase in the size of the PV system. Figure 15 (b) shows the NPV values with a change in the PV system size for the V_{Base} scenario. The energy storage capacity is kept constant at 40 kWh. Since NPV values cannot be compared directly as the investment values for different sizes of the PV system will be different, IRR is a more suitable tool for a relative comparison of investment returns. Figure 16 (a) shows the change in IRR with a change in the PV system size for different energy storage capacities.

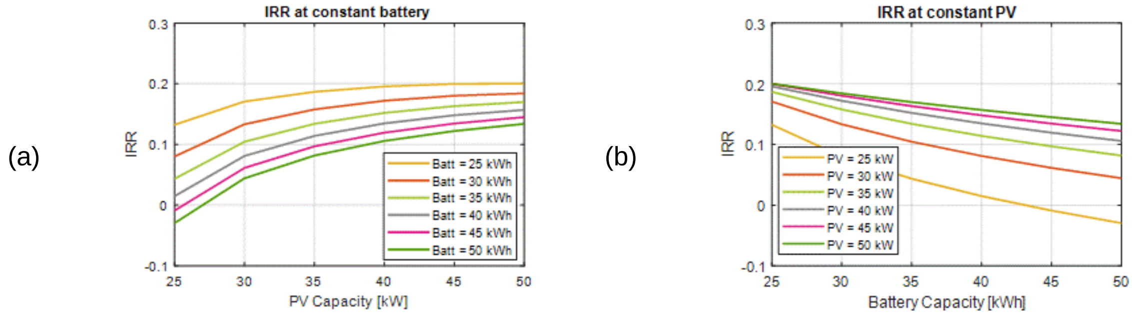


Figure 16: (a) IRR with respect to PV system size for the V_{Base} scenario. (b) IRR with a change in energy storage capacities for the V_{Base} scenario.

Figure 16 (b) shows the IRR with a change in the energy storage capacity for different PV system sizes in the microgrid. The IRR decreases with an increase in battery capacity. As can be seen in Figure 14 (b), the total amount of energy saved does not increase with the increase in energy storage capacity. Hence gains due to self-consumption do not increase with an increase in the energy storage capacity. But the operation & maintenance costs of the battery storage increase with an increase in battery capacity. This is the reason why the IRR for the project reduces with an increase in energy storage capacity.

4.2.3 Comparing different load scenarios

Figure 17 (a) shows the resilience gain values for all the scenarios considered in the microgrid with a change in PV system size. The energy storage capacity is kept constant at 40 kWh.

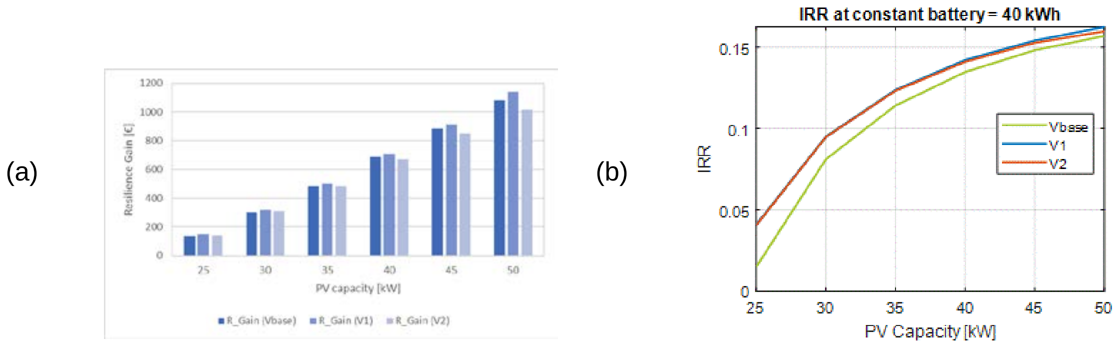


Figure 17: (a) Resilience gain values for the considered scenarios in a microgrid with an increase in the size of the PV system. (b) IRR for the scenarios considered in the microgrid with an increase in the size of the PV system.

Although the gain obtained from resilience varies for each scenario, the IRR for investment in resilience is almost the same for all scenarios. Figure 17 (b) shows the change in IRR with a change in the size of the PV system for all three scenarios of the microgrid. Energy storage capacity is kept constant at 40 kWh.

Hence it can be observed that almost equal IRR for each scenario is obtained despite having different gains from resilience. This is because a major part of the total gain is made up of the gain obtained from selling and saving energy. The gain from resilience accounts for a small part of the total gain. This is shown in Figure 18. It shows the change in total gain i.e., gain from resilience (R-Gain) + gain from selling and saving energy (EL-Gain) for all the scenarios in the microgrid with an increase in the size of the PV system. The energy storage capacity is kept constant at 40 kWh.

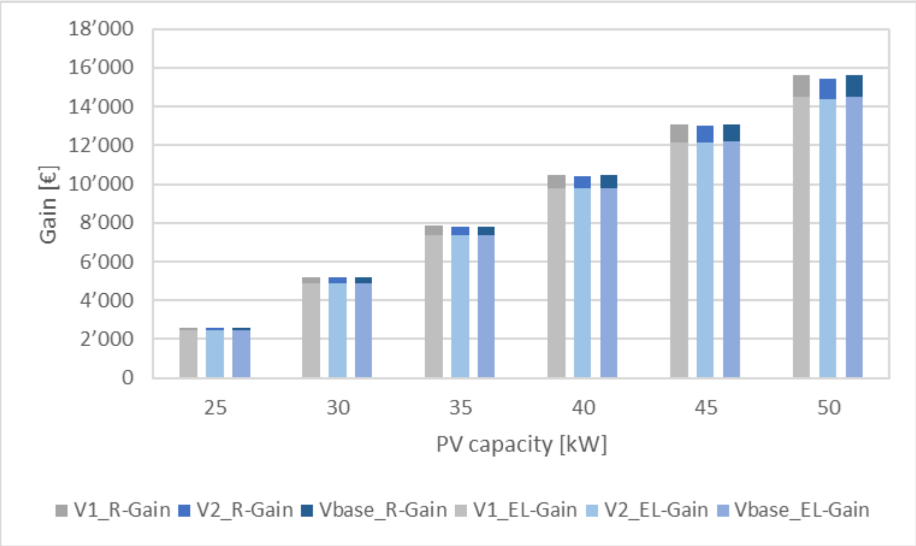


Figure 18: Total gain values for the considered scenarios in the microgrid for an increase in the size of the PV system

As can be seen in Figure 18 the total gain obtained for all scenarios considered is almost the same. Hence the IRR for all the scenarios have similar values.

4.3 Discussion

The objective of this research was to develop a methodology for evaluating the economically optimal level of resilience in a microgrid. The proposed methodology is demonstrated by assuming a community microgrid model. The availability-based resilience evaluation framework is used for quantifying resilience. Two different methods are used for resilience quantification, a deterministic computational method, and a Markov chain-based stochastic method. It is observed that the Markov chain-based method gives more general results considering the probability of all possible load and generation values. Hence the stochastic method should be used to quantify resilience during the planning of the microgrid. In terms of resilience enhancement measures an increase in the size of PV generation capacity of the microgrid and an increase in the amount of energy storage capacity of the microgrid were evaluated.

We find that the increase in the resilience due to an increase in the PV system size is more pronounced compared to an increase in the resilience due to an increase in the energy storage capacity. Amongst the three scenarios considered (V_{Base}, V_1 and V_2), the resilience of scenario V_2 is the highest, whereas the resilience of scenario V_1 is the lowest. This is because the agricultural and residential load profiles considered in scenario V_2 are complementary to each other, i.e., their peak load demand occurs at a different time of the day. Hence, we find that the type of load profile influences resilience significantly. If load profiles are complementary, higher values for resilience are observed.

Using the quantified value of resilience, the economic gain obtained from the increase in resilience is calculated. If only the resilience gain values are considered for the economic evaluation, the NPV for all the cases is negative because the value of the yearly operation & maintenance loss is larger than the gain obtained from resilience. When gains obtained from selling and saving of energy are also considered, the NPV is positive in almost all the cases. From this, we conclude that the gain due to selling and self-consumption is important for the economic viability of the project. The amount of energy sold to the grid is found to be very small and decreases with the increase in the energy storage capacity. Hence the major gain is from the savings obtained through self-consumption of energy and not from the feed-in. Hence, future changes in the feed-in prices will expectedly not have much effect on the economic viability of the microgrid.

The gain due to self-consumption increases with an increase in the PV system size. But an increase in the energy storage capacity does not have much effect on self-consumption. The NPV and IRR of the project rise with an increase in the PV system size. But the NPV and IRR of the project decrease when energy storage capacity is increased. Hence an increase in the energy storage capacity is considered to reduce the economic appeal of the project.

Different scenarios of loads considered in the microgrid have a different value for the gain obtained from the resilience. Despite having different resilience gains the IRR for investment in resilience for each scenario is almost equal. This is because the major portion of the total gain consists of the gain obtained from the self-consumption of energy, and the resilience gain accounts for a very small part of the total gain. These total gain values for each scenario are similar; therefore, the economic benefits from various resilience enhancement measures considered for each scenario are also similar.

It can be concluded that the economically optimal resilience will be obtained with an increase in the generation capacity for the assumed microgrid. The proposed methodology can be adopted for determining the economically optimal level of resilience while planning the microgrids with different types of loads.

5 Conclusion and scope for future research

In this paper, we presented a new methodology for evaluating the economically optimal level of resilience in a microgrid by using an availability-based resilience framework. Deterministic and stochastic methods for resilience measurement were explained. The main aim of this work was to introduce an economic evaluation framework which translates the quantified resilience into an economic value, i.e., by monetizing the resilience value to facilitate decision-making for identifying the optimum technologies to enhance resilience. These enhancement measures should justify their costs in terms of future benefits, and the proposed framework can be used for evaluating, and enhancing, this cost-benefit relation. Stochastic resilience evaluation methods were found to be more suitable while calculating the resilience for investment planning purpose.

The methodology proposed is also useful to evaluate different economic and policy instruments, such as feed-in tariffs and subsidies in order to observe the change in economic performance due to these interventions. In future research, the methodology can be extended to consider the stochastic nature of duration of the outage and change in load demand. This methodology can also be used in conjunction with more sophisticated optimization techniques with the objective to minimize the total Value of Lost Load.

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