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Cost-effective reliability level in 100% renewables-based standalone microgrids considering investment and expected energy not served costs

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ABSTRACT

Loss of load probability (LOLP) and expected energy not served (EENS) are commonly used in electrical power systems to evaluate reliability. LOLP defined as the probability that available generation capacity will be inadequate to supply customer demand. EENS defined as the expected amount of energy not being served to consumers by the system during the period considered due to system capacity shortages or unexpected power outages. Loss of Load Frequency (LOLF) is referred to a number of loss of load (LOL) event happened in the operation life span of the SMG. Loss of Load Reduction (LOLR) is defined as the required reduction in LOLF to obtain a specific reliability level. While power systems are designed to minimize LOLP and EENS, this is constrained by the total cost: investment cost, operation and maintenance cost, and cost of customer interruption (CCI). This research considers Standalone Microgrid (SMG), also known as Autonomous Microgrid which only operates in off-grid mode and cannot be connected to wider electrical power system. When designing a 100 % renewable energy integrated SMGs, it is crucial to determine the cost-effective reliability level (CERL). The CERL occurs when the total cost is minimum. This research proposes an approach to calculate the CERL for a fully renewable SMG. An analytical formulation is proposed to represent the LOLR needed to obtain a specific reliability level as a function of the required size of reliability improvement alternatives. The CCI is evaluated using LOLF and EENS indices. Finally, the total cost of the SMG system is evaluated for each reliability level. Consequently, the total cost of the SMG system is expressed as a function of reliability levels, and the minimum value of total cost and the corresponding reliability level are evaluated. In this research, a Monte Carlo Simulation (MCS) approach is used to find hourly LOLF, considering 25 years (219,000 h) of SMG lifespan, regression analysis is used for an analytical formulation, and mixed integer linear programming (MILP) is used for the investment decision making based on a cost minimisation approach. The result demonstrates that the CERL of the SMG system evaluated in the case study is 98.71 %.

1. Introduction

The first paragraph of the introduction contains a definition of CERL. The paragraph that follows explains why the system reliability level in a microgrid context should be fixed. The introduction then describes how CERL is evaluated. It then considers who should bear the cost of the reliability upgrades. Finally, the relevant literature review is developed.

The investment cost of reliability improvement in any electrical network depends on the reliability improvement solutions chosen and their related expenses. The cost of customer interruption (CCI), on the other hand, is defined by the amount of money lost by consumers as a result of power outages. The total cost is the sum of the investment cost, operation and maintenance (O & M) costs, and CCI. The total cost of any electrical network should be maintained as low as possible. It is vital to evaluate the level of reliability at the lowest possible total cost. This is known as the cost-effective reliability level (CERL).

The utility is responsible for delivering electricity to customers at a reasonable cost while maintaining adequate quality and reliability [1]. The presence of prosumers presents an excellent opportunity for utilities and customers to transition to a sustainable green electricity network in an economically efficient and reliable manner [2]. On the one hand, the

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1. Nomenclature

IC^{k}_{BESS}	Investment Cost of k MW of BESS capacity expansion
IC^{l}_{DR}	Investment Cost of l times 50 kW of DR capacity expansion
IC^{m}_{FR}	Investment Cost of m times 0.01 failure rate reduction
IC^{i}_{PV}	Investment Cost of i MW of PV capacity expansion
IC^{j}_{WT}	Investment Cost of j MW of WT capacity expansion
$MLOLR^{r}_{BESS}$	Marginal LOLR obtained as a result of q MW of capacity expansion of WT
$MLOLR^{s}_{DR}$	Marginal LOLR obtained as a result of s MW of capacity expansion of DR
$MLOLR^{t}_{FR}$	Marginal LOLR obtained as a result of t MW of capacity expansion of FR
$MLOLR^{p}_{PV}$	Marginal LOLR obtained as a result of p MW of capacity expansion of PV
AEMC	Australian Energy Market Commission
AER	Australian Energy Regulator
ASAI	Average Service Availability Index
BESS	Battery Energy Storage System
CAIDI	Customer Average Interruption Duration Index
CCI	Cost of Customer Interruption
CDF	Customer Damage Function
CERL	Cost-Effective Reliability Level
DG	Distributed Generation
DR	Demand Response
DW	Direct Worth
EENS	Expected Energy Not Served
EENSR	Reduction in Expected Energy Not Served
EV	Electric Vehicles
FR	Failure Rate
FTA	Fault Tree Analysis
IIC	Incremental Investment Cost
LOL	Loss of Load
LOLF	Loss of Load Frequency
LOLP	Loss of Load Probability
LOLR	Loss of Load Reduction
MCS	Monte Carlo Simulation
MGDN	MG distribution network
MGDN	Microgrid Distribution Network
MILP	Mixed Integer Linear Programming
MLOLR	Marginal Loss of Load Reduction
MRM	Markov Reliability Model
NPV	Net Present Value
PV	Photovoltaic Power Generation
RBD	Reliability Block Diagram
RI	Reliability Improvement
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCDF	Sector Customer Damage Function
SMG	Standalone Microgrid
SSCDF	Subsector Customer Damage Function
TAC	Total Annualized Cost
TICRI	Total Investment Cost of Reliability Improvement
TTF	Time to Failure
VCR	Value of Customer Reliability
VOLL	Value of Lost Load
WT	Wind Power Generation

utility grid establishes and maintains a reliability standard to maintain a specified level of reliability for the power system network. As a result, independent power producers (IPP) such as microgrids must meet the Utility's reliability level in order to participate in energy trading, particularly for energy export to the grid. Microgrids, on the other hand, can maintain specific reliability level for a variety of reasons, including supplying critical loads connected to the microgrid network. As a result, when the microgrids import power from the grid, the grid must also meet the microgrids' reliability level. This necessitated that the utility grid and the microgrid work together to establish a level of reliability for the entire electricity network. In some cases, the reliability levels may need to be changed between seasons. This is because customers rely heavily on electricity during specific seasons; for example, the agricultural sector in Asian countries requires more reliable electricity supply during a specific season each year. All of these reasons clearly indicate the need for an SMG system to analyze its reliability level and continue to maintain it at a cost-effective level for SMG.

When the utility establishes the reliability level, two research questions must be addressed: how much reliability is adequate from the customer's perspective, and how a utility can best spend money to achieve a specific reliability level. The total cost can be used to answer these two questions. From an economic standpoint, the reliability level that provides the lowest total cost is a typical CERL that must be fixed as a reliability standard for a power system network. The total cost is primarily determined by the sum of the customer interruption cost (CIC) and the investment cost.

Utility companies conduct numerous customer surveys to evaluate the CIC, and optimisation algorithms are used to find the optimum reliability while minimising the total investment cost. The cost of CIC is sometimes a tangible measure, where the impact of the interruption can be weighted in monetary value, and other times it is intangible, where the impact cannot be easily converted into cost [3]. In 2018, the Australian Energy Regulator (AER) assessed the value of customer reliability (VCR) and developed a method for assessing VCR [4]. VCR provides criteria for assessing CIC.

To achieve high supply reliability, the electricity network reliability standards necessitate the construction of additional network infrastructure. This leads to in an additional investment cost to the SMG system. As a result, the customer must eventually bear the cost of increased reliability [5]. "Many outages could be avoided if the electricity network was improved," according to the Australian Energy Market Commission (AEMC). However, the cost of the improvements would be borne by higher electricity bills [4]. As a result, the decision to improve reliability is influenced by the customer's willingness to pay. Customers' willingness to pay for increased reliability has increased since electric utility deregulation [6]. Reliability improvement options for an SMG system typically include installed capacity expansion of renewable energy resources, energy storage systems, demand side management programs, and improved distribution network reliability. The most common option for improving an SMG's network reliability is to reduce the failure rate (FR) of its individual components.

A distribution network's reliability indices are divided into load point reliability indices and system reliability indices [7]. The average failure rate, average annual outage time, and average outage time per failure are the load point reliability indices. System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Customer Average Interruption Duration Index (CAIDI), and Average Service Availability Index are the distribution system indices (ASAI) are the system reliability indices [8]. Lei Xiao et al. [9], investigated the impact of renewable and distributed resources on customer side reliability indices, such as solar PV, BESS, and electric vehicles (EVs).

A value-based reliability planning methodology seeks the lowest cost solution. The marginality condition is evaluated to determine the minimum cost solution, where the marginal cost of reliability enhancement equals to the marginal benefit [1]. The requirement of both lower cost and achieving an acceptable level of service reliability should be met using the concept of value-based distribution system reliability planning [6]. Soheil Mohseni et al. [10], proposed generic reliability-oriented life-cycle cost minimisation method for stand-alone multiple energy carrier microgrid (MECM). The study investigated the affordability, sustainability, and cost-efficiency of the SMGs supplying electricity, as well as the optimum capacity of the MG's equipment using the net present value (NPV) and the probability of power supply failure (LPSP). Adefarati and R. C. Bansal [11] proposed a method for valuing the reliability, economic, and environmental benefits of renewable energy in a microgrid system. The goal of this life-cycle analysis is to reduce the cost of energy, the lifecycle cost, the annual cost of load loss, and the lifecycle cost of greenhouse emissions while also increasing the overall benefit of green technologies in the proposed microgrid system. J. Zhou and Z. Xu [12] proposed optimal sizing and a cost-benefit analysis of SMG based on reliability. This paper proposes a cost-benefit index based on LPSP and total net present value cost (TNPC). N.Zareen et al. [13], proposed a reliability cost-benefit (RCB) model for integrating distributed generation (DG) into an independent MG network. In this paper, a novel decision-making strategy for relating system reliability to cost-benefit is proposed, using economic and signaling-game theory (SGT). Furthermore, an analysis was conducted to correlate various reliability levels with the value of incentives paid to customers for Demand Response (DR) initiatives.

Anoune et al. [14], introduced a deterministic approach for improving MG reliability while reducing the investment cost of hybrid renewable-based energy systems by maintaining a constant temperature for bitumen storage. Sahar Seyyedeh-Barhagh et al. [15], proposed a bi-objective scheduling framework for hydrogen storage system (HSS)-based MGs based on economic and environmental factors. Mehrdad Aslani et al. [16], proposed best probabilistic reliability-oriented SMG planning. The optimal capacity of a hydrogen-based MG subsystem is determined while accounting for energy cost loss. Seyed Mehdi Hakimi et al. [17], assessed the optimal capacity of a renewable energy system in MG while taking market interaction and reliability constraints into account. The majority of researchers [18–20] evaluated the optimal use of energy resources to maximise reliability level, while only a few [21,22] discussed cost-effective reliability level evaluation while considering total cost minimisation.

Based on the literature study, a research gap in identified to evaluate the CERL in comprehensive manner. Therefore, this research problem should address three sub-research problems such as: reliability evaluation approaches, reliability improvement methods that consider cost minimisation, and evaluation of customer interruption cost. As a result, the literature review was further expanded in these three areas.

Analytical and simulation methods can be used to assess reliability. Analytical approaches such as Reliability Block Diagram (RBD), Fault Tree Analysis (FTA), and Markov Reliability Model (MRM) are used to identify which component has a high impact on system failure [23,24]. The simulation approach assesses system reliability by simulating its operation in real time while taking the system's operational life span into account. Most researchers used the Monte Carlo Simulation (MCS) to simulate reliability, with most focusing on either equipment failure events or resource unavailability situations [25–27]. In a previous research paper, the authors [28] proposed a comprehensive reliability evaluation approach that incorporates resource unavailability and equipment failure using hourly data.

Billinton and Karki [18] proposed a method for increasing capacity in a small, isolated power system. The number of healthy states, the number of risk states, and the duration of each state are computed. To generate random risk indices and well-being indices, MCS is used. Ai et al. [20], proposed a computer-aided design for sizing a PV/WT/BESS system in relation to the loss of power supply probability (LPSP) index. The paper ignores equipment and component failure and focuses solely on resource availability. Nelson et al. [19], proposed a method for unit sizing and cost analysis of stand-alone hybrid WT/PV/Fuel-cell power generation systems in which the number of WT units is used as an input parameter to calculate the number of PV panels required to match a specific LPSP level. Recalde and Alvarez-Alvarado [21] proposed a novel design framework for an optimised renewable energy-based DG project in a medium voltage primary distribution system. This strategy serves as a foundation for a new distribution expansion project. By minimising EENS, the DG potential location and sizes are identified.

The cost of unreliability is not equal to the value of reliability, but it can be considered a reasonably representative measure [29]. In order to calculate the cost of a customer outage, three methodologies are commonly used: indirect analytical methods, case studies, and customer surveys. Customers in the industrial sector are typically assessed using the analytical method, whereas customers in the residential sector are assessed using the customer survey approach [30]. Many researchers [29,31–34] used a customer survey to calculate the cost of interruption. The customer survey methodology allows for three different approaches: direct worth (DW), willingness to accept (WTA), and willingness to pay (WTP). Customers are asked to value their own losses due to power outages under the DW approach. This method is usually successful for industrial and commercial customers, but it is not successful for residential customers because not all losses for a residential customer are tangible. Customers are asked how much compensation they are willing to accept for power outages under the WTA method. Similarly, the WTP method involves asking customers how much money they are willing to pay to avoid an interruption [30]. Because the cost of interruption differs between customers in different customer sectors, most researchers [33–35] used a sector customer damage functions (SCDF) approach. To get a more accurate understanding of interruption cost, Sinan and Matti [32] used subsector customer damage function (SSCDF), which divides customers further into sub-sector.

The sufficiency of reserves aids in the maintenance of energy and power balance, as well as the reliable real-time operation of microgrids. As a result, capital and operating costs are critical issues in MGs [36,37]. Because RES integration is dramatically increased in MGs, RES intermittent behaviour should be compensated to maintain system reliability; however, the total cost of the system should be minimised, which can be accomplished by optimising installed capacity sizing [38]. Malaki and F. Pourfayaz [39] proposed using an evolutionary algorithm to determine the optimal size of a hybrid PV/WT/BESS system. The goal function is to minimize total annualized cost (TAC), while the constraint is to balance a user-specified loss of LPSP index. Notably, this study only looked at resource sufficiency; the failure of generating equipment and distribution components was not considered. Khodaei et al. [40], proposed a method for MG planning in the face of uncertainty. The issue is divided into two parts: an investment master problem and an operation sub-problem. The cost of unserved energy, which represents MG reliability, is incorporated into the cost function of MG operation. The Benders decomposition method was used to connect and coordinate these two problems.

Munasinghe and Gellerson [22] proposed a generalised simulation model for optimising reliability by weighing the social benefit and cost of improving power system reliability. The concept is applied to a case study of Cascavel, Brazil, in order to determine a range of optimum reliability levels for long-term electric power distribution system planning. Vahedipour-Dahraie et al. [41], proposed a risk-constrained stochastic framework method to maximise a microgrid operator's expected profit under uncertainties of renewable resources, load demand, and electricity price. The expected profit and cost of EENS are plotted against the value of lost load (VOLL) in this study.

To improve dependability, most studies presented several approaches for calculating the size of installed RES capacity in MGs. No one in this study, to the best of our knowledge, addressed evaluating a certain reliability level as a CERL for a 100 % renewable SMG system.

This study's research question is to examine the CERL. This research problem is addressed with a new approach that involves the phases outlined here. First, SMG's reliability is comprehensively evaluated by assessing equipment and resource availability every hour. Second, for various reliability levels, an investment cost optimisation approach is employed to determine the required size of RES installed capacity. Third, the LOLF penalty payment is included into the EENS cost. Finally, the total cost is computed, and the CERL is determined by combining these.

This paper proposes a method for calculating the CERL of fully renewable standalone microgrids (SMG). This paper's contribution is as follows.

1) Development of an algorithm for determining the cost-effective reliability level for 100 % renewable energy integrated SMG
2) Evaluation of marginal cost of reliability improvement (MCRI) of a hundred percent renewable energy integrated microgrids
4) Development of a new approach for customer interruption cost calculations; and
3) A holistic reliability evaluation approach is used which combines equipment and resource hourly availability.

The proposed methodology for evaluating CERL is an expert approach in which renewable energy resources and energy storages along with the improvement in the equipment reliability are selected optimally for a cost-effective reliability level for 100 % renewable-based microgrids. This approach uses marginal cost of reliability improvement and customer interruption cost along with other cost of reliability improvement to evaluate the effectiveness of each method of reliability enhancement in each iteration of reliability improvement. The reliability improvement is linearized considering the addition of reliability improvements to enhance the applicability of the proposed methodology by reducing the computational efforts. To further analyze the effectiveness of the proposed approach, the sensitivity analysis is performed in this research to provide a comparison platform of the cost-effective reliability levels at different scenarios including different mix of customers.

The novelty and contribution are not limited to a basic minimisation problem, but also to determining the Cost-Effective Reliability Level (CERL). The evaluation of CERL necessitates the use of a non-linear curve fitting technique to evaluate an equation for the total cost curve. The lowest point on the total cost curve is then determine. The best reliability value for this minimum total cost is therefore considered as CERL. In other words, Cost-Effective Reliability Level for 100 % renewable energy integrated SMG typically indicates the highest reliability level that can be reached in a fully renewable SMG while minimising the total renewable and energy storage costs. This research concept is completely new. To validate this research work, the sensitivity analysis performed in this research provides a reasonable comparison of the outcome obtained from the proposed methodology in this study.

The following sections of this work are structured as follows. Section 3 defines the research question. Section 4 displays the research methodology, which includes an explanation of the approach used for reliability evaluation, reliability improvement, and total cost evaluation. Section 5 describes the case study used in this study. Section 6 elaborated on the outcome. Section 7 offers a conclusion.

2. Problem formulation

SMG is a microgrid system that is isolated from the rest of the network. As a result, SMGs frequently experience reliability issues. In this context, improving the reliability of an SMG system is critical; however, the critical research problem is determining what level of reliability is cost-effective. Equipment Redundancy makes it possible to attain 100 % equipment reliability, but it is not always an economical solution. Consequently, while considering cost minimisation, equipment reliability cannot be 100 % since all equipment has a failure rate. As a result, achieving 100 % reliability is not practically attainable. Furthermore, in order to achieve 100 % system resource adequacy, we must invest a significant amount on resources. Therefore, figuring out which level of reliability—such as 99.5 %, 99 %, or 98.5%—is best for minimising the SMG system's overall cost is the main research problem, while maintaining 100 % renewable-based resource profile. Identifying the reliability improvement alternatives while considering cost minimisation became a sub-research problem during the evaluation process. This sub-problem was previously presented by the authors in their previous research paper [42], but the concept is repeated here with a different base case scenario. The second sub-problem is determining the cost of customer interruption (CCI) in relation to LOLF and EENS. The third sub-problem is determining the optimal reliability level while keeping total cost in mind. This is addressed using a mixed-integer linear programming optimisation approach.

The loss of load probability (LOLP) is used in this study to assess the system's reliability. As a result, an investment decision on reliability improvement is influenced by the LOLP value. The customer damage function (CDF), on the other hand, can be represented as a function of LOLP and EENS. As a result, the customer interruption cost (CIC) can be calculated using LOLP and EENS. Thus, the total cost, which is the sum of investment and operation and maintenance costs, can be represented as a function of LOLP and EENS.

Fig. 1 shows that the base case of the MG system consists of a MW of PV, b MW of WT, c MWh of BESS, and d MW of DR, and e number of equipment failure rate (FR), has a LOLP of R_{base}%.

The research sub-problem is to find how much additional energy resources, storage, DR, and failure rate reduction capacities needs to be installed to lower the LOLP from the base case (R_{base}%) to a predetermined reliability target, considering minimisation of the total investment cost of reliability improvement (TICRI). TICRI refers to the sum of the costs associated with investment cost of reliability improvement. The total investment cost is evaluated based on a net present value (NPV) calculation. The reliability increase is obtained by increasing the PV capacity from 'a' MW to the maximum of 'a +7' MW with the step of 1 MW, the WT capacity from 'b' MW to the maximum of 'b+7' MW with the step of 1 MW, the BESS capacity from 'c' MWh to the maximum of 'c+7' MWh by the step of 1 MWh, the DR capacity from 0 to 300 kW in increments of 50 kW, and the equipment failure rate from 0.1 to 0.04 by 0.01 failure rate reduction. As a result, there are seven decision variables for each reliability improvement option, meaning that a total of 16,807 combinations of reliability improvements are feasible.

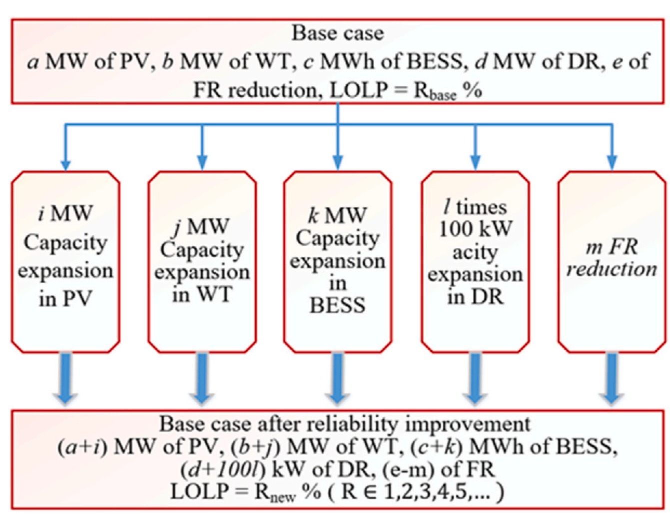

Fig. 1. Base case and base case after reliability improvement.

$$TICRI = IC_{PV}^{i} + IC_{WT}^{j} + IC_{BESS}^{k} + IC_{DR}^{l} + IC_{FR}^{m} \tag{1}$$

Equation (1) represents the TICRI, where *i, j, k, l and m* represent the capacity expansion decisions on PV, WT, BESS, DR, and failure rate reduction. IC refers to investment cost. Hence, IC_{PV}^{i} refers to investment cost of *i* MW of capacity addition on solar PV. As explained earlier, *i, j, k, l and m* can take any value from 0 to 7. To illustrate, if $i = 4, j = 3, k = 2, l = 2, m = 1$ then the decision is to expand PV by 4 MW, WT by 3 MW, BESS by 2 MWh, DR by 100 kW, and reduce equipment failure rate by 0.01 and then, the corresponding IC will be 4 times the cost of 1 MW of PV plus 3 times the cost of 1 MW of WT plus 2 times the cost of 1 MWh of BESS, and one times the cost of failure rate reduction.

The objective function is to minimize the total investment cost of the reliability improvement, subject to LOLR is equal or greater than that of required LOLR to achieve a specific reliability level.

$$f = Min\ (TICRI) \tag{2}$$

$$subject\ to:\ LOLR_{PV+WT+BESS+DR+FR}^{b\rightarrow(b_{new})} \geq LOLR^{*} \tag{3}$$

The constraint of this optimisation problem is to equalize or exceed the system LOLR to a particular value (LOLR*) based on a user-defined value of required LOLP reduction. The user-defined value of LOLP will be converted to LOLF, and then the required LOLR is calculated. For instance, if a user wants 1 % of LOLP reduction, then the LOLF needs to be reduced by 2,190, thus LOLR* = 2190. The simulation is for a period of 25 years'; therefore, it consists of 219,000 h. To obtain 1 % LOLP reduction, the LOLF of 2190 h needs to be reduced.

The research subproblem can be reduced to determining the least expensive weighted alternative to achieve the required LOLR. Different capacities of reliability improvement (RI) alternatives will result in different LOLRs. By subtracting the LOLR obtained by two consecutive capacities of RI alternatives, the marginal loss of load reduction (MLOLR) can be calculated. To illustrate, if the LOLR obtained by expanding battery capacity by 2 MWh and 3 MWh are 3000 and 5000 respectively, the MLOLR obtained by expanding capacity by 2 MWh to 3 MWh will be 2000 (5000–3000). The MLOLR is calculated similarly for all RI alternatives. The MATLAB linear programming solver is used to solve this problem using integer linear programming. The MATLAB optimisation result yields the appropriate total investment cost.

Equation (4) explains the inequality constraint of this research problem, where decision variables of capacity expansions are denoted as *i, j, k, l and m* and the corresponding marginal loss of load reduction is denoted as *p, q, r, s and t*. $MLOLR_{PV}^{p}$, $MLOLR_{WT}^{q}$, $MLOLR_{BESS}^{r}$, $MLOLR_{DR}^{s}$ and $MLOLR_{FR}^{t}$ are the MLOLR due to PV, WT, BESS, DR, and equipment failure rate. The $LOLR^{*}$ is the required loss of load reduction to achieve a particular (user defined) reliability level. For example, if the decision variables *i, j, k, l and m* are 4, 3, 2,1 and 2 respectively, then

$$MLOLR_{PV}^{4} + MLOLR_{WT}^{3} + MLOLR_{BESS}^{2} + MLOLR_{DR}^{1} + MLOLR_{FR}^{2}$$

should be equal to or greater than $LOLR^{*}$. When $i = 1$, $MLOLR_{PV}^{p}$ became $MLOLR_{PV}^{1}$ which represents how much loss of load reduction is achieved when the PV capacity is expanded by the first 1 MW (in this study, the first 1 MW actually means the increment from the 15 MW PV installed capacity base case to the 16 MW of the new case). The MATLAB optimizer performs numerous iterations to find the least cost weighted combination of resource mix which will help to achieve the required reliability level. This optimisation problem does not have any equality constraints.

$$\sum_{p=0}^{p=i} MLOLR_{PV}^{p} + \sum_{q=0}^{q=j} MLOLR_{WT}^{q} + \sum_{r=0}^{r=k} MLOLR_{BESS}^{r} + \sum_{s=0}^{s=l} MLOLR_{DR}^{s} + \sum_{s=0}^{t=m} MLOLR_{FR}^{t} \geq LOLR^{*} \tag{4}$$

3. Methodology

The purpose of this study is to evaluate the CERL. The assessment of CERL is comprised of three sub-problems: the evaluation of base case reliability, the evaluation of reliability improvement alternatives through an optimisation process aimed at minimising total cost, and the evaluation of total cost.

The approach of this study is depicted in Fig. 2. This study is divided into three sub-problems: reliability evaluation, cost required for a specific value of reliability improvement, and CERL evaluation. The reliability will be evaluated both at the start of the simulation and after the reliability improvement alternatives are implemented. The cost of reliability improvement for each improvement level, referred to as MCRI in this study, should be computed after the reliability improvement has been made. Then, utilising all of the data points obtained with varying levels of increased reliability, a plot indicating the total cost of the SMG must be generated. Using this chart, the lowest point of the total cost curve is identified as CERL.

3.1. Reliability evaluation

The system's reliability is determined by two factors: the availability of equipment and the availability of renewable energy resources. To improve the reliability of the MG system, a holistic reliability evaluation method must be used to assess its reliability level. The availability of generating resources, as well as the availability of generating equipment and distribution components, is evaluated in each hour by the holistic reliability evaluation method. A comprehensive mathematical model that incorporates resource and equipment availability in each hour has previously been proposed [28] and is repeated here. The time to failure (TTF) value of each equipment type is evaluated in this model using non-sequential Monte Carlo simulation, which generates random numbers. In this step, two aspects are obtained using random prediction: determining the zero reliability or down (unhealthy) state of the equipment and predicting the TTF of the equipment in each hour. Because this uses non-sequential MCS and is focused on predicting failure events, only the failure rate was evaluated, and repair time was not considered. The PV, WT, BESS, and MGDN reliability models were obtained using the state duration sampling approach [48]. Using the state duration sampling approach, the PV, WT, BESS, and Microgrid Distribution Network (MGDN) reliability models were obtained. Hourly power generation from renewable energy resources is calculated using weather parameters such as solar irradiation, solar temperature, and wind speed at a specific location.

Fig. 3 depicts how the reliability of the MG system is dependent on the availability of equipment and resources; the arrows represent the direction of energy flow.

3.1.1. Equipment availability modelling

In this study, four distinct types of equipment were considered: a solar PV array, a WT, a BESS, and the MG distribution network (MGDN). Partially failed components are not included in this study; rather, component failure is assumed to be a full failure. Failure of 5 MW of PV panels, for example, signifies failure of all cells in that panel. This is because the simulation algorithm described in this study does not take into consideration partial equipment failure. This assumption is introduced to simplify the proposed optimisation procedure.

The analytical approach usually considers the failure rate (λ), which is the number of failure events expected to happen during the operation of a component for a specified period, as a constant parameter. But the λ is not a constant value, it is a time-varying parameter. For example, suppose the of a battery energy storage system is provided as 0.1 failure/year, or an MTTF of 10 years; what is the MTTF value after 5 years of usage? The MTTF will probably change, and a customer cannot expect the new MTTF value to be the remaining balance of 5 years. The MTTF of the battery will tend to decrease due to a variety of factors such as

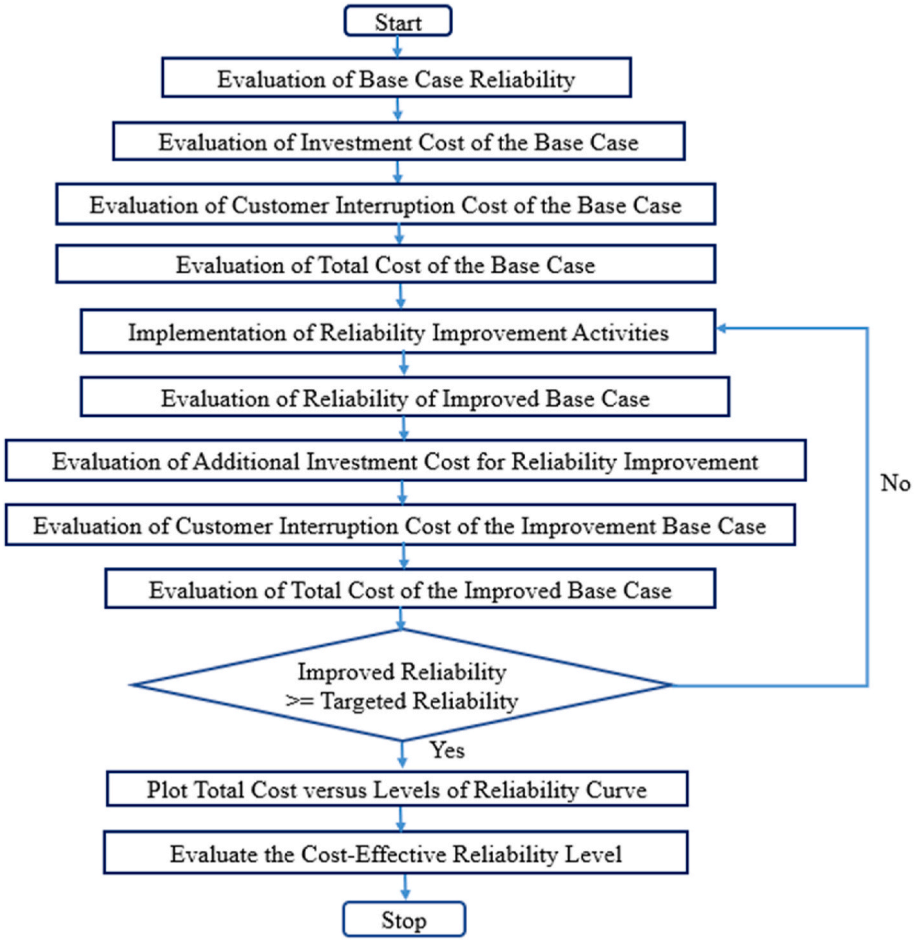

Fig. 2. Evaluation of cost-effective reliability level.

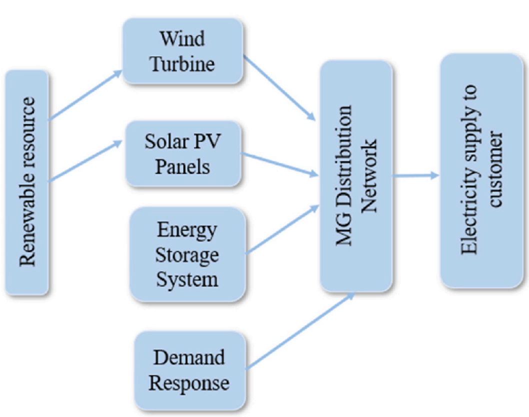

Fig. 3. SMG with equipment and resources availability.

operating temperature and repeated charging-discharging. Similarly, a component may encounter failure in the first year, when the manufacture provided the MTTF of 10 years. The λ or MTTF provided by the manufacturer is the predicted average value. As a result, the MTTF of the component must be dealt with using a probabilistic approach by simulating the real process. MCS is commonly used to test the probabilistic nature of a component's MTTF.

MCS evaluates the time to failure (TTF) value of each equipment type by generating random values. In this step, two elements are determined using random prediction: determining the zero reliability or down state of the equipment and estimating the TTF of the equipment in each hour.

Fig. 4 depicts the transition of any component from up to down state.

Because this uses non-sequential MCS and is focused on predicting failure events, just the failure rate was examined, and repair time was not considered. The PV, WT, BESS, and MGDN reliability models were developed using the state duration sampling approach. The following approach can be used to calculate the time to failure (TTF).

Step 1: 219,600 uniformly distributed random numbers (U∼ (0, 1)) are generated, representing the number of hours in 25 years.
Step 2: compute TTF using (5)

$$TTF = -MTTF \cdot \ln(U) \tag{5}$$

Step 3: Repeat the above two steps to find TTF of each equipment type, such as solar PV array, wind turbine, battery, and MG network separately.
Step 4: Identify which energy resources were supplying electricity to the load at each hour.
Step 5: Calculate the TTF of the system during each hour.

3.1.2. *Resource Availability modelling*

Wind speed and solar irradiation will certainly vary over the day,

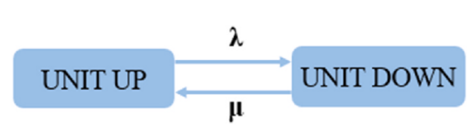

Fig. 4. SMG with equipment and resources availability.

week, year, and over numerous years. As a result, even if the equipment, such as a solar panel, is in good working order at a certain hour, if there is insufficient solar irradiation, there will be insufficient power available for that source at that time. Because emerging novel power system topologies such as microgrid (MG) power generation are primarily integrated with renewable energy systems, system reliability is dependent on two factors: availability of equipment and availability of renewable energy resources. In this sense, it is critical to evaluate the reliability of an MG system using a simulation approach that takes into account both resource constraints and resource availability.

The reliability of the system at any moment in time is dictated by the availability of the components that are in use at that time. As a result, MG's hourly reliability value is derived by establishing which energy sources supply electricity at the current time. In this MG architecture, the variable renewable energy resources WT, solar PV, and BESS operate in parallel, while the MG distribution network operates in series, as shown in Fig. 3. The analysis looks at a few possible scenarios.

➢ If wind power generation, solar PV generation, stored energy in the battery, are individually greater than the load demand, then all these are considered as parallel, and the MG distribution network will be in series with this. $R_W, R_{PV}, R_{BESS}, R_{MGDN}$ represent the reliability of wind turbine, PV panel, battery energy storage system, and distribution network respectively.

$$R^R_{MG} = (1 - (1 - R_{WT}).(1 - R_{PV}).(1 - R_{BESS}))R_{MGDN} \tag{6}$$

➢ If wind power and solar PV generation are both more than load demand, and stored energy is insufficient to meet load need. Wind and solar power generation are viewed as parallel components in this context. This is because at this time, either wind power generation or solar PV generation can supply the load requirement.

$$R^R_{MG} = (1 - (1 - R_W).(1 - R_{PV}))R_{MGDN} \tag{7}$$

➢ If only wind power generation is greater than the load demand, and the battery is fully charged, but not sufficient to supply the load.

$$R^R_{MG} = R_W \cdot R_{MGDN} \tag{8}$$

➢ If wind and solar PV generation together with battery energy storage is greater than or equal to load demand. Here all the components are series in operation.

$$R^R_{MG} = R_W \cdot R_{PV} \cdot R_{BESS} \cdot R_{MGDN} \tag{9}$$

3.2. Loss of load calculation

In each hour, a loss of load (LOL) event occurs if the resource unavailability is encountered. To illustrate, the LOL happens when the total power from renewable energy, power from a diesel generator, and stored power in the battery during the end of the previous hour is less than the power demand of the present hour.

$$\mathrm{LOL}^i = 0 \quad \forall P^i_{PV} + P^i_{WT} + P^{i-1}_{BES} > P^i_L \tag{10}$$

$$\mathrm{LOL}^i = 1 \quad \forall P^i_{PV} + P^i_{WT} + P^{i-1}_{BES} < P^i_L \tag{11}$$

3.3. Reliability improvement (RI)

In this paper, reliability improvement (RI) refers to increasing reliability by adding installed capacity for renewable energy resources, installed capacity for battery energy storage systems, installed capacity for demand response initiatives, and lowering the failure rate of power generation, storage, and distribution equipment within the SMG system. These options for improving reliability can be used alone or in combination.

Using a mixed integer linear programming technique, the proposed algorithm provides decision variables for every reliability improvement level. The method determines the number of loss of load (LOL) events that must be decreased in order to achieve 1 % reliability improvement, for example, if the SMG system needs to be increased by 1 % (marginal reliability improvement). It then offers the option of reliability improvement alternatives based on investment cost minimisation.

3.4. Evaluation of total cost

The evaluation of total cost includes the evaluation of the base case's investment cost, the evaluation of the additional investment cost for reliability improvement, and the evaluation of the base case and the reliability improved based case's customer interruption cost. How the investment cost is calculated is covered in the section that follows. The case study provides numerical examples to clarify the evaluation of customer interruption cost.

3.4.1. Evaluation of incremental investment cost (IIC)

The net present value (NPV) technique is used to find the total IIC. Since this study considers 25 years, the salvage values are ignored.

$$IC^1_{PV} = PV^1_C + PV^1_{O\&M} + PV^1_R \tag{12}$$

where, IC^1_{PV} is the incremental investment cost of 1 MW of PV capacity addition, PV^1_C is the capital cost, $PV^1_{O\&M}$ is operation and maintenance (O&M) cost, and PV^1_R is replacement cost. An assumption is made that the O&M cost incurred in each year is equivalent to 1 % of the capital investment cost [43] Similarly, IC^1_{WT}, IC^1_{BESS} and IC^1_{DR} which represent the incremental investment cost of 1 MW of WT, 1 MWh of BESS, and 100 kW of DR respectively are calculated. To reduce the complexity of this research, the investment cost of capacity additions is assumed as a linear increment in price (i.e., if the total cost of 1 MW of capacity addition of PV is 1 million dollars, then the additional cost of 2 MW of capacity will be 2 million dollars). All the cost values mentioned throughout this paper is in Australian Dollars.

3.4.2. Capital cost

The capital cost of PV, WT and BESS were obtained by analyzing the feasibility studies performed by other researchers [44,45] and reports by the International Renewable Energy Agency (IRENA) [46] and National Rural Electric Cooperative Association (NRECA) [47].

3.4.3. Operation and maintenance cost

The NPV investment cost for the unit quantity (1 MW) of capacity addition is calculated in Table 1. Based on [43], the annualized operation and maintenance cost of PV, WT and BESS are 1 %, 3 % and 3 % respectively of the capital cost of each energy resources.

3.4.4. NPV calculation

Net present value is used to calculate today's value of the future payment stream.

$$NPV = \frac{F}{(1+i)^n} \tag{13}$$

Table 1
Investment cost summary.

	Investment cost of 1 MW of PV (M $)	Investment cost of 1 MW of WT (M$)	Investment cost of x MWh of BESS (M$)	Investment cost of 50 kW of DR (M$)	Investment reduction of 0.01 failure rate (M$)
Total cost	1	1.5	0.5	0.55	2.5

In (13) F is the future value; i is the discount rate and n is the number of years.

$$PV_{O\&M}^{NPV} = PV_{Annual}^{O\&M}\left(\frac{1-(1+i)^{-n}}{i}\right) \tag{14}$$

In (14), the NPV value of O&M is calculated based on annualized O&M cost, and r, n represents the discount rate and the number of years of operation. The discount rate is assumed as 5 % in this research, and n is 25.

3.4.5. Replacement cost

The PV and WT components typically have a lifespan of 25 years and thus do not require replacement. However, the lifespan of Li-ion battery energy storage is typically 12–15 years. According to Ref. [44], it is estimated that the average BESS lifespan is 13 years. Consequently, the 13th year replacement of BESS is simulated in this paper.

$$PV_R^{NPV} = \frac{PV_{MG}^R}{(1+r)^{n1}} \tag{15}$$

where, the PV_R^{NPV} is the NPV value of replacement; and $n1$ denotes the number of years, PV_{MG}^R is the replacement cost at the time of replacement.

3.4.6. Cost of demand response

In this study, demand response refers to a decrease in aggregated demand from microgrids. The reliability improvement achieved with DR is assessed using increments of 50 kW DR. Unlike PV and WT capital costs, DR costs are difficult to calculate because they vary by country and season.

3.4.7. Incremental investment cost summary

Table 1 summarises the investment cost of 1 MW of energy resources, 1 MWh of battery energy storage system, and 0.01 failure rate reduction in this section. The cost of PV, WT, BESS are calculated, and the cost of DR and cost of failure rate reduction are assumed. Evaluation of cost of demand response is a separate research problem. Therefore, to reduce the complexity of this research problem, the cost of DR is assumed. Similarly, the cost of reducing equipment failure rates (replacement of components) fluctuates over time, therefore the cost value is assumed. To elaborate, the costs of PV, WT, and BESS vary over time; however, these costs can be collected from the National Renewable Energy Laboratory's (NERL) annual reports. However, the cost of DR and the cost of reducing equipment failure rate cannot be determined from standard data because they are unique to each MG system. This is important to mention that these two assumptions will not affect the credibility of the proposed CERL technique to find optimum reliability level for a microgrid. Lithium-ion battery energy storage typically has a lifespan of 12–15 years before needing replacement. In this study, the investment cost includes the replacement of BESS after 13 years.

4. Case study

The load demand for the Aberdeen substation in New South Wales, Australia, was downloaded from the Ausgrid website for this study, as were the hourly temperature and irradiation data for this area from the renewable.ninja website. The hourly wind speed is generated at random with a scale parameter of 3 and a shape parameter of 8. This case study takes into account aggregated load demand data from 2016, which has a peak demand of 5.04 MW and a daily average demand of 3.72 MW.

Fig. 5 depicts the Aberdeen substation's load profile. For this study, the base case is chosen so that the three times peak demand occurs correspond to individual solar PV generation and wind power generation, and the battery energy storage is chosen so that it has more than 90 % MG system reliability (less than 10 % LOLP). As a result, the base case includes 15 MW of PV, 15 MW of WT, 15 MWh of BESS, 0 kW of DR, and a 0.1 equipment failure rate. The LOLP in the base case is 5.8 % (reliability is 94.2 %), and the EENS is 36,910 kWh. This simulation study takes into account the SMG's operating duration of 25 years (219,000 h).

5. Result and discussion

This section is divided into three subsections: investment cost evaluation for various reliability levels, CCI evaluation for various reliability levels, and CERL evaluation.

5.1. Evaluation of investment cost for various reliability levels

Each of the base case installed capacities is increased by one unit quantity each time, and a simulation is run for 25 years to calculate the LOLR achieved. The PV and WT capacity are increased from 15 MW to 21 MW in 1 MW unit expansions, the BESS from 15 MWh to 21 MWh in 1 MWh unit expansions, the DR from 0 MW to 0.3 MW in 50 kW of unit expansion, and the equipment failure rate from 0.1 to 0.04 in 0.01 failure rate reduction steps. Sixteen thousand eight hundred seventy different capacity expansion RI mix combinations and their corresponding loss of load reduction (LOLR) are calculated. Equation (16) is evaluated using a linear regression approach, which represents the LOLR of resource mix as a function of LOLR due to individual RI alternatives.

$$LOLR^{RI\ Mix} = 3451 + 0.285p + 0.335q + 0.416r + 0.319s + 1.031t \tag{16}$$

where, $LOLR^{RI\ Mix}$ represents the LOLR that can be achieved by the capacity expansion of the RI mix, and p, q, r, s and t denote the LOLR obtained when PV, WT, BESS, DR, and reduction in equipment failure rate respectively are individually expanded.

To demonstrate, the LOLR of a capacity expansion mix of 4 MW of PV, 6 MW of WT, and 3 MWh of BESS, 50 kW of DR, and a failure rate reduction of 0.01 can be calculated by determining the value of the LOLR due to 4 MW PV alone, 6 MW WT alone, and 3 MWh BESS alone, 50 kW of DR alone, and a failure rate reduction of 0.01 alone. The R square value (also known as the coefficient of determination) for this

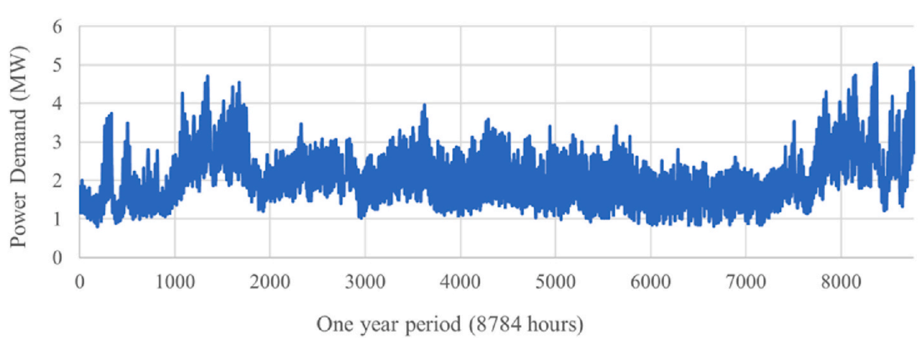

Fig. 5. Load Profile of substation Aberdeen in the year 2016.

equation was 0.97, and the coefficient of multiple correlation was 0.95. In this case, the R square value indicates how many data points fit the equation, and the equation fits 97 % of the data points. The coefficient of multiple correlations indicates how strong the linear relationship between data is, and there is a strong linear correlation of 95 % in this scenario.

Table 2 depicts the capacity expansion choices made by the MATLAB optimisation algorithm (which employs integer liner programming) to reduce the LOLP by a specific value. The base case investment cost is $45 million. The optimisation algorithm, as explained in (6), evaluates the size of installed capacities for each required LOLR and calculates the additional investment cost. To achieve a 1 % reduction in LOLP, the LOLF of 2190 h must be reduced. In other words, the required LOLR to improve reliability by 1 % is 2190. As a result, the cost minimisation approach suggested in this study selects a constraint value of 2190 and then evaluates the required values for the variables PV, WT, BESS, DR, and FR. This is evaluated in such a way that additional investment costs are minimised while meeting the requirement for reliability improvement.

To illustrate, the proposed algorithm calculated the required value of BESS as 2 MWh for the first 2 % reduction in LOLP (4380 h of LOLF reduction), which means that the capacity of the BESS must be increased by 2 MWh from the base case scenario. It is noticeable that only BESS is chosen for capacity increase up to 2.5 % of reduction in LOLP. This is reasonable because the cost weighted LOLR of BESS is lower during this interval than the other alternatives. This also reveals that the base case has excess energy but insufficient storage capacity. BESS and DR are chosen to reduce LOLP to 3 % and 3.5 % levels. The equipment failure rate reduction has been chosen for a reduction in LOLP to 5 % and 5.5 % levels. This means that the reliability is improved by 0.5 % (from 98.7 % in the previous case) by lowering the equipment failure rate from 0.06 to 0.04.

It is worth noting that the MATLAB Mixed-Integer linear programming optimisation algorithm does not consider step-by-step capacity expansion, but rather reliability improvement from base case to new case. To illustrate, when the system requires 97 % reliability, the algorithm evaluates the minimum cost using the data (installed capacity and reliability) of the base case (reliability of 94.2 %); it does not consider the previous reliability level of 96.5 %.

Fig. 6 depicts how investment costs vary with reliability levels. The x variable represents the level of reliability. As a result, the equation represents the total investment cost in terms of reliability levels. A second-degree polynomial equation fits this curve. The curve fitting technique is used to identify the equation, and the R square value (also known as the coefficient of determination) is 0.9987. In this case, the R square value indicates how many data points fit the equation, and the equation fits 99.87 % of the data points.

In traditional investment cost analysis for the reliability improvement, it is needed to upgrade networks and power plant generations in order to achieve a higher level of reliability. Since the whole capacity of the augmented networks and generations are not being used, the incremental investment cost for reliability is much higher as we go toward higher reliability levels. However, in the proposed method in this paper, different approaches are suggested for reliability improvement including renewable and energy storage augmentation and demand response and failure rate improvement. These approaches are available at the smaller incremental steps, for example, energy storages are available in 1 MWh incremental steps or demand response is available in the steps of 50 kW. Therefore, the optimised investment cost associated with such approaches with smaller incremental steps are generally lower compared to the case of using large power plants that usually comes in larger steps. In future work, a sensitivity analysis of investment costs associated with each reliability improvement approach should be incorporated to address variations in optimised investment costs at different reliability levels.

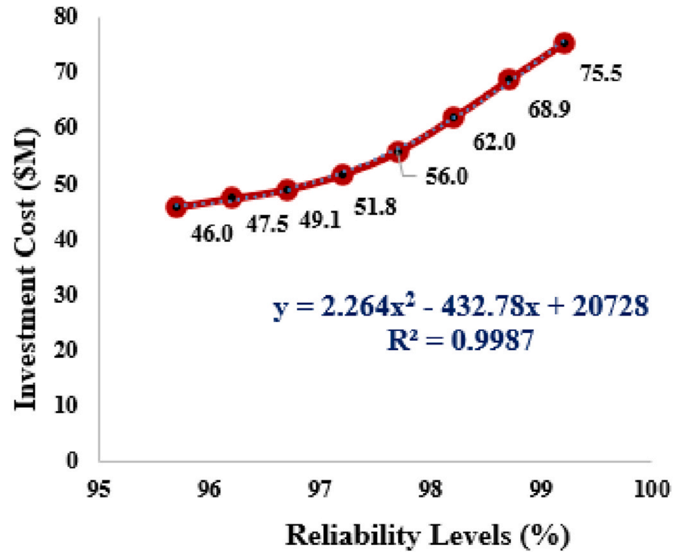

Fig. 6. Investment cost for varies LOLP reduction.

5.2. Evaluation of customer interruption cost for various reliability levels

Numerous researchers [30,31,33–35] from various countries assess the cost of customer interruption. The most common outcome is the interruption cost per kWh of energy. In other words, this is the price of EENS. No researchers intended to use or calculate LOLF or LOLP indices in customer interruption cost. According to the authors of this paper, the customer interruption cost is determined not only by the amount of energy that is not supplied, but also by the frequency with which the interruption occurs. Furthermore, the research in this paper assigns a higher penalty to the frequency of interruption (for LOLF) than to EENS.

In this study, the EENS interruption cost is assumed to be $50/kWh, and the LOLF interruption cost is assumed to be $ 10,000 for LOLF in the 10,000 to 11,000 range, $ 9000 for LOLF in the 9000 to 10,000 range, and $ 1000 for LOLF in the 1000 to 2000 range. This can also be

Table 2
Cost of reliability improvement and total investment cost.

MG reliability (%)	LOLP reduction needed (%)	LOLF reduction needed (%)	Required Capacity Expansion					Cost of Reliability Improvement ($M)	Total investment cost ($M)
			PV (MW)	WT (MW)	BESS (MWh)	DR (Steps)	FR (Steps)		
95.7	2	4380	0	0	2	0	0	1	46.00
96.2	2.5	5475	0	0	5	0	0	2.5	47.50
96.7	3	6570	0	0	6	2	0	4.1	49.10
97.2	3.5	7665	0	0	7	6	0	6.8	51.80
97.7	4	8760	0	1	9	9	0	10.95	55.95
98.2	4.5	9855	0	5	9	9	0	16.95	61.95
98.7	5	10950	0	3	9	9	4	23.85	68.85
99.2	5.5	12045	0	4	9	9	6	30.52	75.52

expressed as AUS$50 per kW of EENS, assuming a penalty factor of $1000 for every 1000 LOLF increments. For example, if an SMG system has a LOLF of 10,100 and an EENS of 2000 kW (over a 25-year operating lifespan), the CCI is $110,000: $100,000 ($50/kWh of EENS) plus $10,000 (penalty for having LOLF in the range of 10,000 to 11,000).

An equation is evaluated to represents the reduction in EENS (EENSR) as a function of reduction in LOLF (LOLR).

$$EENSR = 1002 + 2.9167*LOLR \tag{17}$$

The linear relationship between EENSR and LOLR is depicted in Equation (17). This linear equation aids in calculating the EENSR for a given LOLR.

Table 3 depicts the total customer interruption cost for various SMG system reliability levels. It can be seen that the total interruption cost is M$ 67.74 when the SMG reliability level is 95.7 %. This often indicates that if the SMG provider decides to operate the SMG at this level of reliability, a poor level of reliability, they must pay this amount of total customer interruption cost to various consumers.

Fig. 7 depicts the customer interruption cost for various SMG system reliability levels. The equation is identified using the curve fitting technique, with R squared equal to one. The R square value indicates how many data points fit the equation, and in this case, the equation fits nearly all of them.

5.3. Evaluation of total cost of various reliability levels

The total cost of an SMG system is the sum of the total investment cost (including O&M) and the total customer interruption cost associated with the specific reliability level. Table 4 illustrates the total cost of SMG system.

The total cost curve is shown in Fig. 8. With a R square value of 0.99, the equation is identified using the curve fitting technique. The equation fits 99.97 % of the data points in this scenario.

5.4. Evaluation of Cost-effective reliability level

The cost-effective reliability level is found when the total cost is the lowest. As a result, the problem of determining the CERL is reduced to minimising the total cost curve. Fig. 9 depicts the investment cost, customer interruption cost, and total cost for various reliability levels.

Fig. 9 shows that the minimum total cost value appears between the two highlighted data points. Among these, the reliability level with the total cost of M$70.8 has a higher customer interruption cost of M$8.9, compared to the other reliability level with the total cost of M$72.5; however, the investment cost values showed an opposite trend. This demonstrates that the calculated CERL should have the lowest total cost, which is the sum of the investment cost and the cost of customer disruption.

Using MATLAB solver, the equation for the total cost is evaluated. Equation (18) represents the total cost for various levels of reliability. With a R square value of 0.9997, the equation is identified using the curve fitting technique. In this case, the R square value indicates how many data points fit the equation, and the equation fits 99.97 % of the data points. The minimum value of this equation is identified as 98.25 % using the MATLAB solver. As a result, the SMG system's optimal reliability is 98.25.

$$y = 6.644x^2 - 1305.6x + 64211 \tag{18}$$

5.5. Evaluating investment cost and customer interruption cost for the cost-effective reliability level

The CERL is determined to be 98.25 %. The incremental investment

Table 3
Required RI alternative addition and total investment cost.

MG reliability (%)	LOLF	Interruption cost due to LOLF (M$)	EENS (kWh)	Interruption cost due to EENS (M$)	Total interruption cost (M$)
95.7	8323	66.58	23,133	1.16	67.74
96.2	7228	50.60	19939	1.00	51.59
96.7	6133	36.80	16745	0.84	37.64
97.2	5038	25.19	13551	0.68	25.87
97.7	3943	15.77	10358	0.52	16.29
98.2	2848	8.54	7164	0.36	8.90
98.7	1753	3.51	3970	0.20	3.70
99.2	658	0.66	776	0.04	0.70

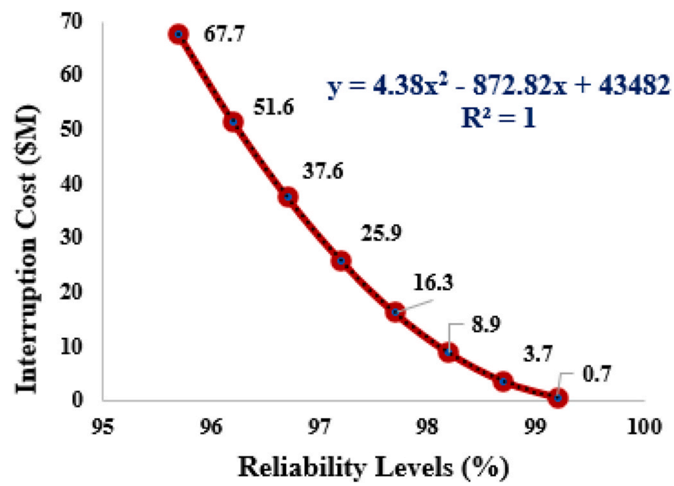

Fig. 7. Customer interruption cost for various reliability levels.

Table 4
Total cost for various reliability levels.

MG reliability (%)	Total investment cost (Million Dollars)	Total interruption cost (Million Dollars)	Total cost (Million Dollars)
95.7	46.00	67.74	113.74
96.2	47.50	51.59	99.09
96.7	49.10	37.64	86.74
97.2	51.80	25.87	77.67
97.7	55.95	16.29	72.24
98.2	61.95	8.90	70.85
98.7	68.85	3.70	72.55
99.2	75.52	0.70	76.22

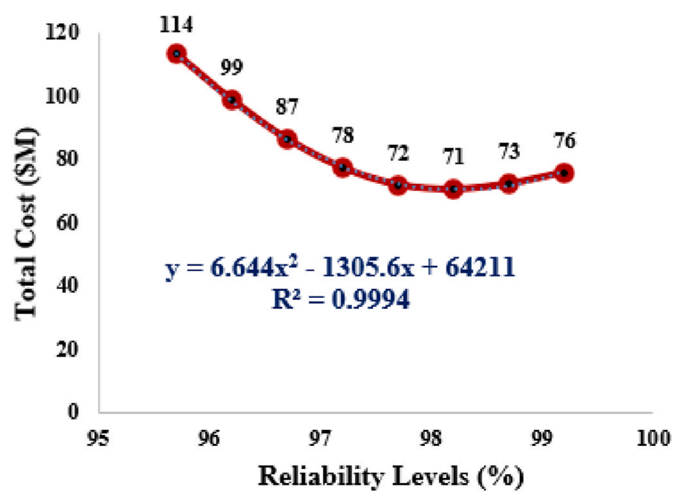

Fig. 8. Total cost for various reliability levels.

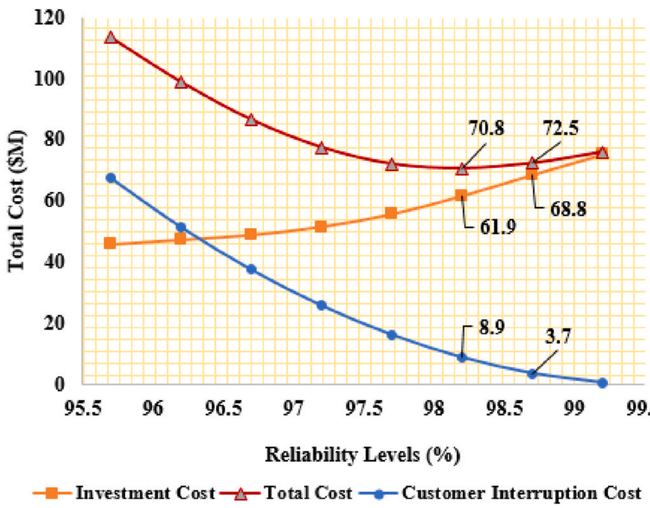

Fig. 9. Investment, customer interruption and total cost for various reliability level.

cost is calculated using Equation (19).

$$IC = 2.264^*R^2 - 432.78^*R + 20728 \tag{19}$$

Where IC is the investment cost and R is the SMG system's reliability level. The investment cost IC in terms of reliability level R is represented by Equation (19). This equation is derived from Fig. 3's investment cost curve by curve fitting technique. Similarly, the cost of customer interruption is calculated using the customer cost curve. Equation (20) depicts the cost of customer interruption as a function of reliability levels. The customer interruption cost curve in Fig. 4 is used to derive this equation.

$$CIC = 4.38^*R^2 - 872.82^*R + 43482 \tag{20}$$

Where CIC is the customer interruption cost and R is the SMG system's reliability level.

The investment cost for the CERL is calculated as 22.94 million AUS$ using Equation (19). Similarly, using Equation (20), the cost of customer disruption is calculated to be $7.02 million AUS$. Thus, the research result can be summarised as follows: the cost-effective reliability of this chosen SMG system is 98.25 %, with a total cost of $70.75M. This result will assist SMG operators in determining what level of reliability should be maintained. This SMG operator will maintain a reliability of 98.25 %.

The identification of CERL is crucial for SMG to minimize its total cost. In this case, if SMG operates at 98.25 % level the total cost will be minimum at $70.75M. If the SMG operate either higher reliability level or lower reliability level the total cost will be higher than $70.75M. Therefore, this finding helps SMG provider to minimize the total cost of the system.

5.6. Sensitivity analysis

The proposed method is tested under a variety of conditions, including changes in investment cost and changes in CCI.

5.6.1. Changes in investment cost

To investigate the algorithm's response to price changes, the investment costs of PV and WT are swapped, as are the investment costs of DR and the cost incurred for MG network equipment failure rate reduction. This is to generate a scenario in which the investment costs differ from the original values. Table 5 displays the investment cost summary that has been assigned for the sensitivity analysis.

Table 6 displays alternative decisions for increasing installed capacity (reliability improvement choices) in order to achieve various targeted reliability levels while minimising cost.

The total cost equation is evaluated using the MATLAB solver. Equation (21) represents the total cost for various levels of reliability.

$$y = 5.6638x^2 - 1118.6x + 55289 \tag{21}$$

This curve fitting is accomplished with a R square of 0.9985. The minimum value of this equation is identified as 98.75 % using the MATLAB solver. As a result, the CERL of the SMG system is 98.75 %, with a total cost of $58.15M. It can be seen that the CERL is increased to 98.75 % from 98.25 % in the base case, while the total cost is reduced to $58.15M from $70.75M in the base case. The most obvious reason for this outcome is that the WT resource's reliability contribution is greater than that of the PV resource. When the cost values of PV and WT are swapped, the WT becomes the less expensive energy resource that contributes more (in comparison to PV) to reliability improvement. Despite the fact that the cost of DR is high in this sensitivity analysis, the overall cost of reliability improvement is lower. This means that the DR's influence is obscured by the low-cost WT's influence.

5.6.2. Changes in cost of customer interruption

The CCI varies according to the customer sector. As a result, in order to assess the CERL in the presence of various customer sectors, the aggregated load demand calculated in this study is: residential; small business; large business; and a combination of all of these sectors. The Australian Energy Market Commission's CCI [49] is used for this analysis.

Table 7 summarises the cost of EENS and LOLF for a 1-h interruption. These sectors are classified so that the small business customer sector consumes less than 160 MWh per year and the large business customer sector consumes more than 160 MWh per year.

Fig. 10 shows the CCI for various customer sectors during a 1-h interruption. In comparison to the other two sectors, the residential sector has the lowest CCI.

The proposed procedure was used to evaluate the CERL of each customer sector using these customer interruption costs. Because this study uses hourly aggregated load demand and hourly availability of resources and equipment, interruptions that last longer than 1 h (and have a higher CCI value) cannot be evaluated. This study's proposed algorithm with MCS approach is only designed to detect 1-h interruptions.

Table 8 illustrates the CERL for various customer sectors. It can be noted that the large business sector has a high CERL with 98.60 %, meanwhile the lowest CERL observed in the residential sector. This is associated to the fact that the residential sector has a low CCI in contrast to other sectors.

Fig. 11 depicts the CERL for various customer sectors. The large business sector stands out with a CERL of 98.6 %. This is due to the high customer interruption cost of this sector in comparison to other sectors.

5.6.3. Changes in proportion of the customer sectors

To assess the impact of each customer sector on the CERL outcome, the customer sectors are assumed to be in varying proportions, as shown in Table 9.

Table 9 shows that when a greater proportion of the Large Business customer sector is included in the load demand, the total cost rises. The

Table 5
Investment cost summary for the sensitivity analysis.

	Investment cost of 1 MW of PV ($)	Investment cost of 1 MW of WT (Million $)	Investment cost of BESS (M$)	Investment cost of 100 kW of DR (M$)	Investment reduction of 0.01 failure rate (M$)
Total cost	1.5	1	0.5	2.5	0.55

Table 6
Require RI alternative addition and total investment cost.

MG reliability (%)	LOLP reduction needed (%)	LOLF reduction needed (%)	Required capacity expansion (MW)					Total investment cost (M$)	Total investment cost (M$)
			PV	WT	BESS	DR	FR		
95.7	2	4380	0	0	2	0	0	1	46.00
96.2	2.5	5475	0	0	5	0	0	2.5	47.50
96.7	3	6570	0	0	4	0	3	3.65	48.65
97.2	3.5	7665	0	0	4	0	6	5.09	50.09
97.7	4	8760	0	0	4	0	8	6.67	51.67
98.2	4.5	9855	0	5	8	0	8	8.84	53.84
98.7	5	10950	0	9	9	0	9	12.31	57.31
99.2	5.5	12045	0	8	9	3	9	18.34	63.34

Table 7
Total cost incurred by different customer sectors due to a 1 hour supply interruption.

	Residential	Small Business	Large Business
Cost of EENS ($/kWh)	20.71	413.12	53.30
Cost of LOLF ($/event)	14	4716	6084

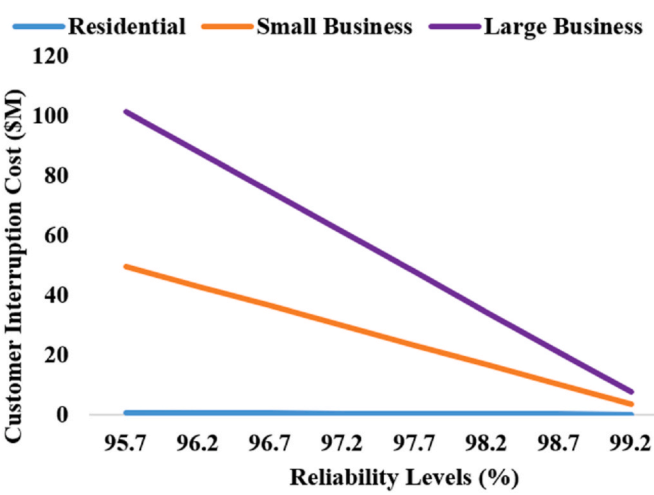

Fig. 10. Cost of customer interruption of various customer sectors, for 1-h interruption.

Table 8
Cost-effective reliability level for various customer sectors.

Customer Sectors	Cost-effective Reliability Level (%)	Total Cost (M$)
Residential	95.61	46.49
Small Business	98.44	77.51
Large Business	98.60	78.55
Combined Sector	97.55	71.44

CERL, on the other hand, shows only a minor difference (less than 1 %).

6. Conclusion

The cost-effective reliability level of a SMS was evaluated in this study using the technique of identifying the minimum total cost, which is the sum of investment cost, operation and maintenance cost, and customer interruption cost. The failure analysis of hybrid renewable energy SMG systems included the availability of equipment and energy resources. Linear regression was used to develop an equation that represents the LOLR of resource mix as a function of LOLR due to individual energy resource. To achieve the required reduction in LOLP, the

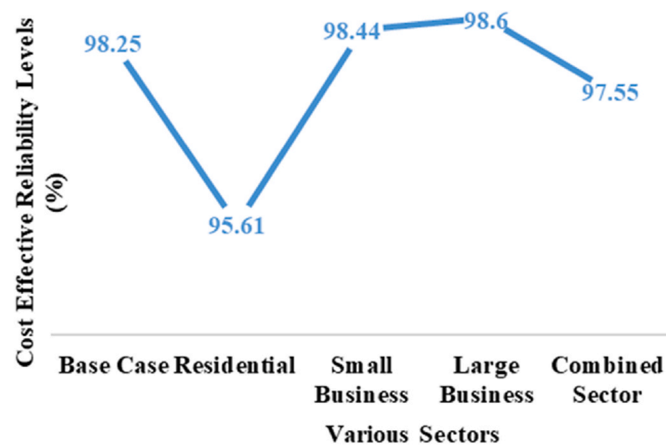

Fig. 11. Cost-effective Reliability Level of various customer sectors, for 1-h interruption.

Table 9
Various proportion of customer sector and cost-effective reliability levels.

Cases	Proportion of Customer sectors	Cost-Effective Reliability level (%)	Total Cost (M$)
1	50 % of Residential, 25 % of Small Business and 25 % of Large Business	97.07	67.53
2	50 % of Small Business, 25 % of Residential and 25 % of Large Business	97.77	73.78
3	50 % of Large Business, 25 % of Small Business and 25 % of Residential	97.81	74.18

MATLAB integer linear programming tool was used to find the lowest cost weighted alternative. Curve fitting technique was used for determining the equation for various curves, such as the investment cost curve, customer interruption cost curve, and total cost curve. To find the total cost and reliability level values from the lowest point in the total cost curve, the MATLAB solver is used.

The cost-effective reliability level was determined to be 98.25 %. This research suggests that the SMG supplier operate the SMG at 98.25 % reliability to minimize total cost. In other words, operating SMG at any other reliability level than 98.25 % will result in a higher total cost to the SMG supplier. This higher total cost is due to higher customer interruption costs if the SMG operated at a reliability level less than 98. 25 %. This high overall cost is due to the higher investment cost if the SMG operated at a reliability level greater than 98. 25 %.

The cost-effective reliability level is evaluated in the sensitivity analysis by modelling changes in investment cost. Similarly, the cost-effective reliability level is assessed by considering various customer sectors and the associated customer interruption cost. Because of the high cost of customer interruption in this sector, the total cost rises when a greater proportion of the Large Business customer sector is included in the load demand. The CERL, on the other hand, shows only a minor difference (less than 1 %). This finding helps SMG provider how to manage the reliability levels when load demand from a particular customer sector suddenly increased or when a greater number of customers from a particular customer sector added into the SMG network. To summarise, the SMG provider should do a comparable analysis as described in this sensitivity analysis to assess the SMG's adaptability to variations in load demand. This sensitivity analysis should be carried out by simulating changes in load demand from each sector. Furthermore, translating the sensitivity analysis results into SMG operating procedures in terms of maintaining reliability level would allow SMG to operate continuously at the lowest total cost. This means that when load changes occur, the SMG provider is aware of the new cost-effective reliability level that should be maintained.

The goal of this research problem is to minimize the total cost and calculate the corresponding reliability level, which is CERL, at this minimum total cost. The CERL is a useful metric for SMG providers to determine which specific reliability level is the most cost-effective for the SMG system. Thus, operating SMG at this CERL will benefit SMG providers economically. Furthermore, this study provides a framework for evaluating investment and EENS costs at the CERL. Future research could investigate the impact of unexpected changes in customer demand, climate change, and price changes in equipment like solar panels on CERL. This means that when SMG system planned to operate at CERL, it should investigate what factors caused CERL to change to a new value.

CRediT authorship contribution statement

Nallainathan Sakthivelnathan: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Ali Arefi:** Writing – review & editing, Visualization, Supervision, Methodology. **Christopher Lund:** Writing – review & editing, Visualization, Validation, Supervision. **Ali Mehrizi-Sani:** Writing – review & editing, Visualization, Supervision. **S. M. Muyeen:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

S.M.Muyeen reports article publishing charges was provided by Qatar University. S.M. Muyeen reports a relationship with Qatar University that includes: employment. No relationship to be disclosed.

Data availability

Data will be made available on request.

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